Hurricane Evacuation Planning using Public Transportation

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February 1, 2016

Abstract

Just before a hurricane is predicted to strike an urban area, millions of people evacuate from impact zones to safer regions. This paper provides a mass-evacuation strategy using public transportation before the strike of a hurricane. The assumptions made are that the evacuation zones, shelter locations, and the time of strike of the hurricane are pre-determined. The evacuation operations commence when the warnings are issued and end when the hurricane strike is predicted to occur. We propose a multi-stage approach. At the first stage is the planning framework, where pickup locations are determined and assigned to shelters, and an initial set of routes is generated along these locations. This is done by weighing each location based on the accumulated demand, and favoring multiple routes to pass through a location with higher demand. In the next stage, each route is assigned a trip number such that 1) routes with higher demand require more trips, and 2) two successive trips to a route are spaced evenly. A simulation tool has been developed to model the dispatching of the given number of buses, stochastic arrival of evacuees, queueing effects at the pickup locations, and the transportation of evacuees to the safety regions. The results from the simulation serve as an evaluation tool for a route design, and a local search heuristic is proposed to effect positive changes in the route design.

Keywords: Humanitarian Logistics, Disaster Operations Management, Evacuation modeling, Transit Planning, Bus Evacuation Problem, Location theory, Simulation modeling

1 Introduction

Hurricanes, typically characterized by spiraling rain bands, strong winds and severe flooding, are the one of the deadliest of natural disasters. They originate over large water bodies of relatively warm temperature and strike coastal regions with very high wind speeds. Hurricane Patricia (2015) recorded a maximum wind speed of 165 mph, the most intense among all major Pacific hurricanes known till date. Coastal flooding triggered by a hurricane is as destructive as the wind, as it poses a severe threat to life and property along the coastline. For instance, the net property loss due to Hurricane Katrina (2005) is estimated to be around $125 billion [16] and that due to Hurricane Sandy (2012) is around $71.4 billion [5]. Hurricanes in the past have also left behind exorbitant damage to human existence. Hurricane Mitch (1998) resulted in a death toll of over 11,000 along the coasts of Caribbean Sea [19], and hence known to be the most destructive hurricane in the recent past.

Technological advances in satellite imagery, radar imagery and aircraft reconnaissance have ensured that sound forecasting models exist today. With accurate forecasting tools, it is possible to determine the timeline of a hurricane landfall about 3-5 days in advance, although the exact location of landfall is still difficult to be predicted early. The benefit of time must be effectively used to provide information to residents living in areas categorized into risk-based zones and more importantly, to setup an evacuation infrastructure where it is deemed necessary.

The objective of this research is to provide a framework for utilizing existing public transportation resources, namely buses, to administer efficient evacuation operations to evacuate people from high-risks zones to shelters located in safe zones. The motivation behind this research is multifold and is as follows.

1. *Pre-disaster evacuation over post-disaster evacuation*

   When a hurricane makes landfall, the extreme winds and flooding cause damage to the transportation infrastructure in the affected areas. Such damage would constrain the evacuation capacity drastically if the roads are affected, and when aerial and water-based support are the only possible modes of evacuation. In addition to that, post-disaster demand surge would lead to delays in the evacuation operations, thereby imposing the additional burden of providing essential relief materials for those who are stranded. Hence, evacuating the maximum number of people possible before a hurricane is of dire importance, and is the primary objective of this research.

2. *Addressing carless population*

   In a recent study conducted by the University of Michigan Transportation Research Institute [25], it was found that 9.22% of all households in the United States do not own a car. This number is much higher in urban areas where public transportation is the primary mode of daily commute. As of 2012, 56.5% of the households in New York City and 37.9% of the households in Washington D.C. do not possess a single car. In the context of a pre-hurricane scenario, the definition of what constitutes carless population would also extend to people who own a car but are not able to (or willing to) use it for evacuation purposes. This can be due to fuel shortages, disability, temporary illnesses, etc. Therefore, it becomes essential to utilize public transportation resources to cater to these population groups.

3. *Reducing congestion*

   In addition to catering to the carless population groups, public transportation is also expected to reduce congestion on the road network. Existing research on pre-disaster traffic assignment problems focus on increasing link capacities by contra-flow traffic assignment, dynamic signaling protocols to allow uni-directional flow of traffic, providing alternate routes for travelers, etc. From the network utilization perspective, the approach of this research is on demand reduction, as opposed to capacity augmentation. Not only does this approach guarantee a reduction in congestion on roads, but will also induce a reduction in vehicle fuel demand, which tends to become scarce during times of demand surge.

With this motivation, we construct a heuristic multi-step procedure. The rest of the paper is organized as follows. In Section 2, we review some of the key literature in the areas of Operations Research and Management Sciences (OR/MS) that were useful in this research. In Section 3, we discuss the discrete optimization models used to identify pickup locations and assigning them to shelters, and also heuristic methods to generate good candidate routes and a dispatch sequence. In Section 4, we describe the simulation tool built to replicate a realistic evacuation operation, where we explicitly consider stochasticity in the arrival of evacuees and queuing effects at pickup locations. Section 5 demonstrates the planning methodology by employing it on a real-world case study based on Hurricane Sandy, with a target evaluation area selected as Brooklyn, New York. In Section 6, we provide a few concluding reflections on this research. Finally, Section 7 spells out considerations for future work.

2 Literature Review

We separately review literature in the general area of hurricane evacuation planning and in bus-based evacuation modeling. This collective literature is relevant to our work. We note that our major contribution to the literature is the provision of a *planning framework* using public transportation for hurricane events

2.1 Literature in hurricane evacuation planning

We first review some of the existing work covering diverse aspects of modeling the evacuation processes of mass-scale disasters. Evacuation modeling falls into the broader set of problems in Disaster Operations Management (D.O.M.). A 2013 study by Galindo and Batta [11] found that a majority of research work published in OR/MS journals focus on the mitigation, preparation and response to a disaster, as opposed to recovery after the disaster, which was the same trend compared to a 2006 study by Altay and Green [2]. They also found that some of the assumptions used in the models in D.O.M. were limited or unrealistic, and models that encapsulate challenges in both the pre-disaster preparation and the post-disaster recovery stages are more in need.

In the context of evacuation planning, Murray-Tuite and Wolshon [21] categorized evacuation models based on the following: evacuation warnings and information dissemination, zoning, demand modeling, route selection and traffic assignment, and strategies for evacuation efficiency improvements.

Effective communication of evacuation orders/warnings from the government bodies to the evacuees is critical, and often, there is little consistency in the terminology in the warning messages used. A recent study by Wolshon [29] found that legally unclear terms such as “Mandatory” and “Voluntary” were the most commonly used phrases. Warnings are not just intended to make evacuees to take the road, but also necessary to provide useful information about the right departure time and the routes to take. Taaffe et al. [27] examined the role of communications during hurricane evacuations in South Carolina and concluded that after the Hurricane Hugo landfall in 1989, the communication infrastructure has improved a lot, with the pervasive use of cell phones and the Internet playing a vital role.

Dividing the study area into geographical zones is crucial for customized delivery of communication orders, and also for modeling demand at the aggregate level. Wilmot and Meduri [28] report that zoning for hurricanes is currently done based on personal judgment to some degree. They suggest that additionally, uniform elevation and homogeneous land use, and crossing political boundaries must be also considered.

