TRB 10- 3097

Optimal Refueling Station Location and Supply Planning for Hurricane Evacuation

Yang Gao, Yi-Chang Chiu*, Shuo Wang
Department of Civil Engineering and Engineering Mechanics
The University of Arizona, Tucson, Arizona 85721
Tel: (520) 626-8462
E-mail: chiu@email.arizona.edu
*corresponding author

Simge Küçükyavuz
Department of Integrated Systems Engineering
The Ohio State University, Columbus, Ohio 43210
Email: kucukyavuz.2@osu.edu

Words: 5,374
Figures and Tables: 8
Total: 7,374

Final Submittal for the publication in the Transportation Research Record

Abstract

The fuel supply shortage problem that has emerged in the last few hurricane events underscores the weakness of existing emergency logistics planning processes. Central to the refueling station location and supply planning decision is an effective modeling approach. This paper documents a research effort based on the simulation-optimization framework integrating a mixed integer program (MIP) formulation and a mesoscopic simulation model. The mesoscopic simulation model was incorporated with decision rules to select refueling stations, methods to model the impact of stalled vehicles on traffic flow, and formula to accumulate each vehicle's fuel consumption under various running speed conditions. The mixed integer program formulation is aimed at maximizing the served demand by deciding on which stations to operate and how much fuel to supply given limited resources. The interplay between the simulation model and the optimization model continues until convergence.

The proposed modeling approach is applied to a case study based on the interstate I-45 corridor between Houston and Dallas to highlight the characteristics of the proposed modeling approach.

1 INTRODUCTION

The devastating destruction potential of a hurricane often forces emergency management agencies to implement mass evacuation. Hurricanes Rita and Katrina of 2005 not only marked historical events, but also called for more effective and reliable hurricane evacuation planning and operation practices, including logistics management.

According to a recent study for Hurricane Rita, fuel supply was one of the major issues encountered in Hurricane Rita evacuation *(1)*. Accounts indicated that during Hurricane Rita, many evacuees stalled en-route to their destination and eventually gave up on evacuation due to the lack of critical supplies. Studies conducted after Hurricane Rita also showed that the number of evacuees ranged from 1.2 to 3.7 million *(1, 2)*. In long-distance intercity travel under congestion, evacuees are likely to run out of gas much faster than under normal driving conditions due to poorer fuel economy *(3)*. Providing sufficient fuel supply along the evacuation route is also crucial from a traffic management standpoint because stalled vehicles reduce roadway capacity, further disturbing traffic flow and aggravating the severity of the congestion. Such a chain reaction could set off a vicious circle, resulting in a rapid traffic breakdown of the entire evacuation corridor. Therefore, an improved refueling strategy is needed as part of the overall emergency logistics plan.

To devise an optimal and effective refueling strategy, one promising approach is to tackle the problem at strategic and operational levels. Strategic level decisions require a longer lead time to plan and execute. Once planned, the decision-makers can choose whether to execute as planned in an evacuation event. Operational decisions, on the other hand, can be refined and adjusted in real time during an evacuation operation. Both strategic and operational decisions are needed for a successful evacuation operation.

The primary focus of this paper is on the strategic decisions on the planning of refueling station locations and capacities. These decisions are sought by formulating and solving a location-allocation (LA) problem that determines the optimal refueling locations satisfying the set objective subject to a number of constraints. To this extent, the main research challenges lie in how to create an appropriate model formulation and how to properly estimate the model inputs and parameters given that the model needs to be sensitive to traffic dynamics and fuel consumption that is subject to congestion levels. Additional factors that need to be considered include: (1) where vehicles can be refueled (e.g. existing gas stations, or even rest areas residing on the state right of way premises), (2) the level of fuel demand at different mileposts along the route (e.g. number of vehicles running out of gas and requiring refueling), (3) total available fuel supply, and (4) the maximum number of refueling locations that can remain open during evacuation.

Among the factors above, the demand is perhaps the most difficult to estimate accurately when considering how fuel consumption may relate to running speed, and different running speeds may occur at different locations along the evacuation route. It is documented that the optimal fuel economy remains in the range of 40 to 60 mph *(3)*. The overall fuel consumption pattern is concave. When running speed is low (between 0 and 4 mph), the fuel economy increases non-linearly with increasing speed. When speed exceeds 60 mph the fuel economy decreases with increasing speed.

