OPTIMIZATION OF THE ISSUANCE OF EVACUATION ORDERS UNDER EVOLVING HURRICANE CONDITIONS

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Wenqi Yi

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Wenqi Yi, Ph. D.

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This dissertation develops a scenario-based bi-level programming model to optimize the issuance of evacuation orders with explicit consideration of (i) the highly uncertain evolution of the storm, and (ii) the complexity of the behavioral reaction to those storm conditions. A solution procedure based on progressive hedging is developed. A realistic case study for the eastern portion of the state of North Carolina is presented. Through the case study we demonstrate (1) the richness in the insights that can be provided by linking the behavioral models for evacuation decision-making with transportation network flow models, (2) the value of developing a contingent evacuation order policy based on the evolution of the storm in contrast to a static policy, and (3) the computational promise of a progressive hedging based solution procedure to solve large instances of the model.

BIOGRAPHIC SKETCH

Wenqi Yi was born and grew up in Chengdu, China. She holds a Bachelor of Engineering in Environmental Engineering from Sichuan University, Chengdu, and a Master of Engineering in Water Resource Systems from Cornell University. Her doctoral studies focus on Civil Infrastructure Systems.

To my family and friends

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CHAPTER 1

INTRODUCTION

Hurricanes are an incredibly powerful force causing powerful winds and deep storm surge risking many millions of lives and billions of dollars in property. Forecasters use a collection of computational models to estimate how a storm will evolve over time. However, these estimates are subject to substantial uncertainty. Hence the task of deciding who should receive an evacuation order and when is very difficult. If the decision is postponed too long, evacuees may encounter hazardous conditions as they evacuate. New York City issued evacuation orders about 8 hours before the Subway System was shut down (Wall Street Journal October 28, 2012) and NYU Medical Center was evacuated after the power failed in Hurricane Sandy. Conversely if the decision is made prematurely many people will leave and encounter more risk in the evacuation than had they remained at home. This occurred in Hurricane Floyd (1999). More than 2.5 million people from Florida to Virginia evacuated, many unnecessarily and at great expense (Dow and Cutter, 2002).

Further, people do not necessarily comply with evacuation orders. In Tropical Storm Irene about 60% of those ordered to evacuate actually did evacuate. In Hurricane Sandy, in New York and New Jersey, in areas that received an evacuation order, about 70% of people did not evacuate (Worrall, 2014). It is also true that individuals may evacuate when no evacuation order is issued. Shadow evacuation can cause substantial congestion, making it difficult for those that need to evacuate to get out of harm's way.

This dissertation proposes a scenario-based model to optimize the issuance of evacuation orders that explicitly incorporates the uncertainty in storm evolution and resolves the dilemma between waiting too long to issue evacuation orders and issuing them too early. Further, rather than assume that individuals will comply with an order or that individuals will not evacuate if no order is issued, the proposed model relies on discrete choice models to estimate who will evacuate at what time, and for those that do evacuate, where they will evacuate to.

The model structure adopted is that of a bi-level programming problem or a Stackleburg leader-follower game in game theory, where the leader (upper level decision maker) is the government deciding when and where to issue orders and the follower (lower level decision maker) is the set of residents in the study area. The decisions made by the residents are if and when to evacuate; and if they are to evacuate, where to go and what route to choose. In this dissertation we assume that the traffic flow that is generated by the residents can be described by dynamic user equilibrium. That is each resident chooses the route that dynamically minimizes their travel time.

This dissertation makes two key contributions. First, this is the first dissertation, to the best or our knowledge, which uses multistage stochastic programming to optimize the issuance of evacuation orders. Second, this dissertation integrates a discrete choice model with that stochastic program to more accurately represent the human dimension to the evacuation decision. Hence this dissertation attempts to bridge the literature focused on the “demand” side of evacuation and the “supply” side of evacuation where the demand side is the human dimension and the supply side is the use of the

transportation infrastructure. The applicability and the efficacy of the model and solution procedure are demonstrated on a large-scale real world case study for the Eastern portion of North Carolina. The problem contains 50,000 origin-destinations pairs, 10,000 directed network links, 22 hurricane scenarios and 22 decision times yielding 226,000 binary variables representing opportunities to issue evacuation orders.

The remainder of this dissertation is organized into five chapters. The second chapter gives an overview of the related literature. The third chapter gives the model formulation. The fourth chapter gives the solution procedure. The fifth chapter gives the case study. The sixth chapter gives conclusions and opportunities for further research.

CHAPTER 2

LITERATURE REVIEW

The literature on hurricane evacuation behavior has seen a great surge in activity since Hurricane Katrina and Rita in 2005. Those evacuations illustrated the failure and tragic consequence of under-evacuation and over-evacuation, respectively. This leads to a renewed research activity focused on understanding evacuation behavior and forecasting evacuation demand accordingly. Extensive reviews can be found in Dash and Gladwin (2007), Lindell (2013), Murray-Tuite and Wolshon (2013), and Yazici and Ozbay (2008). The recent literature provides quantitative characterization of evacuation behavior, mostly by fitting statistical models based on survey data, assuming random utility maximization (e.g. Hasan et al., 2012, 2011; Huang et al., 2012; Lazo et al., 2010; Mesa-arango et al., 2013; Murray-Tuite et al., 2012; Ng et al., 2015; Petrolia and Bhattacharjee, 2010; Sadri et al., 2014; Whitehead, 2005). A majority of these models were developed for explaining the main factors that influence people's evacuation decision, but most formulations are not readily implementable to be integrated with a network traffic model due to the lack of supporting data for the explanatory variables. Wilmot and colleagues conducted the few studies that explicitly aim at predicting evacuation demand over time (e.g. Cheng et al., 2008; Fu and Wilmot, 2006, 2004; Gudishala and Wilmot, 2013, 2012; Wilmot and Mei, 2004). More recently, Xu et al. (2016) proposed a promising alternative forecasting model with the same focus.

There is a vast array of literature focused on the development of optimization and simulation models to support evacuation related decision making. For example, contraflow and lane-based routing is explored in Cova and Johnson(2003), Dixit et al.(2008), Lim and Wolshon (2005), Meng and Khoo (2008), Meng et al. (2008), Shekhar and Min (2008), Theodoulou and Wolshon (2004), Tuydes and Ziliaskopoulos (2006), Williams et al. (2007), and Xie and Turnquist (2011). Public transit is explored in Hana and Wolshon (2011), He et al. (2009), Naghawi and Wolshon (2010), Sayyady and Eksioglu (2010), Song et al. (2009), and Udenta et al. (2013), and location of shelters and other resources in Bayram et al. (2015), Kongsomsaksakul et al. (2005), Kulshrestha et al. (2011), L. Zhen et al. (2015), Li et al. (2011, 2012), Ng et al. (2010), Sherali et al. (1991), Sheu and Pan (2014), Ukkusuri and Ouyang (2015) and Yazici and Ozbay (2007).

Chen and Zhan (2004) is among the earliest studies that explored staged evacuation by encoding and enumerating alternative strategies as sequences of zones to evacuate. They assume everyone will receive an order and they will evacuate when that order is received. The behavioral focus is on the driver behavior element of the evacuation modeling. Sbayti and Mahmassani (2006) extend elements of Chen and Zhan (2004) to larger areas and look at optimizing when people should leave, where they should go and what path to take so as to minimize total system evacuation time. It is important to notice that everyone is assumed to evacuate and the sole decision is how to spread that evacuation demand over time so as to minimize network clearance time. Bish and Sherali (2013) develop a modeling framework that includes high level decisions of when to initiate evacuation of a zone and uses a loading curve (departure curve) to

spread out the evacuation from a zone over time. They use a cell transmission model (Daganzo, 1995, 1994) to represent the traffic flow.

Apivatanagul et al., (2011) integrates the decisions of who should leave and who should shelter in place so as to optimize the trade-off between total risk, total travel time and total time away from home from a societal perspective. They also explicitly include uncertainty in the storm evolution but require all of the decisions to be made prior to any resolution of the uncertainty associated with the storm evolution.

This dissertation also draws as inspiration from Zhang et al. (2014) and Wolshon et al. (2015), both of which use TRANSIMS to evaluate an evacuation plan under different threat conditions along the Gulf Coast. They explicitly use a discrete choice model to describe the behavior of individuals and test the implications of different decisions as to which geographic areas to give orders and when.

As stated previously, we focus on the issuance of aggregate orders (as in Bish and Sherali, 2013, Chen and Zhan, 2004, Wolshon et al., 2015 and Zhang et al., 2014) and the explicit incorporation of the rich behavioral modeling developed in a number of papers so as to represent compliance and noncompliance with evacuation orders including shadow evacuation. We also integrate the concept of optimizing the issuance of orders to achieve region-wide risk reduction and to control congestion as developed in Apivatanagul et al. (2011). Further, we explicitly include a probabilistic representation of the evolution of the storm yielding a multi-stage stochastic program (MSP). Finally, we assume dynamic user equilibrium (DTA) as the governing principle for route selection on the highway system. The remainder of this literature

review focuses on stochastic programming and progressive hedging as a viable solution strategy.

Birge and Louveaux (2011) provides a detailed introduction to MSP. As a special case, two-stage stochastic program (TSP) assumes all decisions are made in the first stage before any uncertainty is realized. Complexity explodes in the number of stages when this single-shot assumption is relaxed. Some examples of TSP applied to disaster management are An et al. (2015), Apivatanagul et al. (2011), Li et al. (2011), Li et al. (2012), and Prentiss (2014). Faturechi and Miller-Hooks (2014) implements the MSP formulation that include mitigation, preparedness and response stages, where evacuation, corresponding to preparedness, is treated as a single stage. To the best of our knowledge, multistage formulation has never been attempted in the modeling of hurricane evacuation. Under a MSP framework, we use sequences of binary integers to represent the sequential evacuation order decisions in the evacuation demand models integrated with the DTA model. This gives rise to a multistage stochastic integer program (MSIP).

The progressive hedging (PH) framework developed in Rockafellar and Wets (1991) is adapted to construct our solution procedure to MSIP. The PH framework was originally devised for problems with continuous variables such as Mulvey and Vladimirou (1991a, 1991b, 1989), but has been extended to problems with integer variables in numerous cases such as Haugen et al. (2001), Lokketangen (1996) and Watson and Woodruff (2010). The key feature of PH that accommodates this flexibility is decomposition by scenario, where the solution procedure for the scenario sub-problems can be tailored to characteristics of the specific problem. Given some

sub-problem procedure, PH procedure has been shown to produce at least a local optimal solution as long as it does converge (Rockafellar and Wets, 1991), even if the problem is nonconvex, as is the case with the model developed in this dissertation.

CHAPTER 3

MODEL FORMULATION

The structure of the evacuation planning problem is shown in *Figure 1*. The upper level multistage stochastic program optimizes the timing of the issuance of evacuation orders and the locations of those orders across an ensemble of scenarios. The results of that model produces a contingent evacuation policy. The lower level model evaluates the costs and risks of such a policy through 1) an evacuee behavioral model that forecasts dynamic origin-destination (OD) tables for each scenario given the evacuation order policy, assuming random utility maximization on the part of the residents, and 2) user equilibrium-based dynamic traffic assignment (DTA) that solves for the paths and travel times of each evacuation trip.