Modeling evacuation demand before a hurricane involves determining the number of people evacuating and spreading them temporally. Many studies have been conducted on identifying the variables that influence whether an evacuee decides to evacuate or not. Recent work like Hasan et al. [14] used a mixed logit model to capture the heterogeneity in the effect of parameters such as voluntary evacuation notice, work requirements, and the number of children in the household. Sorenson [26] first published in 2000 that the time spent in responding to an early warning often follows an S-curve, and many evacuation models have been based on cumulative departure S-curves. An analysis of traffic count data from Southeast Louisiana observed during Hurricane Katrina was reported by Dixit et al. [9] to have back-to-back S-curves as shown in Figure 1. Such a curve is due to the high rise in demand in the morning and vice versa later in the evening. In addition to those who are part of active evacuation, there are others who contribute to the traffic, called background traffic. Zheng et al. [31] define background traffic as those who are not affected by the disaster but maybe affected by the traffic control measures, and those whose origin and/or destination may be affected by the threat.

Among the strategies to improve the efficiency of the evacuation operations, the use of special signal timings to control traffic movement can have significant impact. Studies conducted by Chen et al. [7] and Parr and Kaisar [23] examined such strategies in Washington, DC using a CORSIM simulation model.

The role of mass transportation systems to serve mobility limited populations has been of interest in the wake of Hurricanes Katrina and Rita. Studies conducted by Naghawi and Wolshon [22] used the Citizen Assisted Evacuation Plan for New Orleans to evaluate the efficiency of buses under alternative evacuation routing plans. Wu et al. [30] in 2012 found that mode split was common during Hurricane Katrina, and that 11% of the evacuees did not take their own cars.

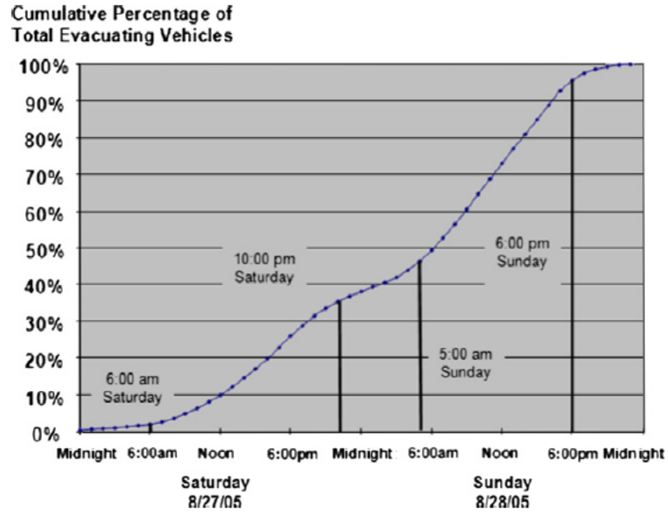

Figure 1: Cumulative evacuation traffic during Hurricane Katrina.*Source: Murray-Tuite and Wolshon [21]*

2.2 Literature in transit-based evacuation

The need for efficient use of public transportation resources was illustrated by Litman [17] using the failures Katrina and Rita emergency response. He found that excessive reliance on automobiles resulted in traffic congestion and fuel shortages. Many optimization-based models have emerged in the recent years to provide efficient solutions for evacuation planning. Abdelgawad et al. [1] proposed a multi-objective optimization framework for combining vehicular traffic and public-transportation for emergency evacuation. They considered minimizing the travel time, waiting time and the fleet cost, and modeled a variation of the pick-up and delivery problem.

Due to their computationally complex nature, optimization models have also been used in conjunction with simulation tools. A bilevel optimization model was proposed by Chen and Chou [6] to determine waiting locations (with deterministic demand) and dispatch buses from their corresponding shelters. A contraflow simulation was developed to simulate the traffic in the network and the results were used to update the routing plans. Liu et al. [18] proposed another bilevel integrated optimization system, where the high level problem is to maximize the throughput for a given duration of time, and the low level problem is to minimize the total time taken for the entire evacuation operations. A microscopic simulation was then used to test the model on the Ocean City evacuation network. Naghawi and Wolshon [22] developed one of the first systematic models to simulate transit-based evacuation strategies, called Transportation Analysis and Simulation System (TRANSIMS). This agent based system analyzed the evacuation plans in New Orleans to study the waiting and travel time of evacuees. The general findings were that transit-based operations are most effective during the non-peak time periods of the day.

The Bus Evacuation Problem (BEP) was formalized by Bish [4] as a variant of the vehicle routing problem, which differs in the objective and the network structure. Pereira and Bish [24] present a formulation for BEP where evacuees arrive at pickup locations at a constant rate that is dependent on the location. The objective function used by them is to minimize the total waiting time at these locations. They then study the effect of changing the maximum number of pickups per location on the fleet size and the total waiting time. Goerigk and Grun [13] formulated the robust bus evacuation problem (RBEP), where the uncertainty in the number of evacuees is captured by dynamic bus dispatching decisions based on the information available at that time period. Goerigk et al. [12] formulated an optimization model to design a set of routes such that the time taken to evacuate people from collection points to a shelter is minimized. They used a branch-and-price strategy, where the pricing problem is the shortest path in a round-expanded path.

Other types of model objectives and considerations have also been explored. Du et al. [10] proposed a mathematical model to improve the average maximal satisfaction for passengers, the average loading rate, and the minimal average bus departure frequency of a bus dispatcher. In this work, the dispatching of buses is looked at from the service-offering point of view. Kaisar et al. [15] evaluated different the evacuation procedures for special needs populations in large urban areas using current public transit systems. Their focus was on people with physical disabilities, older adults, non-English-speaking populations, residents and employees without vehicles, and tourists.

3 Planning Framework

The focus of the first part of this paper is to formulate a procedure that the central user must follow in order to establish evacuation operations effectively. We describe the methodology used to do this by solving a sequence of sub-problems that aim to produce optimal/near-optimal solutions to objectives that best suit evacuees' interests.

3.1 Overall methodology

The setting up of an evacuation planning framework is composed of solving the following sub-problems: 1) identification of pickup locations and assignment to shelters, 2) generation of route designs with shelters acting as depots, 3) evaluating the performance of a route design using a realistic simulation model, and to 4) heuristically improve the route design. Figure 2 illustrates the various stages of the proposed methodology.