In this paper, we propose a simulation-optimization framework which includes the interplay between a mixed integer programming (MIP) model and a mesoscopic simulation model. The mesoscopic simulation model tracks fuel consumption of each individual vehicle and the locations where vehicles are running low in fuel to estimate the demand to each gas station. The MIP problem optimizes the location decisions: which station to open and how much capacity to allocate to each opened location for a given estimate on fuel demand. The location decision then feeds back to the simulation model to estimate the demand. The process continues until a stopping criterion is met.

This research provides one of the first systematic treatments to the planning of the refueling station locations for hurricane evacuation, allowing both researchers and practitioners to further explore the opportunities to improve fuel supply planning for hurricane evacuation.

The rest of this paper is organized according to the following structure. Section 2 reviews the prior related literature. The overall methodology is discussed in Chapter 3, followed by a case study based on the IH-45 corridor between Houston and Dallas using data collected for Hurricane Rita.

2 LITERATURE REVIEW

Over the past decade, a number of models have been developed to assist in emergency evacuation planning and operations. However, the planning of refueling station locations has not been widely recognized until 2005 Hurricane Rita, in which a large number of evacuation vehicles encountered the fuel shortage problem en route to their intended safe destination. The problem of interest can be modeled as a location-allocation (LA) problem. The LA problem has attracted researchers from areas of operations research, management science and spatial analysis. The topics of interest include allocating different types of facilities, such as emergency facilities, schools, warehouses and retail facilities. LA models in networks focus on locating the optimal service facilities as well as the associated demand. Demand for facility service is often assumed to be generated or could be expressed by a set of nodes that covers the entire region of interest. Under this assumption, the goal of LA models is to locate facilities at nodes to optimize a spatial function, usually in the form of a weighted total distance or time to travel between demand nodes and facility nodes. Three basic facility LA models can be found in literature *(4, 5)*. Hakimi *(6, 7)* defined the *p-median* and *p-center* problems and proposed corresponding solution algorithms. The *p-median* model identifies locations for *p* facilities in some space (such as the Euclidean plan or a road network) to serve *n* demand points so that the total weighted distance (or cost) between the facilities and the demand points they serve is minimized. The *p-center* problem addresses the problem by minimizing the maximum distance between where the demand originates and where the closest facility is, given a set of pre-determined facilities. Another type of known model is the maximum covering location model (MCLP) by Church et al. *(8)*, which locates *p* facilities within distance *S*, so as to cover the maximum population within *S*. All the three basic LA models assume that demand occurs at nodes, and therefore their goals are to optimize the weighted distance, or the distance of the direct path from node to facility.

Hodgson *(9, 10)* and Berman *(11)* proposed different models that suggested that demand in a network might be expressed as flow passing through the facility. Berman argued that in retail business, such as convenience stores, gasoline stations, and banking machines, an increasing number of services were consumed by customers who don't make a purposeful trip to the facility. More likely for these services the customer is already on a pre-planned trip, and if (s)he passes the service facilities on his(her) preplanned route, (s)he may consume that service. Hodgson presents the Flow Capturing Location Model (FCLM), aiming at locating facilities to serve as many of passing flows as possible. Any flow that uses a path that passes through the location of the facility was considered to be captured. His model is also designed to prevent flow cannibalization: capturing flow more than once at the expense of flows elsewhere in the network not being captured at all. Hodgson shows that the FCLM is a special case of the Maximal Covering Location Problem. Berman et al. *(11)* proposed a model similar to FCLM, but they used the term "discretionary service facilities" to refer to facilities that capture passing flows. Considering demand in the real world is often expressed as either passing flows or consumers centered in the residential areas, aggregated as nodes, Hodgson and Rosing *(10)* developed a hybrid model with dual objective (flow capturing and p-median) to serve both types of demand.