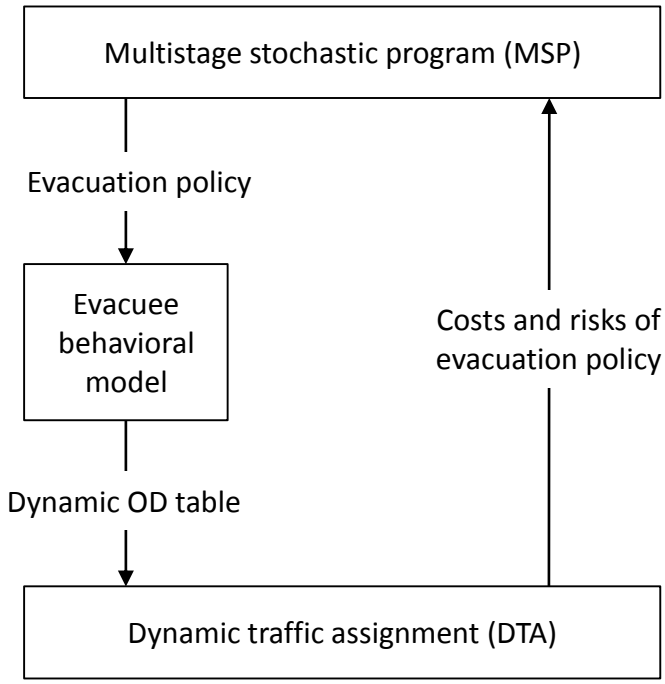

Figure 1 Schematic of the formulation of evacuation planning problem

Suppose the planning horizon is divided into a finite number of time periods, $t = 1, \dots, T$. Those periods are assumed to coincide with the time periods for which the emergency management authorities make decisions of whether to issue evacuation orders and for which the uncertainty associated with the storm progression is resolved. The region of interest for potential evacuation is divided into a finite number of zones, $z = 1, \dots, Z$, which also delineate the traffic analysis zones where evacuation trips originate for the lower level DTA. In particular, we consider a network representation given by the graph $G = (N, A)$, where N is the set of directed links and A is the set of nodes. The links are roadway links and the nodes are origins and destinations of evacuation trips and road intersections.

In the remainder of this section, the representation of the underlying uncertainties is first given, followed by the definition of the decision variables and the key constraint of nonanticipativity. We then describe the objectives considered.

3.1 Uncertainty representation

The uncertainties in the evolution of a storm are represented by a finite number of scenarios, each of which is associated with a probability of occurrence, p_s. At each time period t, the set of all scenarios is partitioned by grouping the scenarios that are "observationally indistinguishable" (Rockafellar and Wets, 1991) from one another into disjoint sets, this yields the partition, for each time period t,

$$\begin{aligned}\mathcal{A}_t = \{A_t | s \text{ and } s' \text{ are indistinguishable at } t \\ \text{if and only if } s \in A_t \text{ and } s' \in A_t\}.\end{aligned} \tag{1}$$

We assume that scenarios always become more or at least no less distinguishable from an earlier time period to a later time period, which reflects that we expect to gain more or at least no less information about a storm as it evolves. We further assert, by borrowing the argument in Rockafellar and Wets (1991), that for most purposes it would be reasonable to suppose that at each time period t 1) the partition $\mathcal{A}_t$ is more or at least no less refined than $\mathcal{A}_{t-1}$, and 2) that each disjoint set is a union of one or more disjoint sets at the subsequent time period, which can be expressed as

$$\text{If } A_{t-1} \in \mathcal{A}_{t-1} \text{ then } \exists A_t \in \mathcal{A}_t \text{ such that } A_t \subset A_{t-1}. \tag{2}$$

The latter assertion gives rise to a tree-like structure if we think of each set of indistinguishable scenarios as a node that branches into one or more disjoint sets in the subsequent time period as they become more distinguishable.

3.2 Decision variables

We assume the decision maker has the ability to issue evacuation orders to each individual zone at a collection of different time periods. The decision on the contingent evacuation policy, when and to where to issue evacuation orders as the uncertainty about storm scenarios resolves, is represented by a matrix $\boldsymbol{w}$ with the components $(w_1, \dots, w_S)$, where for each scenario $s = 1, \dots, S$, w_s is a binary matrix that represents the evacuation plan under scenario s and is composed of entries

$$w_{s,t,z} = \begin{cases} 1, & \text{If an order is given for the first time in zone } z \\ & \quad \text{in time period } t \text{ under scenario } s \\ 0, & \text{Otherwise} \end{cases}$$

for time period $t = 1, \dots, T$ and zone $z = 1, \dots, Z$.

We also define the variable $x_{s,t,z}$ to indicate whether zone z under scenario s at time period t is under an evacuation order. More formally, $x_{s,t,z}$ is defined as follows:

$$x_{s,t,z} = \begin{cases} 1, & \text{If an order is or has been given in zone } z \\ & \quad \text{in time period } t \text{ under scenario } s \\ 0, & \text{Otherwise} \end{cases}$$

for time period $t = 1, \dots, T$, zone $z = 1, \dots, Z$, and scenario $s = 1, \dots, S$. Let $\boldsymbol{x}$ denote the matrix composed of S components, each of which is the binary matrix that represents the evacuation plan under scenario s and is composed of entries $x_{s,t,z}$. Constraint (3) maintains the relationships between the variables $w_{s,t,z}$ and $x_{s,t,z}$.

$$x_{s,t,z} = \sum_{\tau \leq t} w_{s,\tau,z} \quad \forall t. \tag{3}$$

3.3 Nonancticipativity constraint

For all the time periods, t, in which any two scenarios are indistinguishable (i.e. belong to the same set A_t) the evacuation decisions, $x_{s,t,z}$ must be the same. Equation (4) imposes this restriction.

$$x_{s,t,z} = x_{s',t,z} \;\; \forall s, s' \in A_t, \forall t, \forall z. \tag{4}$$

3.4 Objectives

The objective function of the upper-level multistage stochastic program is

$$\min_{\boldsymbol{x}} F(\boldsymbol{x}), \tag{5}$$

where the overall objective function $F(\boldsymbol{x})$ is the weighted sum of the objective functions of scenario sub-problems

$$F(\boldsymbol{x}) = \sum_{s=1}^{S} p_s f_s(x_s), \tag{6}$$

The objective function for each scenario sub-problem is the weighted sum of the evaluation function of four objectives

$$f_s(x_s) = \sum_{i=1}^{4} h_i v_{s,i}(x_s) \;\; \forall s. \tag{7}$$

The evaluation functions, $v_{s,i}(x_s)$, are as follows: 1) total travel time, 2) total travel risk, 3) total time away from home, and 4) total risk of sheltering-at-home. These are

the same objectives considered in (Apivatanagul et al., 2011). Their formulation is described in *3.4.1* through *3.4.3*.

3.4.1 Evacuee behavior

Given an evacuation policy, we can obtain a contingent dynamic OD matrix by utilizing the discrete choice models for predicting household-level decisions of the time (Fu et al., 2006) and destination (Mesa-arango et al., 2013) of evacuation. Appendix A describes an implementation of the two aforementioned references with some modifications. Using those models, we define $q_{z,y,t}^{s,\tau}$ as the evacuation travel demand from origin zone z to destination y at time period t if an evacuation order is given at time period τ to zone z under scenario s where we allow τ to equal zero if no order is issued.

It is important to notice that conceptually, this input data to this model can be pre-computed for all possible choices of the time of evacuation order for each scenario. In practice, this computation can be done once the solution procedure tests the assignment of an evacuation order in a specific time period under a specific scenario. Once a storm is within 24 hours of landfall, no new orders are assumed to be issued. At this point the evacuation focus shifts to rescue. In reality, some people will still choose to leave. We do represent this continued evacuation but assume that they do not leave at this point under an evacuation order. Notice that since we know who is evacuating, we can also compute the number of people that stay at home in each zone based on if and when an order issued.

3.4.2 Dynamic traffic assignment

Let $Q_{z,y,t}^{s}$ be the number of trips from origin z to destination y at time period t under scenario s obtained from input data $q_{z,y,t}^{s,\tau}$ and evacuation plan x_s. The paths and travel times of evacuees can be obtained by employing the solution procedure of (Li et al., 2013) for the lower-level DTA given the dynamic OD table $Q_{z,y,t}^{s}$. Generally, the time periods in the upper level model are substantially longer than in the lower level model. Hence, we uniformly assign the entries in the origin-destination table to the more refined time periods for the use of the DTA algorithm. In practice, the time periods in the upper level model are on the order of several hours whereas the time periods in the DTA algorithm are on the order of a few minutes.

Let k denote the lower-level time period, where $k = 1, \dots, K$, $\bar{Q}_{z,y,k}^{s}$ the number of trips assigned to time period k, and $b_{z,y,k}^{s}$ the travel time of the trip that leaves from origin z for destination y at time period k under scenario s. The objective function $v_{s,1}(\cdot)$, total travel time, is then defined as

$$v_{s,1}(x_s) = \sum_{z=1}^{Z}\sum_{y=1}^{Y}\sum_{k=1}^{K} b_{z,y,k}^{s}\bar{Q}_{z,y,k}^{s} \ \forall s. \tag{8}$$

And objective function $v_{s,3}(\cdot)$, the total time away from home, is defined as

$$v_{s,3}(x_s) = \sum_{z=1}^{Z}\sum_{y=1}^{Y}\sum_{k=1}^{K} (K-k)\bar{Q}_{z,y,k}^{s} \ \forall s. \tag{9}$$

3.4.3 Risk evaluation

The risk exposure of evacuees and people sheltering-at-home is evaluated using the risk functions as defined in Apivatanagul et al. (2011). Let $\gamma_{z,y,k}^{s}$ denote the risk of the trip that leaves from origin z for destination y at the lower level time period k under scenario s and η_{z}^{s} the risk of sheltering at home at zone z under scenario s. The objective function $v_{s,2}(\cdot)$, total travel risk is defined as

$$v_{s,2}(x_s) = \sum_{z=1}^{Z}\sum_{y=1}^{Y}\sum_{k=1}^{K}\gamma_{z,y,k}^{s}\bar{Q}_{z,y,k}^{s} \ \forall s. \tag{10}$$

And objective function $v_{s,4}(\cdot)$, the total risk of sheltering at home, is defined as

$$v_{s,4}(x_s) = \sum_{z=1}^{Z}\eta_{z}^{s}\left(\rho_z - \sum_{y=1}^{Y}\sum_{k=1}^{K}\bar{Q}_{z,y,k}^{s}\right) \forall s, \tag{11}$$

where ρ_z is the population of zone z.