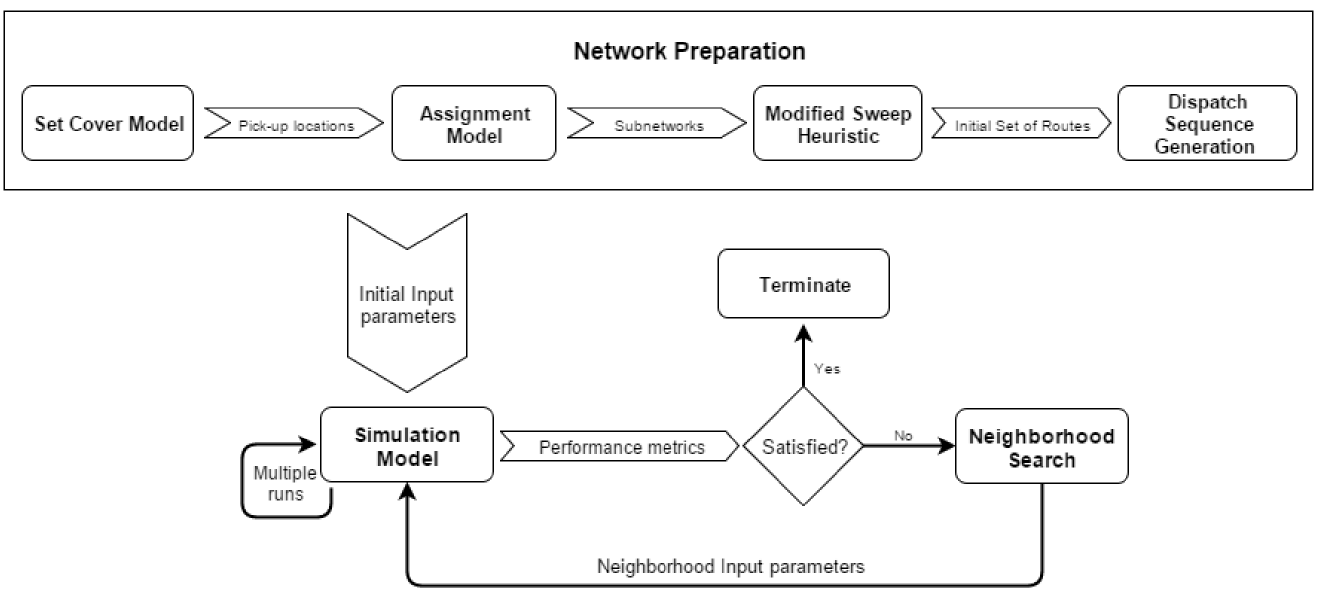

Figure 2: Flow chart depicting the overall solution methodology.

3.2 Identification of pickup locations

The problem of determining pickup locations has to be investigated with several parameters of concern. These parameters would play an important role in an evacuee's effort to reach a pickup location, and it's location might even affect the evacuee's decision to evacuate or not. We have identified 3 such parameters to consider, namely - familiarity, accessibility and coverage. The familiarity aspect is addressed by making use of the existing bus-stops served by local public transportation. The motive behind this is that most evacuees who use public transportation for daily commute would already be familiar with the locations of these bus-stops. It is also easier to provide evacuation instructions to evacuees when the infrastructure is already set up in that place. The goal is now select a subset of these bus-stops to serve as pickup locations.

The selected locations must be also accessible to as many evacuees as possible. But at the same time, it is also important that we do not select too many pickup locations, as that would impact the quality of the routing problem. To resolve this trade-off, we model the selection problem as a Set Cover problem, and formulate it as an Integer Program (IP). The feasible set of solutions is the set of all bus-stops. The problem is to select the minimum number of bus-stops that cover all the demand points in the evacuation region to ensure 100% coverage. We define coverage of a demand point to be the presence of a pickup location within an accessible distance from the demand point. This accessible distance is generally the threshold (or maximum) distance evacuees would be willing to walk. If r is the accessible distance from a demand point, we pre-compute a set of bus-stops $J_i(r)$ for each demand point i. Then, the following IP formulation is solved using a commercial solver.

3.2.1 Notation

I	Set of all demand points
J	Set of all bus stops
$J_i(r)$	Set of all bus stops within an accessible distance r from demand point $i \in I$

Define $\forall\, j \in J$, the decision variables $y_j = \begin{cases} 1, & \text{if bus stop } i \text{ is chosen to serve as a pickup point} \\ 0, & \text{otherwise} \end{cases}$

3.2.2 Formulation

Minimize

$$\sum_{j \in J} y_j \tag{3.1}$$

Subject to

$$\sum_{j \in J_i(r)} y_j \geq 1 \qquad \forall\ i \in I \tag{3.2}$$

$$y_j \in \{0, 1\} \qquad \forall\ j \in J \tag{3.3}$$

The objective in (3.1) states that the number of chosen bus stops is to be minimized. The constraints in (3.2) ensure that there is at least one bus stop chosen within an accessible distance of every demand point. Constraints (3.3) enforce binary values to the decision variables. It is useful to note that since the constraint matrix in the formulation obeys unimodularity property, the linear relaxation of the problem provides the optimal solution in polynomial time.

3.3 Assignment to shelters

The next stage of the problem is to determine where these evacuees are moved to. Right after evacuation warnings are issued, government agencies set up shelters in areas where there is a much lesser chance of hurricane impact than the evacuation regions. These shelters are typically government-run institutions, such as high schools, post-offices, etc. and they can only accommodate a certain number of people. The shelter capacity is computed with considerations to the living space requirements, as well as the available ration of survival requirements such as food and water at each of these shelters.

We then aim to assign each of the pickup locations to the closest shelter. The additional constraint is that the total demand from the pickup locations assigned to the same shelter does not exceed the capacity of the shelter. This problem is modeled as a relaxed version of the Capacitated Facility Location Problem (CFLP) where all the facilities (shelters) are opened to serve the customers (pickup locations) and the cost of opening a shelter is not explicitly a part of the objective function. The formulation is described as follows.

3.3.1 Notation

J	Set of all pickup locations
K	Set of all shelters
r_{jk}	Distance between pickup locations $j \in J$ and shelter $k \in K$
d_j	Total demand at pickup location $j \in J$
c_k	Capacity of a shelter $k \in K$

Define $\forall\, j \in J$ and $k \in K$,

$$\text{the decision variables } x_{jk} = \begin{cases} 1, & \text{if pickup location } j \text{ is assigned to shelter } k \\ 0, & \text{otherwise} \end{cases}$$

3.3.2 Formulation

Minimize

$$\sum_{j \in J} \sum_{k \in K} r_{jk}\, x_{jk} \tag{3.4}$$

Subject to

$$\sum_{k \in K} x_{jk} = 1 \qquad \forall\ j \in J \tag{3.5}$$

$$\sum_{j \in J} x_{jk}\, d_j \leq c_k \qquad \forall\ k \in K \tag{3.6}$$

$$x_{jk} \in \{0, 1\} \qquad \forall\ j \in J,\ k \in K \tag{3.7}$$

The objective in (3.4) states that the total distance between the pickup locations and the assigned shelters is to be minimized. The constraints in (3.5) ensure that each pickup location is assigned to exactly one shelter, and constraints in (3.6) make sure that total demand from pickup locations to each assigned shelter does not exceed the shelter's capacity. Constraints (3.7) enforce binary values to the decision variables.

3.4 Initial route design

Once the pickup locations are chosen and are assigned to shelters, the next step is to construct a set of routes that traverse through these pickup locations as well as the shelters. The advantage of assigning pickup locations to their closest possible shelter allows us to divide the network into subnetworks, each comprised of a shelter, and the pickup locations assigned to it. With the shelters serving as a depot within each subnetwork, we then model the initial route design as a Vehicle Routing Problem (VRP) for each subnetwork with the shelters acting as the depots.

The VRP was first coined by Dantzig and Ramster [8] in 1959 and numerous variations of the problem has been widely studied in the literature. The problem definition as follows: Determine the minimum-cost set of routes taken by k trucks, each having a capacity of C, such that they deliver a quantity d_i to every node $i \in V$ from a central depot in a network $G(V, E)$. The routes have the property that they collectively traverse each non-depot node exactly once. For the case where $C \geq \sum_i d_i$, this becomes the Traveling Salesman Problem (TSP), with one route traversing all the nodes. But in most applications, that is not the case.

In the bus evacuation problem, we reformulate the VRP to capture evacuation operations as illustrated in the following.