CHAPTER 4

SOLUTION PROCEDURE

The problem given by (3)-(11) is solved by a heuristic procedure that leverages the concept of progressive hedging algorithm (PHA) (Rockafellar and Wets, 1991), which is in turn based on Lagrangian relaxation through decomposition by scenario and solution policy aggregation. Let r denote a penalty parameter, where $r > 0$. The augmented Lagrangian form of our optimization problem (5) is defined as

$$\min_{(x_1,\ldots,x_S)} \sum_{s=1}^{S} p_s \left(f_s(x_s) + \sum_{t=1}^{T} \sum_{z=1}^{Z} u_{s,t,z} x_{s,t,z} + \frac{1}{2} r \left(x_{s,t,z} - \hat{x}_{s,t,z} \right)^2 \right), \tag{12}$$

where $\hat{x}_{s,t,z}$ denotes the entries of the aggregated solution policy defined as

$$\hat{x}_{s,t,z} = \sum_{s \in A_t} p_s x_{s,t,z} \Big/ \sum_{s \in A_t} p_s \;\; \forall t, z, \forall s \in A_t, \forall A_t \in \mathcal{A}_t, \text{ and } \forall \mathcal{A}_t, \tag{13}$$

and $u_{s,t,z}$ is the multiplier such that

$$\left(\sum_{s \in A_t} p_s u_{s,t,z} \Big/ \sum_{s \in A_t} p_s \right) = 0 \;\; \forall t, z, \forall s \in A_t, \forall A_t \in \mathcal{A}_t, \text{ and } \forall \mathcal{A}_t. \tag{14}$$

Note that $\hat{x}_{s,t,z}$ satisfies the non-anticipativity constraint (4) while $u_{s,t,z}$ satisfies the complementarity condition $u_{s,t,z} \hat{x}_{s,t,z} = 0 \; \forall s, t, z$. At each iteration of PHA, problem (12) decomposes into the following sub-problem for each scenario s:

$$\min_{x_s} f_s(x_s) + \sum_{t=1}^{T} \sum_{z=1}^{Z} u_{s,t,z} x_{s,t,z} + \frac{1}{2} r \sum_{t=1}^{T} \sum_{z=1}^{Z} \left(x_{s,t,z} - \hat{x}_{s,t,z} \right)^2. \tag{15}$$

Problem (15) is solved separately for each scenario s by a search procedure through decomposition across zone z and then enumeration across time period t for each zone. Let x_s^v denote the evacuation plan solution for scenario s at iteration v of PHA, where $v = 0,1, \ldots$. Let $x_{s,t,z}^v$ denote the entries of x_s^v for zone z at time period t, and $u_{s,t,z}^v$ the Lagrangian multiplier. The solution procedure is described below in two parts as *Master Procedure* and *Subproblem Procedure*.

Master Procedure: Progressive hedging algorithm

Step 1. Initialize: $v = 0$, $u_{s,t,z}^0 = 0$, and $x_{s,t,z}^0 = 0$, $\forall s, t, z$.

Step 2. Increment iteration number: $v = v + 1$.

Step 3. Calculate the aggregated solution policy from $x_{s,t,z}^{v-1}$ by

$$\hat{x}_{s,t,z}^{v-1} = \sum_{s \in A_t} p_s x_{s,t,z}^{v-1} \Big/ \sum_{s \in A_t} p_s \quad \forall t, z, \forall s \in A_t, \forall A_t \in \mathcal{A}_t, \text{ and } \forall \mathcal{A}_t,$$

and update Lagrangian multipliers from $u_{s,t,z}^{v-1}$ to $u_{s,t,z}^v$ by

$$u_{s,t,z}^v = u_{s,t,z}^{v-1} + r\left(x_{s,t,z}^{v-1} - \hat{x}_{s,t,z}^{v-1}\right) \ \forall\, s, t, z.$$

Step 4. Obtain the new solution x_s^v by solving the following sub-problem for each scenario s using *Subproblem Procedure*:

$$x_s^v = \arg\min_{x_s} f_s(x_s) + \sum_{t=1}^{T} \sum_{z=1}^{Z} u_{s,t,z}^v x_{s,t,z} + \frac{1}{2} r \sum_{t=1}^{T} \sum_{z=1}^{Z} \left(x_{s,t,z} - \hat{x}_{s,t,z}^{v-1}\right)^2.$$

Step 5. Go to Step 2 unless one of following termination criteria is met:

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a. $v = V$, where V is the predetermined maximum number of iterations.

b. $\sum_{s=1}^{S} p_s \sum_{t=1}^{T} \sum_{z=1}^{Z} \left(x_{s,t,z}^{v} - \hat{x}_{s,t,z}^{v-1}\right)^2 < \varepsilon$, where ε is a predetermined error threshold.

c. $\sum_{z=1}^{Z} \delta_z^v < n$, where δ_z^v is defined as

$$\delta_z^v = \begin{cases} 1, & \text{If } \exists s, t \text{ such that } x_{s,t,z}^{v} \neq \hat{x}_{s,t,z}^{v} \\ 0, & \text{Otherwise.} \end{cases}$$

Then $\sum_{z=1}^{Z} \delta_z^v$ is the total number of zones which are assigned evacuation policy that violates the non-anticipativity constraint (4), and n is a predetermined integer threshold.

Subproblem Procedure: Search procedure for scenario sub-problem

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At iteration v for scenario s in Step 4 of *Master Procedure*:

Step 1. Calculate the dynamic OD table $\bar{Q}_{z,y,k}^{s,v-1}$ for scenario s given the evacuation plan x_s^{v-1}using evacuee behavioral models.

Step 2. Solve the lower-level DTA problem given by G and $\bar{Q}_{z,y,k}^{s,v-1}$ and obtain $c_{a,k}^{s,v-1}$, the travel time of link a in the lower level time period k.

Step 3. Solve the static shortest path problem given by G and $c_{a,k}^{s,v-1}$ for each $k = 1, \ldots, K$ and for each OD pair to obtain the path travel time $\beta_{z,y,k}^{s,v-1}$ and the risk of the path $\varphi_{z,y,k}^{s,v-1}$.

Step 4. Let $\bar{q}_{z,y,k}^{s,\tau}$ denote the number of trips assigned to the lower level time period k if an evacuation order is given at time period τ to zone z under scenario s, where we allow τ to equal $T+1$ if no order is issued.

a. For each $\tau = 1, \dots, T+1$, the contribution to the objective function of the scenario sub-problem from each zone z is calculated as

$$\tilde{f}_{s,z}^{v}(x_{s,z}) = \sum_{y=1}^{Y}\sum_{k=1}^{K} h_1 \beta_{z,y,k}^{s,v-1} \bar{q}_{z,y,k}^{s,\tau} + h_2 \varphi_{z,y,k}^{s,v-1} \bar{q}_{z,y,k}^{s,\tau}$$

$$+ h_3 (K-k) \bar{q}_{z,y,k}^{s,\tau} + h_4 \eta_z^s \left(\rho_z - \sum_{y=1}^{Y}\sum_{k=1}^{K} \bar{q}_{z,y,k}^{s,\tau} \right),$$

and the contribution to the augmented Lagrangian is then calculated as

$$\tilde{L}_{s,z}^{v}(x_{s,z}) = \tilde{f}_{s,z}^{v}(x_{s,z}) + \sum_{t=1}^{T} u_{s,t,z}^{v} x_{s,t,z} + \frac{1}{2} r \sum_{t=1}^{T} \left(x_{s,t,z} - \hat{x}_{s,t,z}^{v-1}\right)^2,$$

where $x_{s,z}$ denotes the evacuation order representation for zone z if an evacuation order is given at time period τ such that $x_{s,z} = (x_{s,1,z}, \dots, x_{s,T,z})$ and $\tau = T + 1 - \sum_{t=1}^{T} x_{s,t,z}$.

b. Solve $\min_{x_{s,z}} \tilde{L}_{s,z}^{v}(x_{s,z})$ by enumerating over time period $\tau = 1, \dots, T+1$ and assign the solution vector as the new evacuation order solution for zone $z = 1, \dots, Z$, as follows:

$$x_{s,z}^{v} = \arg\min_{x_{s,z}} \tilde{L}_{s,z}^{v}(x_{s,z}) \; \forall z,$$

which collectively forms the new evacuation plan solution for scenario s as $x_s^v = \left(x_{s,1}^v, \dots, x_{s,Z}^v\right)$.

Step 5. If there is another scenario sub-problem to solve, go to Step 1 of *Subproblem Procedure*. Otherwise, go to Step 5 of *Master Procedure*.

CHAPTER 5

CASE STUDY

We demonstrate the MSP model formulation and solution procedure on a case study of Eastern North Carolina, which is illustrated in *Figure 2*. There are about 470 zones in the study area (extending to include about half of Raleigh, NC) which are home to about 3 million residents. Census data from the year 2000 were used to populate the discrete choice models that are used to estimate who will evacuate, to where and when.

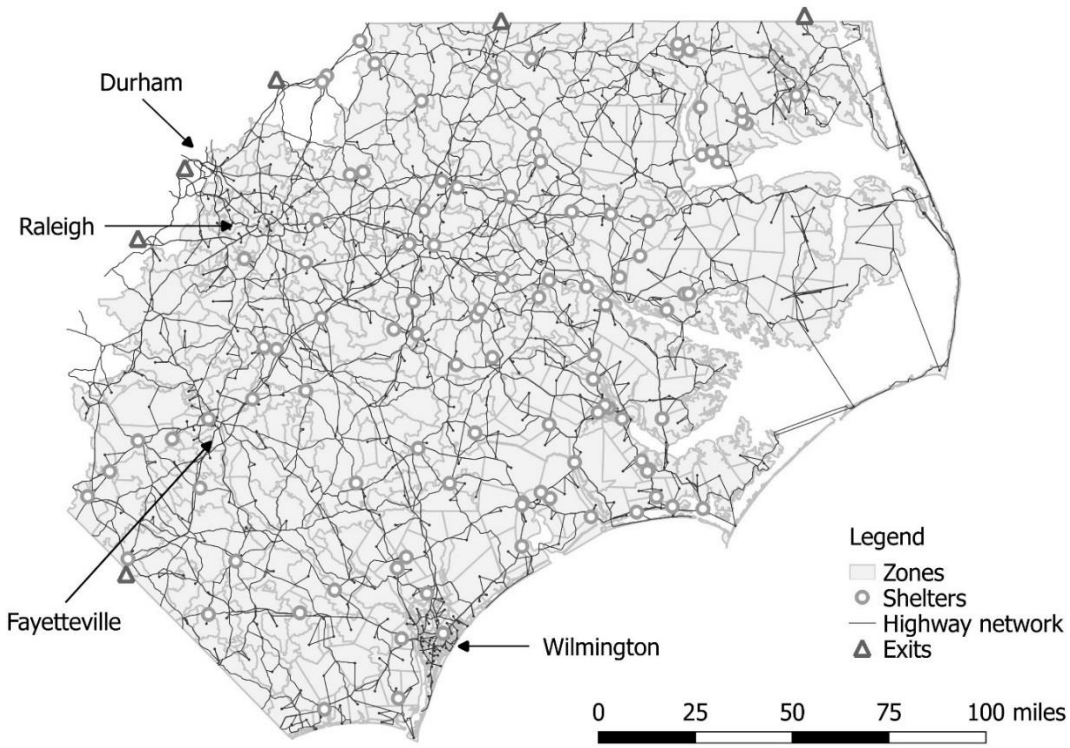


Figure 2 Zones, shelter Locations, highway network and exits

Figure 2 also illustrates the highway network in the study area, shelter locations and

exits from the study area. It has about 3,600 nodes and about 10,000 directed links. Evacuees either make use of one of the 100 Red Cross shelters located in the study area or simply evacuate the region via one of the exits at the boundary. While not illustrated, all 100 shelters are directly connected to a different dummy destination which serves as the ultimate destination for those evacuating to a Red Cross shelter; the trips evacuating to exists are evenly distributed among the six.

The planning horizon spans six and a half days, or 156 hours. Decision makers can issue evacuation orders during the first five and a half days. But no orders can be issued during the last 24 hours (which roughly coincides with landfall or the dissipation of the storm). This 156-hour planning horizon is divided into 26 six-hour time periods. At the beginning of each time period, the decision-makers obtain additional information about the storm and can issue additional orders. To more accurately represent traffic dynamics, the lower level DTA uses time increments of 15 minutes and the modeled time horizon extends to the network clearance time. The link travel time is estimated by the Bureau of Public Roads (BPR) formula $c_a(t) = c_a^0\left(1 + \alpha\left(\frac{\chi_a(t)}{\mathrm{X}_a}\right)^{\beta}\right)$ with parameter $\alpha = 0.15$ and $\beta = 4$.

To represent the underlying uncertainty, an ensemble of 22 hypothetical storm scenarios were generated using the meteorological model Weather and Research Forecasting (WRF) (Skamarock et al., 2005). A map of the storm tracks, along with the study area is shown in *Figure 3* below. Each scenario is assumed to have an equal probability of occurrence. The scenarios are grouped into disjoint sets at each time period using a clustering algorithm (Yang et al., 2016), which gives the scenario tree

that characterizes the progression of the storm and therefore the resolution of uncertainty, as illustrated in *Figure 4*.

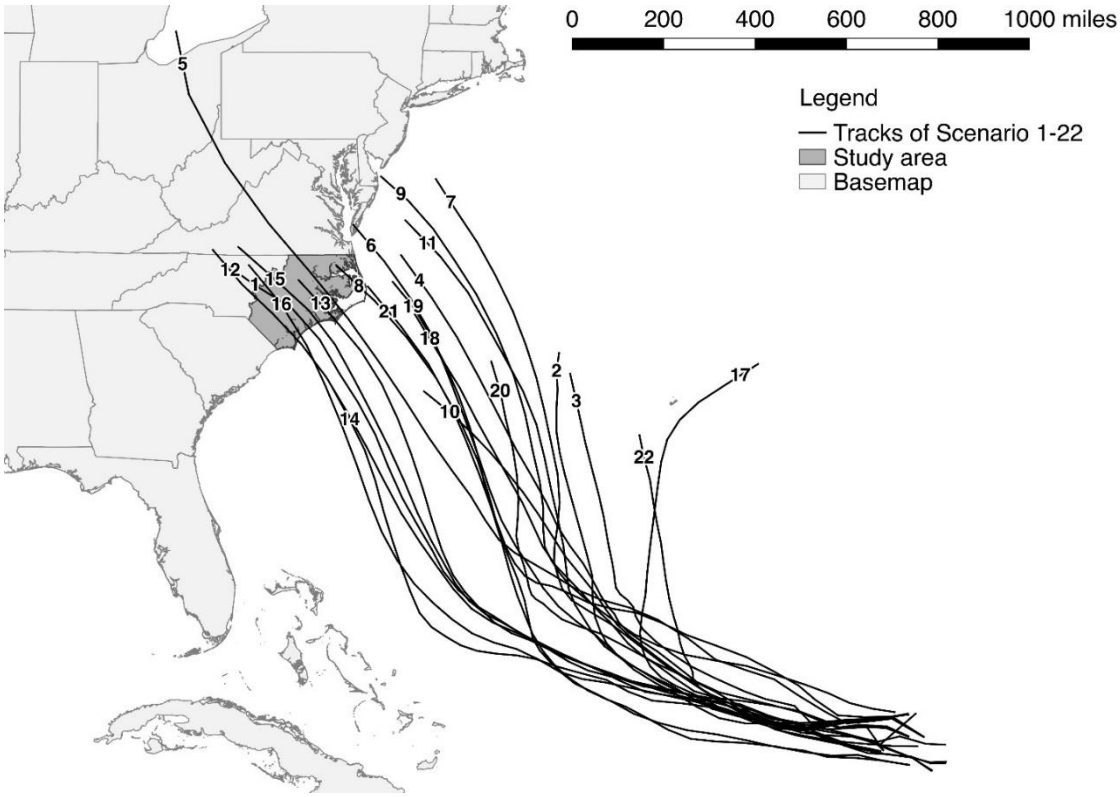


Figure 3 Tracks of the ensemble of 22 scenarios

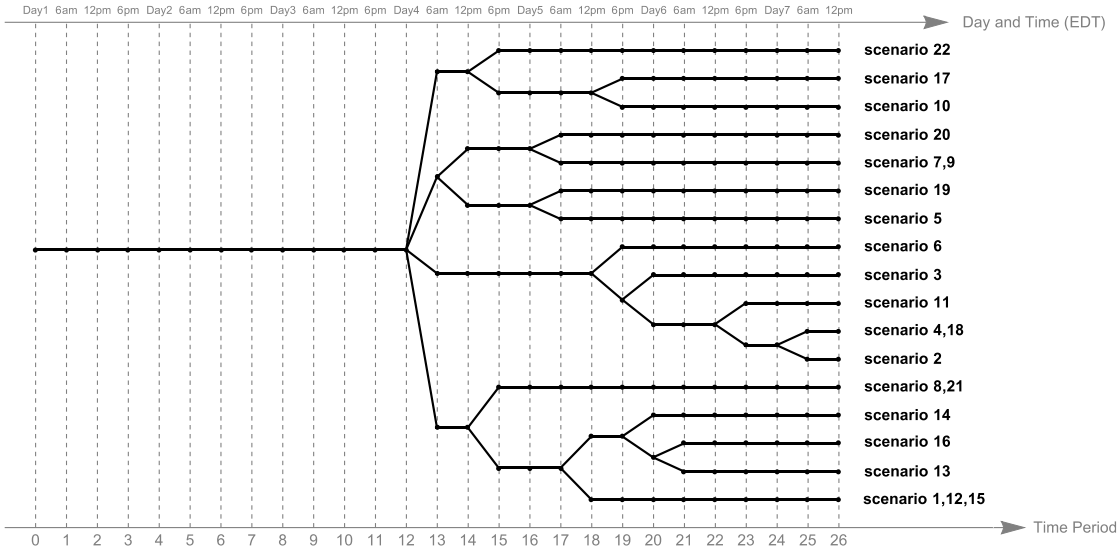
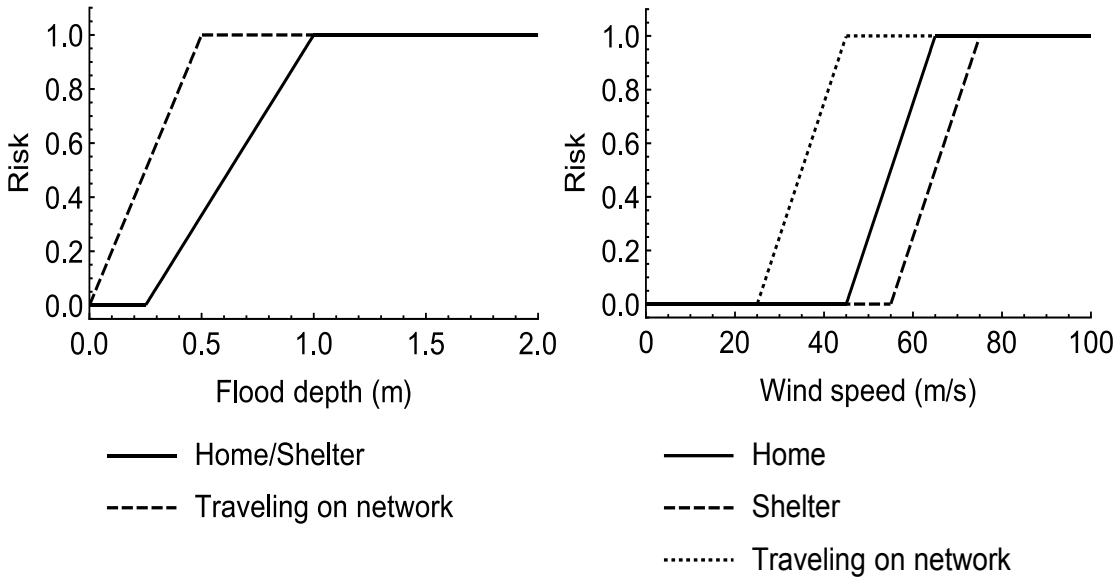


Figure 4 Scenario tree

For each hurricane scenario, peak wind speed and flood depth in each zone over the DTA time horizon are computed from the output of WRF using the hydrological model Coupled Routing and Excess Storage (CREST) (Wang et al., 2011) in combination with the storm surge and wave model ADvanced CIRCulation (ADCIRC) (Dietrich et al., 2011; Westerink et al., 2008). The functions that map the wind and flood hazard to risk are shown in the graphs of *Figure 5* (Apivatanagul et al., 2011). Zones where the risk of sheltering at home is zero over the entire planning horizon across all scenarios are not considered for potential evacuation order.