- We retain the graph structure of a central depot dispatching vehicles to traverse all the nodes.
- Instead of each vehicle delivering a quantity to each node it traverses, it picks up a certain number of evacuees from each pickup location visited. We model the demand at the locations not as a fixed quantity, but as an arrival process with a constant rate. A more realistic time-variant arrival rate is modeled in the Simulation as discussed in Section 4. Constancy is assumed only for creating an initial set of routes which represents a time-slice of, say, the peak demand time period.
- More than one routes is allowed to traverse through a pickup location. This is allowed especially if the location's accumulated demand is more than the available capacity in the vehicle by the time it reaches there.

The VRP is known to be an NP-Hard problem and the Integer Programming formulation is computationally expensive to solve for optimality. In addition to that, we also keep track of the time taken by a vehicle to reach a particular node, in order to use the demand rate to determine the number of evacuees waiting to be picked up at that node. With these considerations, in Section 3.4.1, we propose a modified version of the Sweep Heuristic to generate near-optimal solutions.

3.4.1 Sweep heuristic with constant demand rate

The Sweep Heuristic is a procedure to cluster nodes based on their geographic positions and sequentially builds routes in a rotational direction relative to the central depot (shelter). Evidence indicates that this heuristic is computationally efficient and produces an average optimality gap of 10% [3].

In a network $G(N, E)$, let $t_{i,j}$ be the time taken for a bus to travel the link $(i, j) \in E$. Let d_i be the rate of arrival of evacuees at a pickup location $i \in N \backslash 0$, where 0 is the index for the shelter. Let C be the capacity of a bus, and *rem_cap* be the remaining capacity of a bus during an iteration of the heuristic. The following steps constitute the proposed modified sweep heuristic, where we construct the routing graph one edge at a time.

1. Locate the nodes (pickup locations) and the depot (shelter) on a 2 dimensional plane based on their geographical coordinates.
2. Choose one of the nodes to be the starting node, say i.
3. Set $rem\_cap = C$. Add the link $(0, i)$. If $C \leq d_i \times t_{0,i}$ (demand accumulated exceeds capacity), add the link $(i, 0)$ and "close" the route.
4. Else, set $rem\_cap = rem\_cap - d_i \times t_{0,i}$. Investigate the next node (say j) in the clockwise direction with respect to the shelter. If $rem\_cap \leq d_j \times (t_{i,j} + t_{0,i})$, add the link $(i, 0)$ and proceed to step 3 with $i = j$. Else, add the link (i, j) and update $rem\_cap = rem\_cap - d_j \times (t_{i,j} + t_{0,i})$. Investigate

the next node after j in the clockwise direction with respect to the shelter, and so on until the route is closed.

5. Repeat Steps 3 and 4 and terminate when all the nodes have been added to the graph.

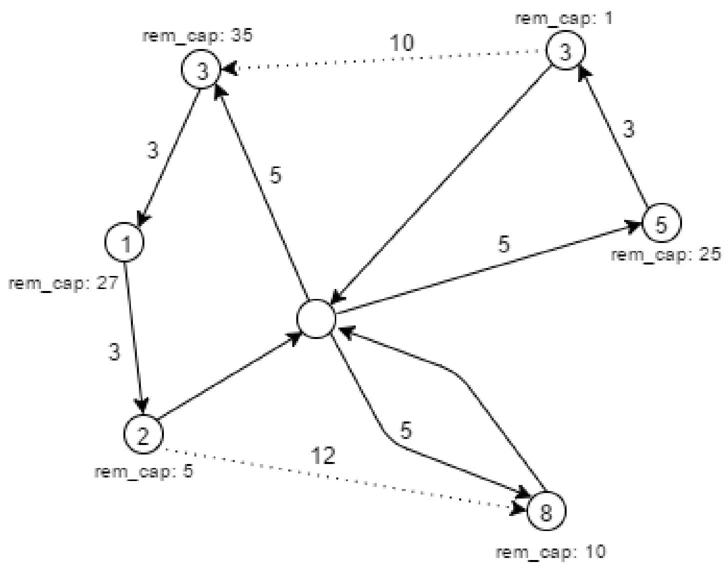

Figure 3: A sample illustration of the Sweep Heuristic with Constant Demand Rate. The vehicle capacity used for this example is 50. The values in the node bubbles represent the demand rate for the nodes and the link attributes are the travel time to traverse the links. Also listed alongside the each node is the remaining capacity right after that node was traversed.

This procedure would give us a set of routes after inculcating the time component into the standard sweep heuristic. It is to be noted that the choice of the starting node affects the quality of the route design. Also, the choosing a different direction of the sweep - anti-clockwise over clockwise - could lead to different solutions. Hence, we compute all the $2*|N|$ possible route designs arising for the N starting nodes and sweeping along the two directions. We then test their performance in the simulation tool, as described in Section 4.

3.5 Dispatch sequence generation

With an available fleet of buses at their disposal, the central user has to decide how these buses can be put into operation. In this paper, we provide a systematic way to address this. First, we recognize that each shelter acts as the central depot for each subnetwork and hence will act as a dispatching center for that subnetwork. Then, we divide the available number of buses to be allotted to each of the subnetworks based on the proportional demand from their corresponding shelters. Let d_s be the demand from a subnetwork s, which is the total demand from all the pickup locations assigned to the corresponding shelter. If b is the total number of buses available, let us allocate $\lfloor b \times (\frac{d_s}{\sum_s d_s}) \rfloor$ buses to each subnetwork.

With the number of buses allocated to a subnetwork known, the question to be addressed in this section is this - how can these buses be dispatched along the different routes in the subnetwork in an organized way?

It is reasonable to argue that the characteristics of the dispatch operations must be such that those routes which traverse pickup locations with higher demand arrival rates must be traversed more frequently than those with lesser demand arrival rates. With this goal as the primary assumption of dispatch modeling, one might model this as a frequency setting problem used commonly in transit planning. But the assumption behind solving for the frequency for each route is that the travel time to traverse a certain route is constant. Since in our methodology we propose dynamic alterations to the route traversals as detailed in Section 4, the dispatch modeling must be compatible with such dynamic alterations.

Hence, we aim to produce what we call a "dispatch sequence" for each shelter, which is basically the sequence of routes that buses must be dispatched in. If b_s is the number of buses assigned to a shelter s, first, all of them are dispatched along the first b_s routes in the dispatch sequence. Then, whichever bus arrives back at the shelter next is dispatched along the next route in the sequence, and so on. For example, if the dispatch sequence is {1,2,3,2,3,1} and $b_s = 2$, the two buses are first dispatched along routes 1 and 2. If bus 2 reaches the shelter first because traversing route 2 took less time than traversing route 1, bus 2 is dispatched next along route 3. If bus 1 reaches the shelter next, it is then dispatched along route 3. This goes on until the evacuation time period is completed.

The need for sequence-based dispatch modeling is more so because the time taken to traverse a route is not just the total travel time along the links, but also the time taken for evacuees to board the bus, which depends on the random number of evacuees at the pickup locations. This sequence effectively augments the simulation tool.

We propose to use a heuristics-based approach to generate such a dispatch sequence. In 1978, Maxwell and Muckstadt [20] published a methodological framework for using automated guided vehicles in a manufacturing facility to transport goods between a warehouse and the assembly units. They have provided a systematic heuristic-based dispatch technique to assign routes to "trips". In our paper, we adopt this procedure for evacuation operations. A "trip" here corresponds to the index of an element in the dispatch sequence, or in other words, an instance of traversing a route.