(a) *(b)*

Figure 5 Risk functions for (a) flood depth and (b) wind speed

5.1 Computation

The MSP model and solution procedure is implemented in Java SE 7 and run on a Linux cluster made up of computing nodes built with 10-core 2.45GHz Intel E5-2670 v2 processors and with 64 GB RAM per node. Using one core for a single scenario, the sub-problem procedure, which is the most computationally expensive step, requires around 100 seconds per iteration. Specifically, Step 2 of the *Subproblem Procedure* (i.e. DTA over 641 lower level time periods) takes about 60 seconds and Step 4 (i.e. enumeration across 23 time periods for each zone) takes about 40 seconds. The weights of objectives h_1, h_2,h_3, h_4 and the penalty parameter r are chosen such that in Step 4 of the *Subproblem Procedure*, each of the weighted objective values and the penalty terms are in about the same order of magnitude. Hence, the values are set

to $h_1 = 0.001$ (traveler·hour)$^{-1}$, $h_2 = 0.02$ (person in danger)$^{-1}$, $h_3 = 4 \times 10^{-5}$ (traveler·hour)$^{-1}$, $h_4 = 0.03$ (person in danger)$^{-1}$ and $r = 0.5$. The solution procedure exhibits fast convergence, as shown in *Figure 6*. The following two quantities are plotted as measures of convergence versus the number of iterations v:

$$\sum_{s=1}^{S} p_s \sum_{t=1}^{T} \sum_{z=1}^{Z} \left(x_{s,t,z}^{v} - \hat{x}_{s,t,z}^{v-1}\right)^2$$

and

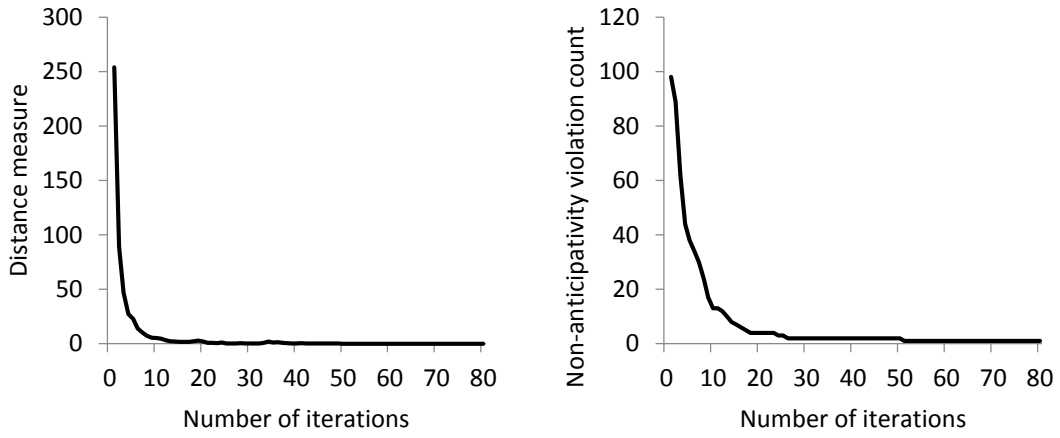
$$\sum_{z=1}^{Z} \delta_z^v,$$

where

$$\delta_z^v = \begin{cases} 1, & \text{If } \exists s, t \text{ such that } x_{s,t,z}^{v} \neq \hat{x}_{s,t,z}^{v} \\ 0, & \text{Otherwise} \end{cases}.$$

The former, a distance measure, is the expected Euclidean distance between a solution and its aggregation; the latter, a count of nonanticipativity violations, is the total number of zones which are assigned evacuation solution that violates the nonanticipativity constraint.

Due to the heuristic nature of the solution procedure, full convergence to nonanticipativity, i.e. $\sum_{z=1}^{Z} \delta_z^v = 0$ or $\sum_{s=1}^{S} p_s \sum_{t=1}^{T} \sum_{z=1}^{Z} \left(x_{s,t,z}^{v} - \hat{x}_{s,t,z}^{v-1}\right)^2 = 0$, is not guaranteed, though both convergence measures decrease by more than 95% within 20 iterations. If they do not reach zero, the aggregated solution $\hat{x}_{s,t,z}^{v}$ $\forall s, t, z$ can be rounded to the nearest feasible solution that also satisfies nonanticipativity constraint. Note that this is only necessary for the few remaining zones where $\delta_z^v = 1$.



(a) *(b)*

Figure 6 Convergence performance in terms of (a) distance measure and (b) nonanticipativity violation count

5.2 Solution policy

The solution to the MSP problem forms a contingency policy indicating to whom and when to give evacuation orders as the storm evolves, as illustrated in *Figure 7* below. The behavior of the evacuees under such an evacuation order policy, modeled by the discrete choice models, is also illustrated as the series of numbers in *Figure 7* as well as departure curves in *Figure 8*. Notice that *Figure 7* gives the number of zones and people under an order in each time period based on the remaining uncertainties in the storm. For example, on Day 5 at Noon, based on current information which narrows the storm down to either storm Scenario 10 or 17, 12 evacuation orders have been issued to a total of 103,000 people while about 217,000 people have chosen to evacuate. Notice that some people who have left are not currently under an order. It is also useful to notice that over the entire planning horizon and across all scenarios, no

orders are issued after 6 pm at night. This occurs because the discrete choice model is reflective of the behavior of individuals who strongly prefer not to leave at night.

It is also useful to notice how the number of evacuation orders varies across the 22 storm tracks. The tracks for storms 2, 3, 10, 17, 20 and 22, as illustrated Figure 2 dissipate off the coast. The tracks for storms 4, 6, 7, 9 and 11 reach the coast but to the north of the state. Storms 18, 19 and 21 impact the Northern tip of the state most. In contrast, the tracks for storms 1, 5, 8, 12, 13, 14, 15 and 16 strike large parts of the state. The largest number of evacuation orders are associated with these last 8 storms. For example, the models suggests that for storm 5, which is the fastest moving storm and is a direct hit on the state, 107 zones should receive evacuation orders.

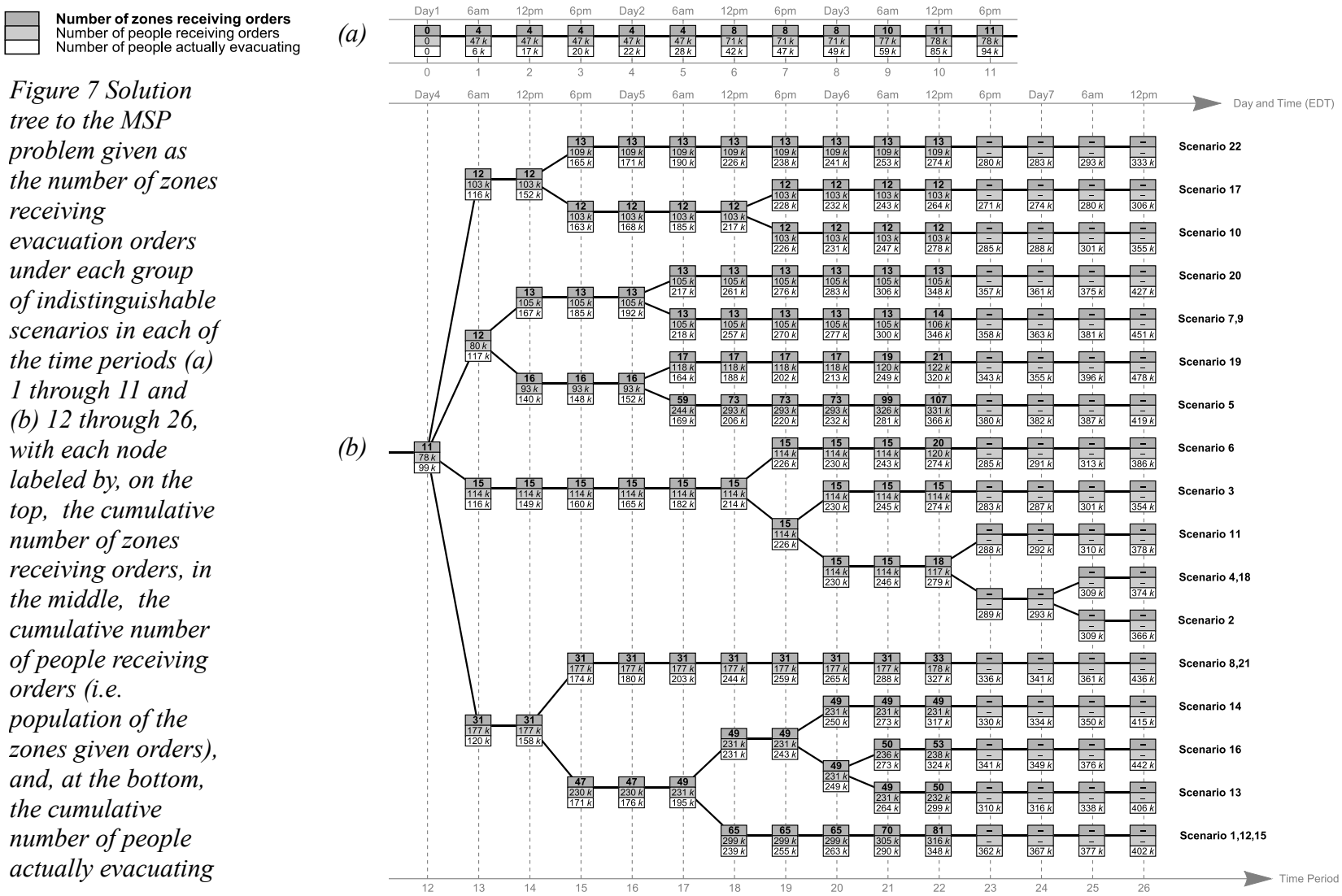


Figure 7 Solution tree to the MSP problem given as the number of zones receiving evacuation orders under each group of indistinguishable scenarios in each of the time periods (a) 1 through 11 and (b) 12 through 26, with each node labeled by, on the top, the cumulative number of zones receiving orders, in the middle, the cumulative number of people receiving orders (i.e. population of the zones given orders), and, at the bottom, the cumulative number of people actually evacuating

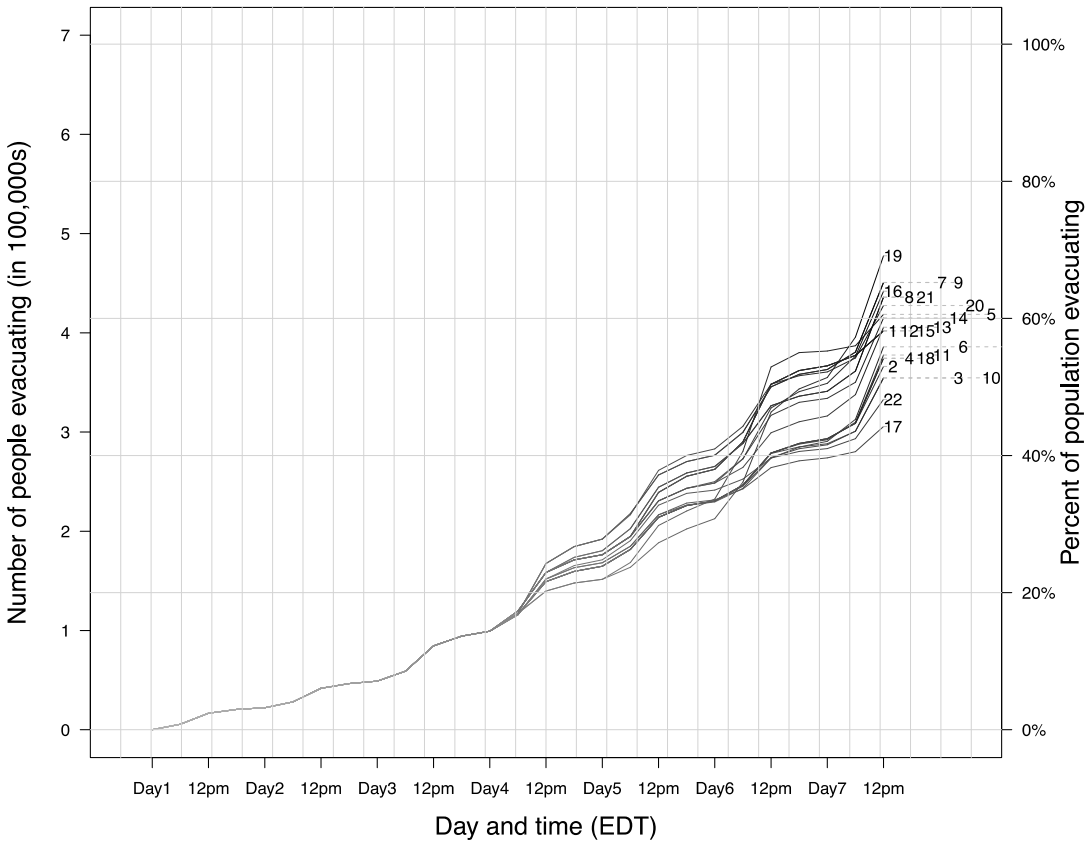
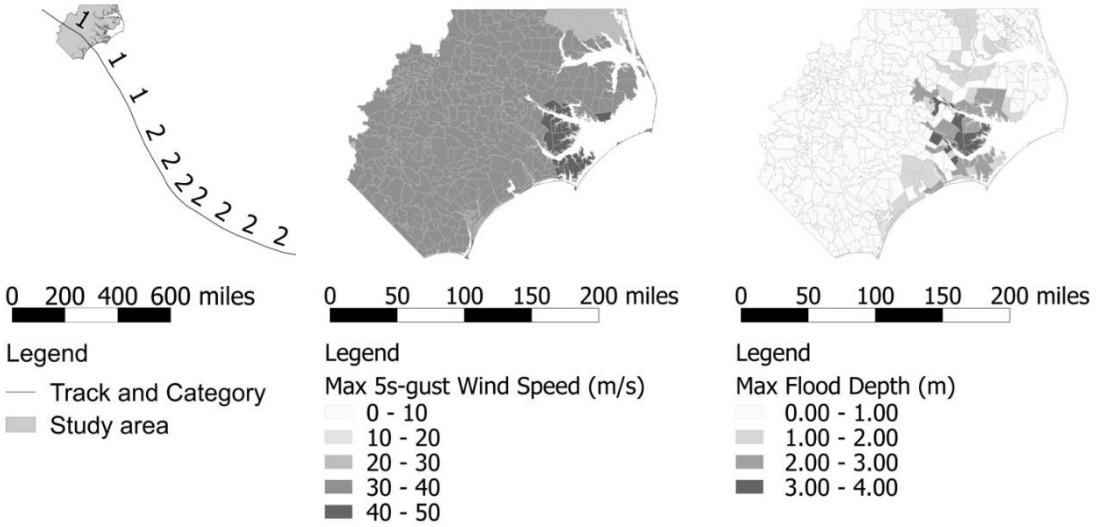


Figure 8 Evacuee departure curves over the planning horizon for Scenario 1 through 22 in terms of, shown on the left axis, cumulative number of people evacuating and, shown on the right axis, cumulative percentage of people evacuating out of the population residing in the zones considered for potential evacuation orders

To illustrate the elements of the solution, let's focus on Scenario 1. Suppose we do not know that the storm is actually as is given in Scenario 1, but, over the planning horizon consistent with the tree illustrated in *Figure 4*, we learn that it is the case. As one of the stronger storms among the ensemble set, Scenario 1 stays a Category 2* for a substantial duration along its track, weakens to Category 1 only shortly before it

* Saffir-Simpson hurricane wind scale

makes landfall in the Southern shores, and brings floods and winds that are most hazardous in the South of the sound area, as shown in the maps in *Figure 9*.



(a) *(b)* *(c)*

Figure 9 Maps of evolution of hurricane Scenario 1 and the maximum wind and flood hazard: (a) track of the hurricane center and hurricane category from the start of Time Period 12 or Midnight on Day 3-4, (b) maximum peak wind speed, and (c) maximum flood depth

Under Scenario 1, the course of action to take follows the path that starts from the root of the solution tree in *Figure 8* at Time Period 1, or Midnight on Day 0-1, and arrives at the node that represents the scenario set containing Scenario 1 at Time Period 22, or Noon on Day 6. Such a path of implementation, or the corresponding subgraph of the solution tree, is shown in *Figure 10 (a)* for Time Period 12 through 26, or Midnight on Day 3-4 through the end of the planning horizon. Over the span of two and a half days, a total of 70 zones and 238,000 people receive evacuation orders in 6 out of a total of 10 six-hour time periods, in addition to the 11 zones and 78,000 people that are

already given orders during Time Periods 1 through 12, or Days 1 through Day 3. As shown in the sequence of maps in *Figure 10 (b)*, among the first to receive evacuation orders are the zones near the location of landfall, the Southern shores, and the zones where the most hazardous floods and winds occur, the South of the sound area. The zones under an order subsequently expand to the Southern outer banks as well as most of the Southern shores, and then extend further northward to include more of the flooded areas in the North of the sound, along with a few inland areas on the banks of estuaries. By the Noon on Day 6, or five and a half days into the planning horizon, a total of 81 zones and 316,000 people receive evacuation orders with 348,000 choosing to evacuate. An additional 54,000 people, though not under an order, evacuated within the final 24 hours, which amounts to a total of 402,000 evacuees over the entire planning horizon or almost 60% of the population residing in the zones considered for evacuation orders.

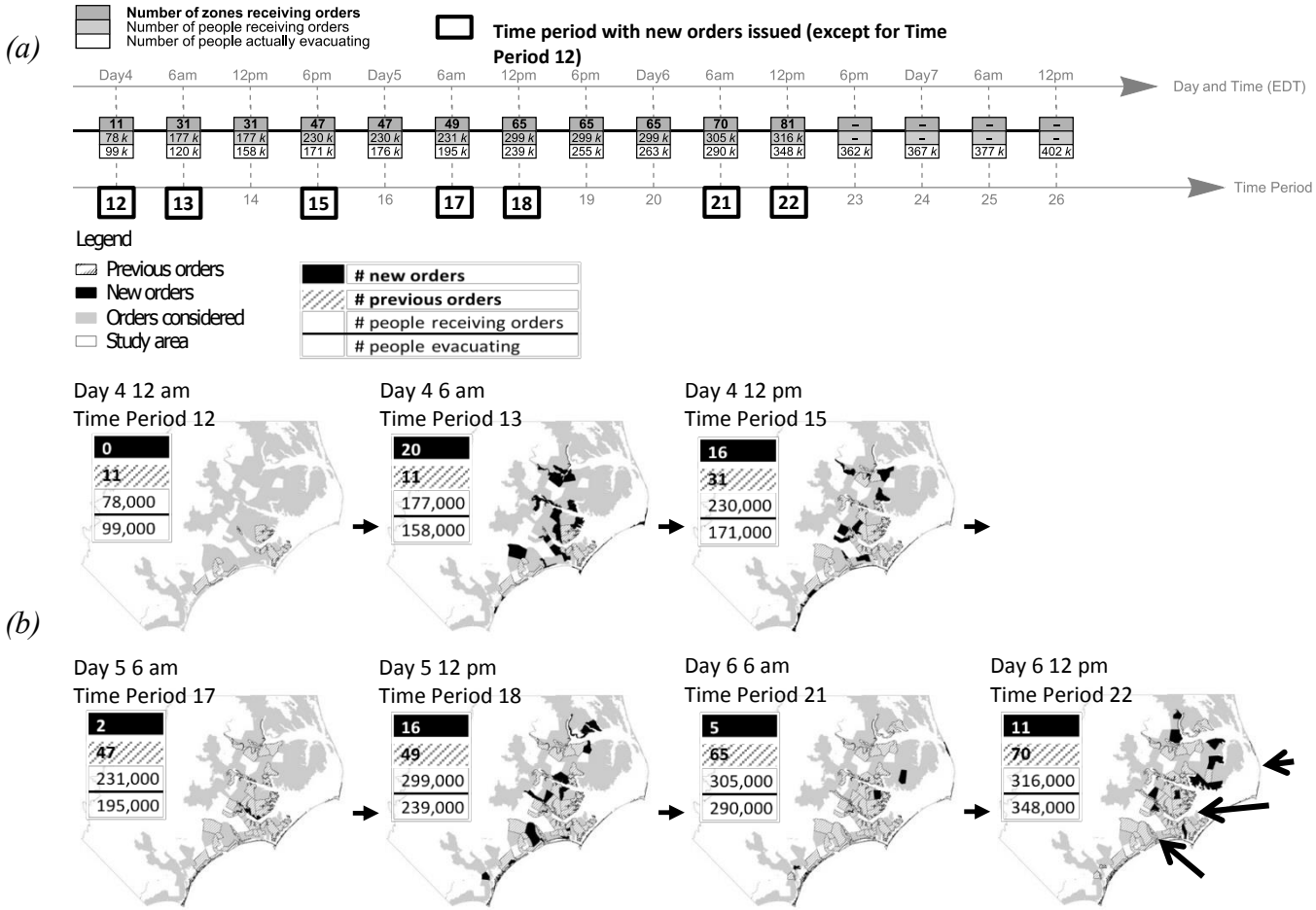


Figure 10 Implementation of the MSP solution policy following the progression of Scenario 1: (a) Number of zones receiving orders, number of people receiving orders, and number of people actually evacuating in each of the Time Period 12 through 26 (b) Map of zones given evacuation orders for Time Period 12, 13, 15, 17, 18, 21, and 22 in which new orders are issued, indicating, in black, the zones where new orders are issued, in diagonal line pattern, where orders have been issued in a previous time period, and, in gray, where potential evacuation orders are considered

The map of evacuation orders for Time Period 22 includes three arrows. These three arrows identify three locations where orders are not issued. For example, the model does not recommend evacuation orders for a piece of the northern section of the Outer Banks, as indicated by the top arrow. This is due to the fact that the input data suggests relatively less storm surge and lower wind speeds in this section since the storm strikes in the southern part of the state, as illustrated in *Figure 9*. The middle and bottom arrows point to locations with very small populations. The middle arrow points to the Piney Island Bombing Range (9 people) and the bottom arrow the eastern portion of the Croatan National Forest (65 people).