The first step is to compute the number of trips required for each route. For this, we normalize the route demand for all the routes and then re-calibrate with a multiplying factor. Let $d(r)$ be the absolute demand for route $r \in \{1, 2, ..., R\}$. Then, the number of trips for route r is given by $\lceil \frac{d(r)}{\min_r d(r)} \times k \rceil$ where k is the multiplying factor. Then we sort the routes in the descending order of the number of trips. Let $m(r)$ be the number of trips of the sorted list of routes, then it is to be noted that the index r used from this point onwards is the index of the sorted list. That is, $m(r) > m(r+1) \ \ \forall r \in \{1, 2, ..., R-1\}$. Also, let $M = \sum_{r=1}^{R} m(r)$, the total number of trips. The following steps are used to produce the trip to route assignment.

1. For each route r, a relative trip number is calculated such that the first trip on a route has a relative trip number of 1. Let $n_r(k)$ be the relative trip number of trip k on route r. Then,

$$n_r(k) = < \frac{M}{m(r)}(k-1) + 1 >, \quad \forall k = 1, 2, ..., m(r) \tag{3.8}$$

   where $< . >$ is the nearest integer function.

2. Next, trips are assigned trip numbers. Then, assuming that no trips have been assigned a trip number, for each of the routes $r = 1, 2, ..., R$, the following steps are followed:

   - The first unassigned trip number is obtained, say $j(r)$.
   - For $k = 1, 2, ..., m(r)$, visit k of route r is assigned to the trip number $[n_r(k) + j(r) - 1]$ mod M. While doing this, a trip of route r may be assigned the same trip number as a trip of a previously considered route.

3. This step is to resolve the trip to trip-number assignment conflicts. For each trip number $j = 1, 2, ..., M$, if more than one trip is assigned to trip number j, a conflict exists. In such a case, the largest trip assigned to trip number j is found, and then reassigned that trip to that unassigned trip number nearest to trip number j.

Step 1 produces a list of trips for each route in such a way that successive trips are spread out evenly. Even spreading of routes across trips is necessary, since the time-variation of demand arrival is similar across the pickup locations, and hence for routes as well. Step 2 tries to ensure that unassigned trip numbers are utilized as the first trip number for each route, and then amplifies the spacing between trips such that almost all of the trip numbers are assigned. But since there are still conflicts possible, Step 3 systematically removes conflicts by moving routes with lesser trips (lesser priority) to unassigned trips. These steps would produce a unique mapping of routes to trip numbers. This mapping is then reformatted to construct the dispatch sequence.

Before using this sequence in the simulation tool, we modify the sequence by multiplying it periodically several times so that the final sequence does not run out of trips by the end of the evacuation period.

4 Simulation Modeling and Neighborhood Search

We now discuss the Simulation model that is built to reproduce a real world environment to study the effect of certain control parameters on the evacuation operations. We also employ this model to serve as an evaluation tool for several route designs, which are then improved using a neighborhood search procedure.

4.1 Simulation overview

The motive behind using a Simulation model is that the development of such a tool 1) enables the central user to observe and make dynamic decisions during the evacuation process, 2) inculcates stochastic variability in the interaction between the evacuation process and the external systems (demand arrival, congestion effects on the travel time, self-evacuation decisions, etc.), and 3) provides a quantification (performance metric) for a given set of decision parameters. These metrics are then used to seek neighborhood parameters with the intention of improving the performance of the overall system, as illustrated in Figure 2.

With a given route design, available buses and an evacuation time period within which the operations must cease, the goal of the evacuation process is to maximize the "effectiveness" of evacuation, which we discuss in the next few sections.

4.2 Input parameters

The Simulation takes as input the following features. Some of these features are route-design features obtained from Section 3, and the others are specific to the operational characteristics of the evacuation process.

- *Set of shelters and subnetworks:* From the Assignment model in Section 3.3, we obtain the optimal assignment of pickup locations to shelters. But not all shelters may be assigned pickup locations, and so only a few of them can be considered to be operational. Those shelters and their subnetwork (list of assigned pickup locations) serve as input to the model.

- *Demand arrival distribution:* Given the total number of evacuees to be evacuated from each of the pickup locations, we distribute them over time using a suitable discrete-time probability distribution function that best represents the departure time of evacuees. For this, we collect real-life departure time values and fit the data using a best-fit method. This is described in more detail using a case study in Section 5. At the end of the curve fitting, we generate multiple instances of the demand distributed across time. Each instance is represented by a matrix with each element being d_{it}, which is the number of evacuees arriving at pickup location i during the time period t. This time period t can be of any length, but in our case study, we choose it to be one minute. If T_{evac} is the total number of minutes available for evacuation (evacuation time period) and N is the number of pickup locations, the dimensions of this input matrix are $N \times T_{evac}$. The simulation is run multiple times using each of these instances for each run.

- *Travel time:* The shortest path travel-time between the pickup locations and the shelters is computed using the underlying network, and is stored as a matrix. If S is the number of shelters, the dimensions of the matrix are $(N+S) \times (N+S)$. This is done by first computing the shortest path distances, and then dividing them by the average speed along those paths.

- *Set of routes:* If R is the total number of routes, each route $r = 1, 2, ..., R$, is associated with a list of pickup locations traversed by the route r. The first and last element of this list is the index of the shelter corresponding to that route, to denote that the route begins and ends at the shelter.

- *Dispatch sequence:* The periodically repeated sequence of routes produced from Section 3.5 for a given set of routes is computed and stored. A suitable data-structure is used such that for each shelter, there is a corresponding list (or sequence) of routes associated with it.

- *Other parameters:* The number of buses available to the system, as well as the capacity of each bus are key input parameters. Also, since we use a queuing model to simulate arrival at pickup locations, we input the threshold values for reneging and balking. A percentage of those evacuees who renege or balk may even self evacuate, and so we also consider this percentage to be a control parameter. In addition, the evacuation time period T_{evac} itself is an input parameter.

4.3 Discrete time simulation

In this paper, we simulate the evacuation process as a sequence of events that are scheduled to occur at discrete time intervals. The granularity of the time-interval is to be kept as small as possible (1 second, in our case study) so as to achieve a simulation model that is very close to the real-world. There are two kinds of events considered: bus-based events, which are events involving decisions taken by the each bus, and evacuee-based events, which are events involving evacuee decisions.

4.3.1 Bus-based events

Each bus originates from its assigned shelter, starts along the next route in the dispatch sequence, and traverses through all the pickup locations in that route. Let's say the current simulation time is t. The following are the events that are possible to occur:

- *Travel:* If a bus is dispatched from a shelter at time t or leaves a pickup location at time t, it is scheduled to arrive at the next destination at time $t + traveltime$ (current_location, next_location).

- *Arrive at a pickup location:* If a bus arrives at a pickup location at time t, it is scheduled to leave after a certain *boarding time* to the next destination.

  - This boarding time is a linear function of the number of evacuees boarding the bus (more discussion in the case study).
  - The number of evacuees that can board is given by $min(rem\_cap, w_{i,t})$, where $w_{i,t}$ is the number of evacuees waiting at the location i at time t, and rem_cap is the remaining capacity on the bus when it arrived at i. After boarding, the rem_cap variable for that bus is incremented by the number of evacuees boarded.
  - The next destination assigned to the bus depends on the whether $rem\_cap = 0$ or not. If it is 0, then, the bus is made to directly go back to the shelter, else, it follows the next destination as per the route. It is to be emphasized that this dynamic decision making is what makes the simulation tool more powerful.