For the Piney Island Bombing Range Zone (with 9 people), no evacuation order is locally optimal with respect to the augmented Lagrangian in all scenarios, but it is not locally optimal with respect to the weighted sum of four objectives in all except Scenario 3 (in which no evacuation order remains locally optimal with respect to the weighted sum of four objectives); however, the difference that an alternative (e.g. issuing evacuation order at the beginning of the planning horizon) would make, as measured by the change in the contribution from this zone to the objective functions, is very modest. The grand total of the augmented Lagrangian across all scenarios and zones is 79,544. From the Piney Island Bombing Range Zone, the contribution is 3.5. Since no evacuation order in this zone across all scenarios is a policy that honors nonanticipativity, 3.5 is also the contribution from this zone to the weighted sum of four objectives. If evacuation were ordered at the beginning of the planning horizon in all scenarios, the contribution would be 2.96, a saving of about 0.54. The small population and therefore the modest impact on the four original objectives is not

sufficient to overcome the change in the penalty terms in the augmented Lagrangian that penalize deviations from the inherent nonanticipativity in the initial solution (i.e. no evacuation order in the Piney Island Bombing Range Zone across all scenarios). For the zone in the east of the Croatan National Forest (with a population of 65), considering Scenarios 1, 12 and 15 and the weighted sum of four objectives, it is better not to issue an order than to issue it in Time Period 18 through 22. Similarly, it is better not to issue an order than to issue it in Time Period 15 through 17 considering Scenarios 1, 12, 13, 14, 15 and 16, and the same applies to Time Period 13 through 14 considering Scenarios 1, 8, 12, 13, 14, 15, 16 and 21. As a final point of comparison, it is better not to issue an order than to issue it in any of the Time Period 1 through 12 considering all scenarios. To summarize in another word, for the Eastern Croatan National Forest Zone, were there perfect information that allowed distinguishing Scenario 1, 12 and 15 from the rest of the scenarios upon the onset of the planning horizon, it would be better to issue an order in these three scenarios at the very beginning than not to issue an order at all; however, with the given evolution of the uncertainty, the set of Scenario 1, 12 and 15 remains indistinguishable from other scenarios until Time Period 17, by which time it is no longer advantageous to issue an evacuation order earlier and, furthermore, after which time the model suggests it is better not to issue an order at all.

5.3 Model Efficacy

Central to the goal of the MSP model for hurricane evacuation are, first, to strike a trade-off among the objectives associated with the costs and risks of evacuation that

can be competing and/or collaborating, second, to attain a well-hedged solution that is robust under a wide range of scenarios, and third, to leverage the value of the increasing amount information, or, the decreasing degree of uncertainty over time. We therefore assess the efficacy of the MSP model from these three perspectives through comparisons with: 1) the "do-nothing" (DN) case where no evacuation orders are issued at all and 2) a two-stage stochastic programming model (TSP) which assumes no information is gained over time until all uncertainty is resolved.

The formulation and solution procedure presented in the previous sections can be readily configured for the DN case and the TSP model. In particular, we solve the TSP using the aforementioned solution procedure but with a scenario tree for which all scenarios are bundled together as indistinguishable across the entire planning horizon. The phased evacuation plan obtained from solving the TSP model is illustrated in *Figure 11*. Note that the number of the zones given evacuation orders and their locations, though not shown here, are identical in the solution of the TSP model and that of the MSP for Time Period 1 through 8, during which all scenarios remain indistinguishable. By the end of the planning horizon, a total of 45 zones are given evacuation orders. This is between the two extreme cases of 12 zones in Scenario 10 and 17 versus 107 zones in Scenario 5 under the MSP.

Figure 12 gives the evacuee departure curves for the DN case and the TSP solution as well as for each path along the MSP solution tree. The effect of evacuation orders is evident from the gap between the curves for DN and TSP.

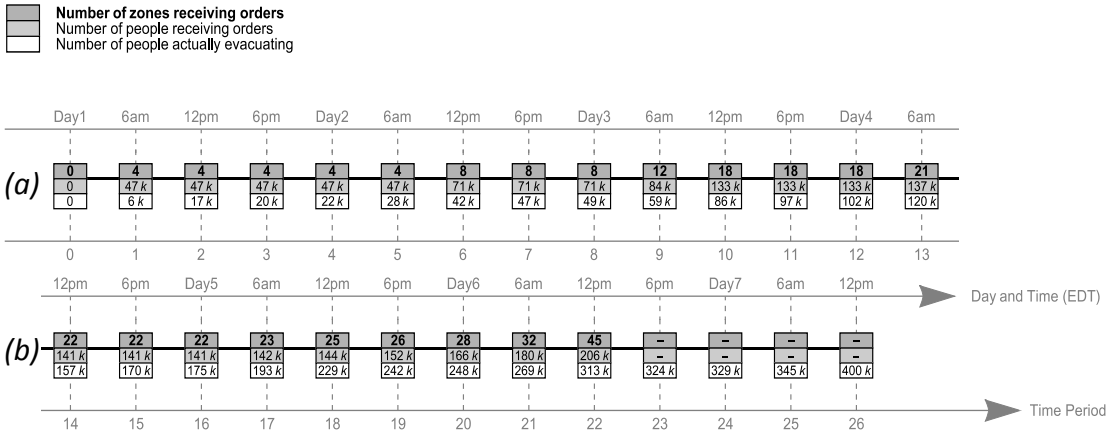


Figure 11 Solution to the TSP model in terms of number of zones and people receiving orders and number of people actually evacuating in each of the time periods (a) 1 through 13 and (b) 14 through 26

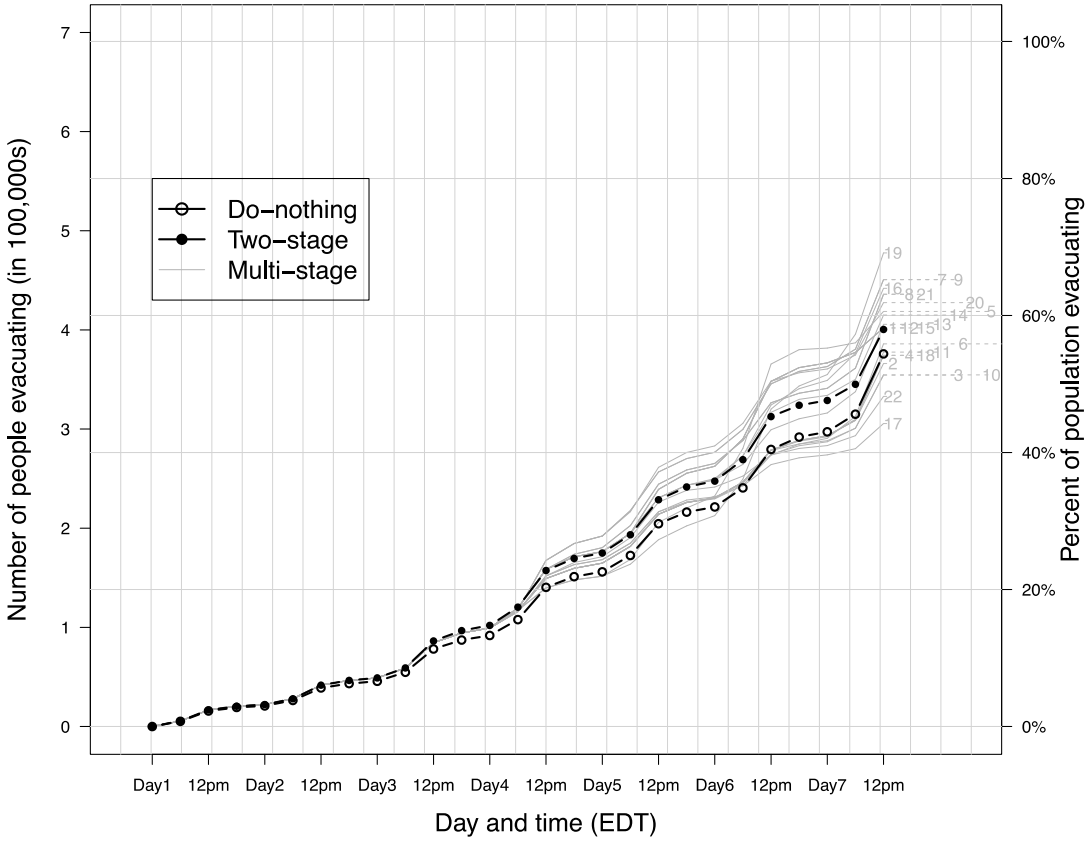


Figure 12 Evacuee departure curves of the DN case and the TSP solution in the foreground, with departure curves of MSP in the background

The percent changes in the four objective values across all scenarios are summarized in *Table 1*. Compared with DN, the MSP solution policy reduces the risk of sheltering at home by 15%-36%. The total travel time and total time away from home inevitably increase as a result of more people evacuating, by 3%-14% and 6%-15%, respectively. However, it is worth noticing that the risk of traveling decreases in most scenarios under the MSP solution policy despite more people choosing to evacuate. This means more people are potentially exposed to risks en route in the DN case. While this seems counter intuitive initially, the reason can be identified in *Figure 12*, that is, without the influence of orders, evacuees tend to leave relatively later when strong winds and heavy rainfalls often occur. Overall, the MSP solution policy attains significant reduction in risks relative to the DN case, at an only moderate cost of the increased travel time and longer duration of displacement. This is true across all scenarios and in turn suggests the robustness of the MSP solution policy.

The changes in the objective values from TSP to MSP are smaller than the changes from DN, ranging from less than 0.5% to 15% in the absolute value. Nevertheless, the trade-off in the costs and risks associated with evacuating versus the risks of sheltering at home is still evident, as decreases in the former always accompany increases in the latter, and vice versa. With the scenarios sorted in the ascending order of storm intensity, it is immediately noticeable that, compared with TSP, the MSP solution policy reduces the total risks of sheltering at home for the stronger storms, yet increases the same objective value for the weaker ones. Such a pattern could be traced back to the differences in the number of evacuation orders. As illustrated in the MSP solution policy in *Figure 11* in contrast with the TSP solution in *Figure 7*, more

evacuation orders are given over time as the scenarios are narrowed down to the strong storms under the MSP solution policy, while fewer or no orders are issued as the scenarios evolve toward the weak ones. In another word, the TSP solution tends to "over-evacuate" in the wrong places for the weaker storms and "under-evacuate" in the strong storms. This in turn suggests the advantage of leveraging the information gained over time with the contingency evacuation policy from MSP.