- *Arrive at a shelter:* If a bus arrives at a shelter at time t, it is scheduled to leave after a certain de-boarding time to the next destination.
  - This de-boarding time is also a linear function of number of evacuees de-boarding the bus (more discussion in the case study).
  - The bus de-boards all the evacuees on it and the *rem_cap* variable is set to 0.
  - It is then assigned the next available route as per the dispatch sequence and travels towards the first location in that route.

4.3.2 Evacuee-based events

Evacuees arrive periodically at the pickup locations and the number of evacuees arriving every period follows the demand distribution, which is an input to the model. The following events occur once an evacuee arrives at their pickup location.

- *Balk:* If the length of the queue (number of evacuees waiting at the location) is more than a certain amount, the evacuee refuses to join the queue. This amount is the balking threshold and is given as an input parameter.
- *Join the queue:* Upon arrival at the pickup location, if the balking condition is not met, the evacuees join the queue and the $w_{i,t}$ variable is incremented.
- *Renege:* After joining the queue, if no bus reaches the location within the certain amount of time, the evacuee leaves the queue. This time is the renege threshold and is also an input parameter.
- *Self-evacuate:* Evacuees who balk or renege may still choose to evacuate. With a certain probability that is given as an input, each of these evacuees decides to evacuate on their own.

4.4 Performance measures

During each simulation run, there are multiple variables in the system that change state from one time period to the next. We keep track of some of the variables with the goal of obtaining useful metrics that can quantify the efficiency of a given set of simulation parameters.

The primary objective in this paper is to evacuate the maximum number of people from the pickup locations. For this, we calculate the percentage evacuated as opposed the absolute number of evacuees because each simulation run involves stochasticity in demand arrival and self-evacuation, and to have a standardized metric for these variations, computing the percentage is more meaningful.

Another performance metric of interest would be the average waiting time for the evacuees. It would also be useful to compute the percentage of evacuees dissatisfied with the service and left the system through balking or reneging.

As an additional insight, we also keep track of the total distance traveled by each bus. This is a helpful computation if one is interested in finding out the exact amount of vehicle fuel that needs to be pre-positioned at the shelters at the start of the evacuation process. There is a reasonable assumption that re-fueling can be done at the shelters while the evacuees de-board in order to save time.

4.5 Simulation runs

For a given set of input parameters, we generate multiple instances of the demand distribution, and then run the simulation for each of those instances. For most of the runs, the percentage evacuated (the primary objective) is very close. So a terminating rule based upon convergence of the mean is used. After every iteration r, the average of all the percentage evacuated values till that iteration is computed, say $x(r)$. Then, for a very small ϵ, if $|x(r) - x(r-1)| \leq \epsilon$, we terminate the simulation in the r^{th} iteration.

4.6 Neighborhood improvements

In this paper, we focus on making changes only to the route design while fixing the rest of the parameters. We start with the initial set of route designs obtained from modified sweep heuristic, and pick the one which has the highest objective function value. The idea is to iteratively make a small change to the route design and test this change by running it into the simulation. We propose to do this by 1) randomly choosing one of the subnetworks which contains more than one route, and then 2) randomly choosing two pickup locations from the two randomly chosen routes in the subnetwork, and *swapping* their places. If the altered route design is tested and produces no improvement to the primary objective, we reject this solution and continue performing more swaps. This heuristic is terminated with an upper limit on the number of iterations or computation time, whichever happens first.

5 Case Study

For the purpose of testing our models in a real-world case study, we use datasets to analyze the evacuation during Hurricane Sandy and focus our target evacuation area to be Brooklyn, New York. The reason behind this choice is that New York (of which Brooklyn is a part) has the highest percentage of residents who solely rely on public transportation for any type of commute, and our research aims to address this particular population group. Availability of a variety of data-sets for analysis is another reason for this choice.

5.1 Data collection

5.1.1 Shelter locations and evacuation zones

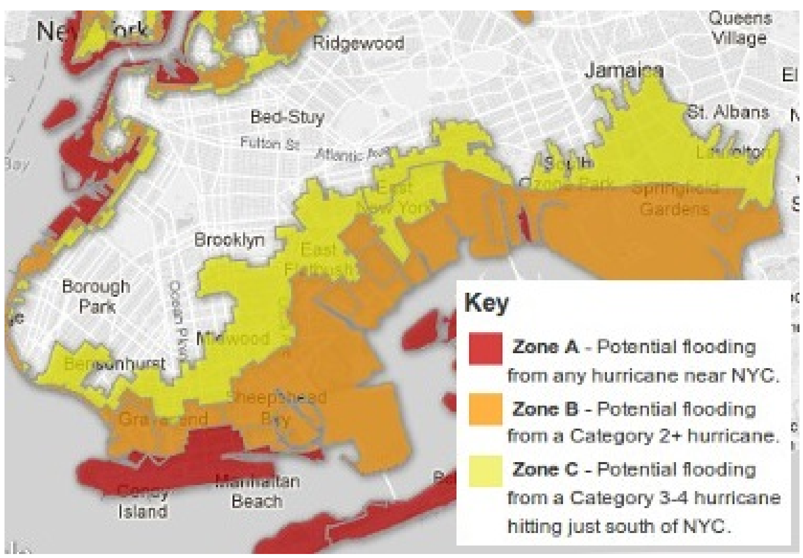

Figure 4: Evacuation zones in Brooklyn, NY. *Source: NYC DataMine*

The City of New York's Emergency Management division has issued a useful preparedness guide for residents to follow in the event of Nor'easters, tropical cyclones and hurricanes. In this guide, they have identified and categorized areas into 6 evacuation zones, ranked by the risk of storm surge impact, with zone 1 being the most likely to flood. Figure 4 shows these zones marked by different colors. In our paper, we focus only on zones ranked 1 and 2 (red and orange), as they are the ones that are typically given mandatory evacuation orders. Also, the locations of 20 shelters (high schools and post offices) in this area have been provided along with their maximum capacities.

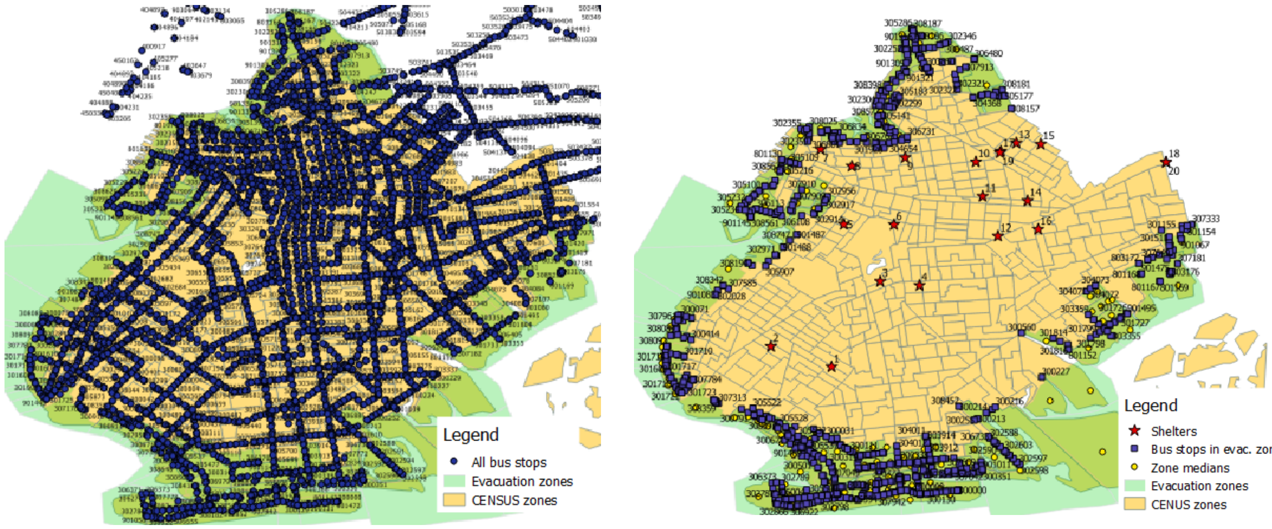

Figure 5: Left: All the bus stops in Brooklyn, NY. Right: Candidate bus stops in the evacuation zones.

5.1.2 Set of bus stops

We gather the full list of about 3700 bus stops served by the local public transportation, the Metropolitan Transportation Authority (MTA) and locate their geo-positioning coordinates to identify those bus stops that are within the evacuation zones of interest. This list of 756 bus stops that will serve as the input to the Set Cover Model. We also find out the locations of aggregate demand points from the Brooklyn Census track dataset. These are depicted in Figure 5.

The smallest possible accessibility distance for which all the demand points have at least one bus stop within its coverage is 0.6 mile. We run the Set Cover Model to obtain an optimal set of 25 bus stops that will serve as pickup locations, as depicted in Figure 6. For an accessibility distance of 0.7 mile, we get a set of 22 bus stops.

5.1.3 Other input parameters

From NYCMTA, we also gather the underlying road network and compute the shortest path distances between the shelters and the pickup locations. This is then divided by the average vehicle speed in that path, to gather an estimate of the travel time matrix across these locations. We then run the Shelter assignment model to create the subnetworks. This in turn is an input to the Initial-route generation model. The results from all of these models act as inputs to the simulation.

The following are the other fixed inputs to the simulation model.

- Demand arrival time period: 1 minute
- Evacuation period: 24 hours, or 1440 minutes
- Capacity of a bus: 56
- Total number of available buses: 100
- Balk threshold: 56 evacuees
- Renege threshold: 45 minutes
- Percentage of dissatisfied evacuees self-evacuate: 50%

It is to be noted that the number of buses is fixed only for comparing the performances of the different route designs. We discuss a sensitivity analysis in the next section by varying the number of buses.

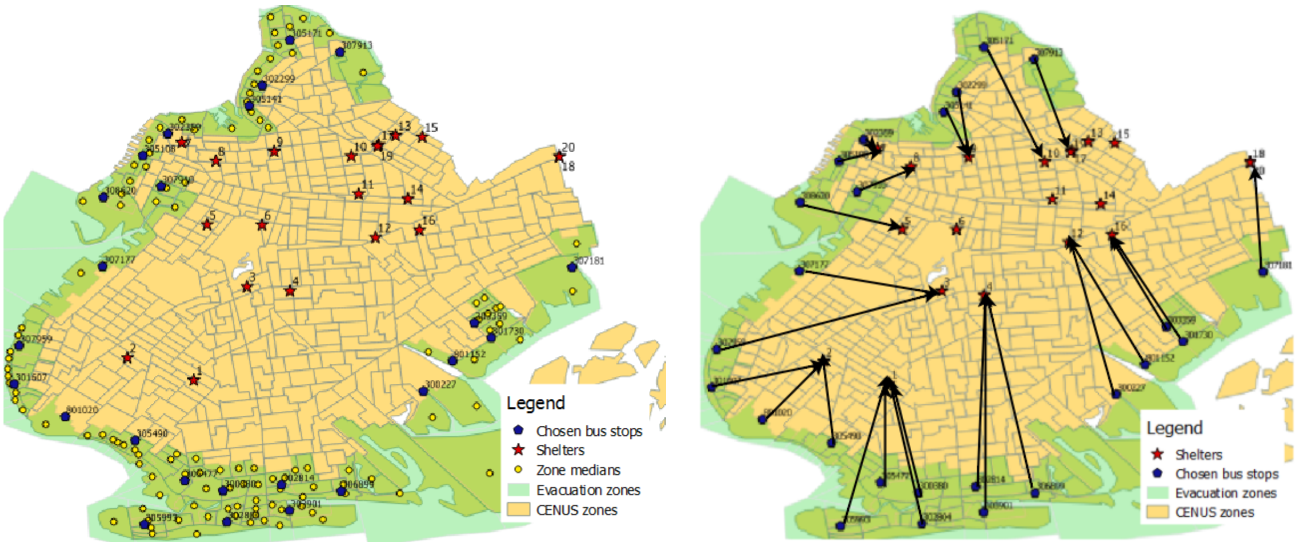

Figure 6: Left: Optimal set of chosen to serve as pickup locations for an accessibility distance of 0.6 mile. Right: Assignment of pickup locations to capacitated shelters

5.2 Computational results

This section presents the computational results from the simulation runs. For each route design, we run the simulation for different instances of the randomly generated demand arrival curve. Table 3 shows the result for one of the initial solutions, which terminates by mean convergence after 9 iterations.

Iteration (r)	Percentage evacuated	$\lvert x(r) - x(r-1) \rvert$	Run time (sec)
1	69.836 %	-	12.73
2	69.179 %	0.328	12.12
3	69.731 %	0.074	11.96
4	69.393 %	0.047	12.63
5	67.910 %	0.325	11.74
6	68.978 %	0.038	12.01
7	68.779 %	0.056	13.74
8	69.540 %	0.053	14.47
9	69.080 %	$0.009 \leq 0.010$	13.27

Table 3: Results from multiple runs of a sample route design for $\epsilon = 0.01$

Once the neighborhood search is terminated, and we have obtained the best possible route design given the parameters, our next goal is to understand and analyze the evacuation model. Figure 7 shows the total number of evacuees waiting at all the pickup locations when plotted against each minute (time step) of the simulation for the optimal route design. We can observe that there are multiple steep drops in numbers every time a bus arrives, and gradual drops representing those who balk or renege. At the end of the simulation time of 24 hours, every evacuee still waiting finally reneges. We can also observe a local-maxima around 720 minutes (noon time), which is a reflection of the peak in the demand curve used.