Table 1 Percent increase in objective values of the MSP solution from that of the DN case and the TSP solution, with scenarios arranged in the order of increasing storm intensity[3]

		Percent increase from DN				Percent increase from TSP			
Scenario	**Hurricane intensity[3]**	**Total travel times[1]**	**Total travel risk[2]**	**Total time away from home[1]**	**Total risk of sheltering at home[2]**	**Total travel times[1]**	**Total travel risk[2]**	**Total time away from home[1]**	**Total risk of sheltering at home[2]**
20	869	4%	-2%	7%	-34%	-2%	0%	-3%	10%
3	970	6%	4%	9%	-18%	-2%	-1%	-2%	6%
7	1,116	4%	-2%	7%	-29%	-2%	0%	-3%	7%
11	1,496	5%	-2%	9%	-20%	-2%	0%	-2%	5%
22	1,824	6%	-1%	8%	-23%	-2%	-1%	-3%	8%
9	1,831	3%	-4%	6%	-36%	-2%	0%	-3%	8%
2	2,162	5%	-2%	8%	-23%	-2%	0%	-2%	8%
17	2,322	6%	2%	7%	-25%	-3%	-1%	-3%	7%
19	2,337	3%	-4%	7%	-24%	-2%	0%	-3%	8%
10	2,383	5%	0%	8%	-15%	-3%	-1%	-3%	10%
4	2,501	5%	-3%	8%	-21%	-2%	0%	-2%	8%
21	2,567	5%	-9%	10%	-31%	0%	0%	0%	0%
18	2,570	4%	-5%	8%	-25%	-2%	1%	-2%	12%
8	2,594	5%	-9%	10%	-34%	0%	-1%	0%	1%
14	2,807	7%	-9%	11%	-34%	1%	-1%	2%	-6%
6	3,704	5%	-1%	9%	-15%	-2%	0%	-2%	3%
13	5,216	9%	-3%	13%	-22%	2%	0%	2%	-2%
16	7,161	8%	-5%	13%	-24%	2%	-1%	2%	-6%
5	7,879	14%	2%	14%	-27%	4%	3%	3%	-15%
12	8,685	14%	4%	15%	-20%	4%	5%	3%	-7%
15	8,903	13%	4%	14%	-28%	4%	4%	3%	-12%
1	9,787	13%	4%	14%	-26%	4%	5%	3%	-12%

[1] in traveler · hour

[2] in number of people in danger

[3] sum of risk function values of all zones over the planning horizon

Legend

Positive percent increase in the objective value

Negative percent increase in the objective value

CHAPTER 6

CONCLUSION

This dissertation proposed a bi-level optimization model for the identification of an optimal policy of where and when to issue evacuation orders based on evolving storm conditions so as to identify the optimal trade-offs between 1) the cost and risk associated with evacuating versus sheltering at home, and 2) the value of waiting for better information versus that of acting sooner. This model explicitly takes into account how the residents will incorporate evacuation orders into their own personal decisions of if and when to evacuate and to where. A dynamic user equilibrium model is used to describe evacuee's route choice behavior. A heuristic method based on progressive hedging was constructed to solve the proposed formulation. To illustrate the applicability of the model, a large scale case study was constructed in Eastern North Carolina using a suite of 22 possible futures for a specific hurricane. The results indicated the benefit of constructing a contingent policy instead of constructing a single time line of what orders to issue and when as a compromise across the 22 scenarios.

This dissertation makes two key contributions to the literature. First, this dissertation develops an evacuation model using multi-stage stochastic programming and illustrates the value in doing so. For example, when a simpler two-stage model is used, the compromise policy leads to over evacuation in smaller storms and under evacuation in large storms. Second, this dissertation links a "supply side" model with

a “demand side” behavioral model for optimization for hurricane events. Linking the behavioral and supply side is natural to the urban transportation planning context but it has not reached fruition in the hurricane context.

The opportunities for future research exist in at least the following five areas. First, this model solely focused on evacuation in private vehicles. There are those without access to private vehicles. As Hurricane Katrina demonstrated, it is critical to integrate other forms of transportation into the modeling. Second, this model focused on private residences. Evacuation decisions must also be made for special facilities like hospitals, nursing homes and prisons; hence addressing the special needs populations is important. Third, this model assumed that the shelters were available and there was adequate capacity to handle all evacuees that appeared; hence integrating capacity constraints and the shelters is useful. Fourth, this model assumed dynamic user equilibrium as the routing behavior. Under hurricane threat, it is unlikely that people have perfect information as to evolving traffic conditions; hence relaxing the assumption of perfect travel time information is valuable. Fifth, for zones with very small populations, it is important to extend the algorithm to better balance the solution consistency terms (i.e. penalty terms) with the four original objective terms.

APPENDIX A

DISCRETE CHOICE MODELS FOR CALCULATING CONTINGENT DYNAMIC OD TABLES

Assume public shelters and exits out of the study area are the only two types of destinations for evacuees. Under a certain hurricane scenario, let $\mathrm{P_{z,t}(evac)}$ denote the probability of a household choosing to evacuate at time period t and $\mathrm{P_{z,t}(shelter \mid evac)}$ the conditional probability of evacuating to a shelter given that the household chooses to evacuate. Then the probability of the household evacuating from origin z to a shelter at time period t is

$$\mathrm{P_{z,t}(shelter,evac) = P_{z,t}(shelter \mid evac)P_{z,t}(evac)}.$$

The probability of the household evacuating to an exit at time period t is

$$\mathrm{P_{z,t}(exit,evac) = \left(1 - P_{z,t}(shelter \mid evac)\right) P_{z,t}(evac)}.$$

$\mathrm{P_{z,t}(evac)}$ can be obtained by an implementation of the time-dependent sequential logit model (TDSLM) of Fu and Wilmot (2004) and then $\mathrm{P_{z,t}(shelter \mid evac)}$ the nested logit model (NLM) of Mesa-arango et al. (2013), with modifications as described below.

1. Modifications to TDSLM

For the case study of Eastern North Carolina in this dissertation, we use the same set of explanatory variables and the coefficient estimates as Gudishala and Wilmot (2012). The constant is calibrated by trial-and-error until the output roughly matches

the evacuation participation rate under actual evacuation orders. Both the evacuation partition rate and the record of the actual evacuation orders are reported by PBS&J (2005).

2. Modifications to NLM

In Mesa-arango et al. (2013) the model is estimated to predict choices among four types of destinations: 1) public shelters and churches, 2) hotels, 3) friends and relatives, and 4) other. In our case study, we merge the latter three types of destinations into one and define it as exits out of the study area. In addition, a subset of explanatory variables is used in the implementation because of the lack of supporting data for the other variables. The variables used are as follows:

1. Indicator variable for evacuation order
2. Natural logarithm of the average distance between the hurricane and the centroid of the ZIP code area where the household is located measured at the evacuation time
3. Indicator variable for low income
4. Indicator variable for work during evacuation
5. Indicator variable for white race

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GLOSSARY

1. *Formulation notation*

Decision variables	
$\boldsymbol{w}$	A matrix with S components, $(w_1, \dots, w_S)$, where for each $s = 1, \dots, S$, w_s is a binary matrix with entries $$w_{s,t,z} = \begin{cases} 1 & \text{If under scenario } s\text{, an evacuation order is issued for the first time at time period } t \text{ to zone } z. \\ 0 & \text{Otherwise.} \end{cases}$$ for $t = 1, \dots, T$, and $z = 1, \dots, Z$.
$\boldsymbol{x}$	A matrix with S components, $(x_1, \dots, x_S)$, where for each $s = 1, \dots, S$, x_s is a binary matrix with entries $$x_{s,t,z} = \begin{cases} 1 & \text{If under scenario } s\text{, an evacuation order is or has been issued at time period } t \text{ to zone } z. \\ 0 & \text{Otherwise.} \end{cases}$$ for $t = 1, \dots, T$, and $z = 1, \dots, Z$.
Sets and indices	
A	Set of all directed links in the network representation
N	Set of all nodes in the network representation
G	Graph representation of the network, $G = (N, A)$
S	Number of scenarios
s	A scenario, $s = 1, \dots, S$
Z	Number of evacuation zones
z	An evacuation zone, $z = 1, \dots, Z$

Y	Number of destinations
y	A destination, $y = 1, \dots, Y$
T	Number of time periods of the upper level multistage stochastic program
t	A time period of the upper level multistage stochastic program, $t = 1, \dots, T$
A_t	A set of scenarios that are indistinguishable at time period t
$\mathcal{A}_t$	A partition of all scenarios into disjoint sets of scenarios that are indistinguishable at time period t
K	Number of time periods of the lower level DTA
k	A time period of the lower level DTA, $k = 1, \dots, K$
i	An objective, $i = 1, \dots, 4$, including 1. Total travel time 2. Total travel risk 3. Total time away from home 4. Total risk of sheltering-at-home
Parameters and intermediate variables	
p_s	A weight assigned to scenario s that represents the relative importance of s among all scenarios
h_i	Weight of objective function v_i
$q_{z,y,t}^{s,\tau}$	Evacuation travel demand from origin zone z to destination y at time period t if an evacuation order is at time period τ to zone z under scenario s

$\bar{q}_{z,y,k}^{s,\tau}$	Evacuation travel demand from origin zone z to destination y assigned to lower level time period k if an evacuation order is at time period τ to zone z under scenario s
$Q_{z,y,t}^{s}$	Number of trips from origin z to destination y at time period t under scenario s given some evacuation plan
$\bar{Q}_{z,y,k}^{s}$	Number of trips from origin z to destination y assigned to lower level time period k under scenario s given some evacuation plan
$b_{z,y,k}^{s}$	Travel time of the trip that leaves from origin z for destination y at time period k under scenario s given some evacuation plan
$\gamma_{z,y,k}^{s}$	Risk of the trip that leaves from origin z for destination y at time period k under scenario s given some evacuation plan
η_{z}^{s}	Risk of sheltering at home in zone z under scenario s
ρ_{z}	Population of zone z
Functions	
$F(\cdot)$	Overall objective function of the multistage stochastic program
$f_s(\cdot)$	Objective function of the scenario sub-problem for scenario s
$v_{s,i}(\cdot)$	Evaluation function of objective i under scenario s

2. *Solution procedure notation*

Indices and parameters	
v	Iteration counter of *Master Procedure* (progressive hedging)

V	Maximum number of iterations in *Master Procedure*
r	Penalty parameter of the modified scenario sub-problem, or, the augmented Lagrangian
ε	Error threshold of convergence,
n	Integer threshold of convergence, or the maximum number of zones assigned evacuation policy that violates nonanticipativity
Variables and functions	
$\hat{x}_{s,t,z}$	Entry of the aggregated solution policy for time period t, zone z, scenario s, which is computed as the conditional expectation of the decision variable values over the set of indistinguishable scenarios for time period t, zone z
$u_{s,t,z}$	Lagrangian multiplier for time period t, zone z, scenario s
$c_{a,k}^{s,v-1}$	Travel time of link a at time period k under scenario s given some evacuation plan at iteration v
$\beta_{z,y,k}^{s,v-1}$	Travel time of the trip that leaves from origin z for destination y at time period k given some evacuation plan under scenario s at iteration v
$\varphi_{z,y,k}^{s,v-1}$	Risk of the trip that leaves from origin z for destination y at time period k given some evacuation plan under scenario s at iteration v
δ_z^v	Binary integer indicating whether zone z is assigned evacuation solution that violates the nonanticipativity constraint at iteration v, defined as $\delta_z^v = \begin{cases} 1, & \text{If } \exists s, t \text{ such that } x_{s,t,z}^v \neq \hat{x}_{s,t,z}^v \\ 0, & \text{Otherwise.} \end{cases}$

$\tilde{f}_{s,z}^{v}(x_{s,z})$	Contribution of the solution x to the objective function of the scenario sub-problem s from zone z at iteration v
$\tilde{L}_{s,z}^{v}(x_{s,z})$	Contribution of the solution x to the augmented Lagrangian of the scenario sub-problem s from zone z at iteration v

3. Abbreviations

ADCIRC	ADvanced CIRCulation
CREST	Coupled Routing and Excess Storage
BPR	Bureau of Public Roads
DN	Do-nothing
DTA	Dynamic traffic assignment
MSP	Multistage stochastic program
MSIP	Multistage stochastic integer program
PH	Progressive hedging
PHA	Progressive hedging algorithm
TSP	Two-stage stochastic program
WRF	Weather and Research Forecasting