The analysis so far assumed that the central user had already decided on the fleet size. We extend the following analysis to assist this decision making process. We use the simulation to record the effect of the number of buses used on the performance of the system. In Figure 8, we can observe that increasing the number of buses produces vast improvements in the percentage evacuated for a small number of buses, and negligible impact beyond a certain number of buses. At the same time, as in Figure 9, we can observe

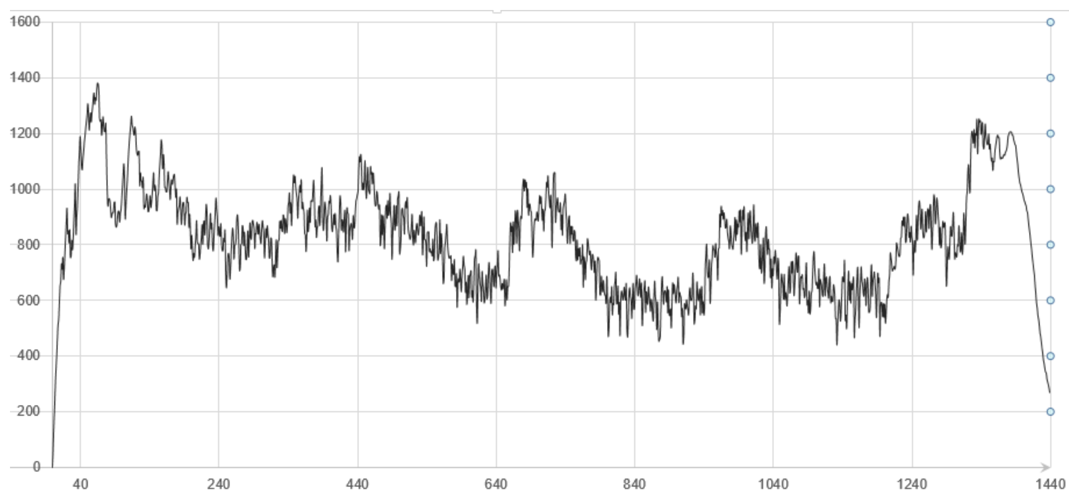

Figure 7: Number of evacuees waiting in all the pickup locations. The x-axis is the simulation time (in minutes) and the y-axis is the total number of evacuees waiting at all the pickup locations at each time step.

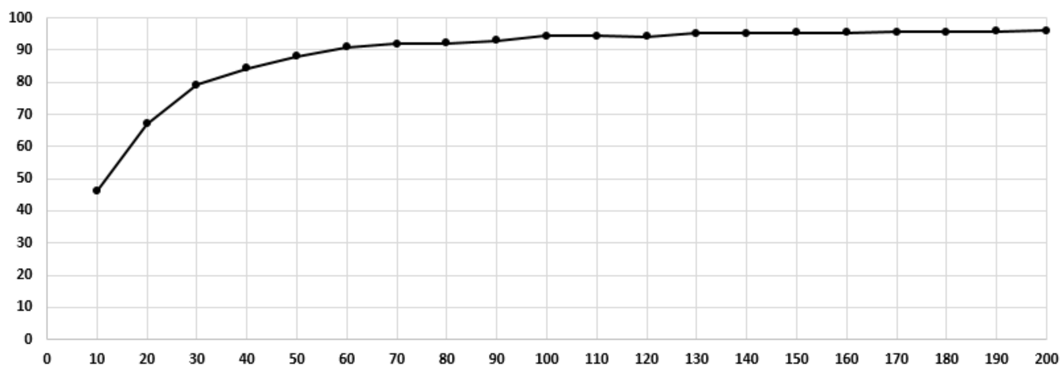

Figure 8: Effect of the number of buses on the percentage evacuated. The x-axis is the number of buses used and the y-axis is the % evacuation achieved.

that for every new bus added to the system, the amount of vehicle fuel, and hence the operational cost of the evacuation increases linearly.

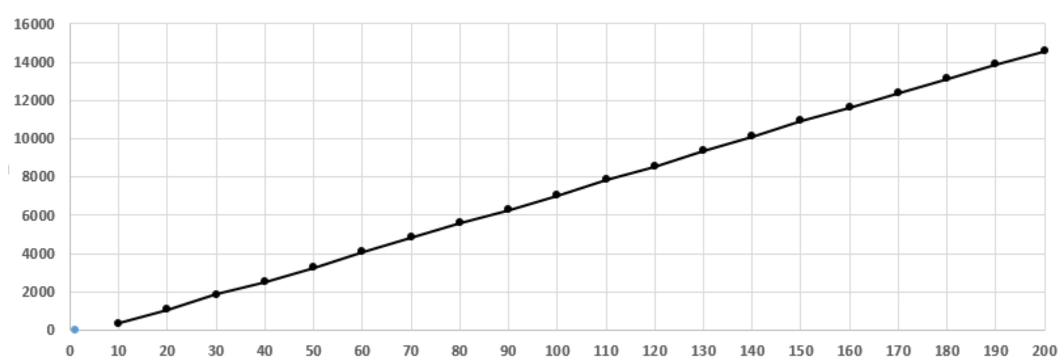

Figure 9: Effect of the number of buses on the amount of vehicle fuel consumed. The x-axis is the number of buses used and the y-axis is the total amount of vehicle fuel consumed (in gallons).

If the user wishes to take into consideration the amount of vehicle fuel into decision making, one can do so with a suitable objective function to resolve such a trade-off. The curve in Figure 10 is approximately a convex function that assists this form of decision making.

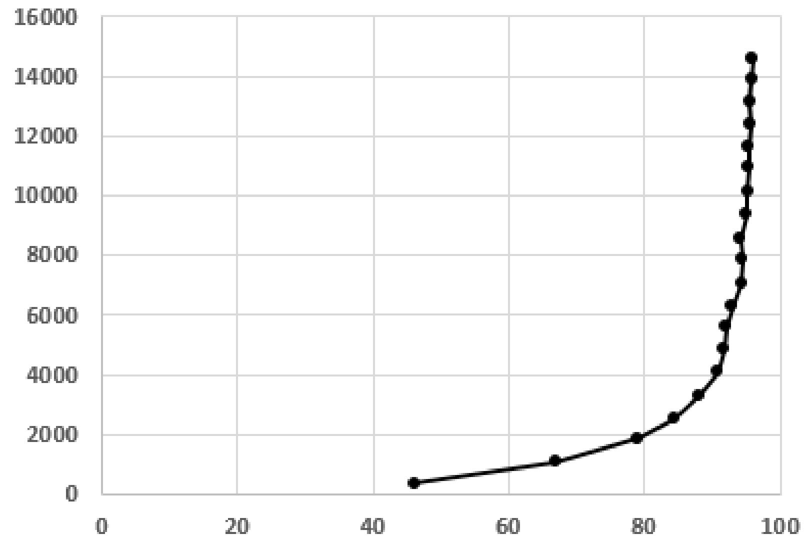

Figure 10: Curve showing the relationship between percentage evacuated and vehicle fuel consumed

6 Conclusions

We have presented a methodological framework for evacuating people who solely rely on public transportation before a hurricane. The proposed methodology only requires data that is easily obtainable from various open-source repositories. In addition, the models used are computationally efficient and one can obtain good results within the time-frame that is typically available to plan such an operation. The general nature of the framework makes it easy to adapt this procedure for evacuating residents from any region where there is a reliable transportation infrastructure, be it a city or a village.

7 Considerations for Future Work

In this section, we provide aspects not included in this paper, that one can consider while developing future models in this area.

- The main contribution made by this paper is the sequential modeling framework using various subproblems and the real-world simulation of evacuation operations. A possible alternative methodology could be involve integrating the models closer to link the various subproblems.
- The simulation results in this paper are used to improve the route design while fixing the rest of the input parameters. It could also be possible that one might alter other input parameters such as alternate pickup locations or a different dispatch sequence, that could give us better solutions.
- A more rigorous treatment of congestion effects on travel time would be recommended, although the current treatment may be sufficient for the sake of comparisons *between* the route designs, even if it doesn't capture real-world travel time.
- We have presented the framework using the percentage evacuated as the primary objective, and the operational cost (vehicle fuel) as a metric that could either be a constraint, or be a part of the

objective. More such parameters can be considered to formulate a multi-objective optimization-based model involving all the stake holders.

- Apart from buses, the influence of other means of transportation such as local trains and car rentals, must also be looked into for a comprehensive framework.

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