Traditionally, LA models for gas station planning are used for infrastructure and/or economic development purposes. Bapna et al. *(12)* developed a LA method for infrastructure development for alternative fuel. The multi-objective formulation considers three objectives such as cost minimization, demand orientation, and environmental concern. Their model is called maximum covering/shortest spanning sub-graph (MC3SP) problem. Goodchild and Noronha *(13)* proposed their model for maximizing market share based on two types of demand, similar to Hodgson and Rosing's model *(10)*. Kuby et al. *(14)* proposed a flow refueling location model (FRLM), based on FCLM, especially for the gas station location problem. The FRLM optimally locates *p* refueling stations on a network so as to maximize the total flow volume refueled. Kuby et al. argued that the FCLM cannot be directly applied to the refueling problem, since a single flow might need to be refueled more than once, while FCLM was designed not to double count flows captured by more than one facility along their path. In other words, in FCLM, each driver is assumed to stop only once. The FRLM considers a flow refueled only if an adequate number of stations are spaced appropriately along the path, and uses feasible facility combinations to refuel network paths. In this research, we allow vehicles to demand fuel more than once, which is necessary as will be illustrated in our case study.

Goodchild and Noronha's model was applied to the problem of rationalizing a company's set of gasoline stations after merging with another company on economic value *(13)*. The FRLM can handle the multiple refueling stops needed for paths longer than the vehicle's range, but the demand is based on origin-destination (O-D) flows. Under an evacuation situation, considering the unpredicted number of evacuees, it's hard to estimate the O-D flows unless a simulation-based approach is used. Besides, the demand for gas under the evacuation circumstance would be quite challenging to estimate based on simple analytical methods because fuel economy is affected by congestion and running speed. Refueling behavior needs to be properly accounted for in estimating demand. For example, most of the travelers would refuel only at the downstream stations since turnaround would be risky or prohibitive under an evacuation situation. Therefore, directly utilizing a *p-median*, *p-center* or MCLP model to represent the refuel facilities allocation problem may not be adequate.

Other than the static optimization problems, two-stage stochastic formulations attracted considerable attention in recent years. In a two-stage model, a decision is made with incomplete information before observing the realization of some other stochastic factors. Subsequently, an opportunity may be available for correcting the preliminary decision. The recourse action may compensate for the incomplete information in the first stage. This results in a two-stage model which formulates a preliminary planning problem in the first stage and a recourse problem in the second stage *(15)*. However, most of the stochastic programming literature assumes that the distribution of the random variable is independent of the decisions made in the first stage. In our problem, however, the decisions in the first stage (namely the station locations and capacity) affect the distribution of the random variable (demand for refueling in different locations).

In conjunction with optimization models, simulation models allow to find a good solution to some decision problems, but also to observe a system under different sets of assumptions *(16)*. In the past 30 years, simulation models have been developed and commonly used to evaluate the performance of emergency response systems. They also provide the possibility to test new operational strategies such as different ambulance locations or dispatching rules. In this research, both simulation and optimization modeled integrated into a unified framework for the problem of interest.

3 MODELING FRAMEWORK AND SOLUTION PROCEDURE

In general, the refueling problem for evacuation falls into the LA problem class. However, the traditional LA problem falls short in realistically estimating the model input such as the demand that is intrinsically sensitive to congestion. If a vehicle can find the nearby gas station with sufficient supply, it can continue the journey. If no gas station can be reached with the remaining fuel, the vehicle will stall and create disturbance to traffic flow. Such a phenomenon and the resulting traffic condition and demand can only be realistically estimated with simulation.

The objective of this paper is to propose a simulation-optimization framework and model formulation. Instead of estimating refueling demand from making considerable assumptions in O-D flows or generation nodes, we use a simulation model to incorporate the refueling behavior, capture traffic congestion phenomenon and estimate fuel consumption based on time-varying running speed. As shown in Figure 9, the process starts from preparing necessary dataset including network configuration, locations of gas stations and initial fuel level for every vehicle.

The simulation model DynusT outputs the location of each fuel requesting vehicle and whether they could be served by the existing location and capacity planning decision. The demand for each station resulted from simulation is also outputted. More modeling details in DynusT are presented in Section 3.1.

The optimization model is a mixed integer program (MIP) that decides on which gas stations to operate and how much fuel supply to provide to each station (more details are discussed in Section 3.2). After verifying the convergence by comparing demand with demand from last simulation iteration, the algorithm terminates or the solution is fed back to DynusT for another simulation run to re-estimate demand. This process repeats until the stopping condition is met.

FIGURE 1 HERE

3.1 Mesoscopic Vehicular Simulation for Fuel Consumption and Fuel Supply

The simulation model applied to this research is **Dyn**amic **U**rban **S**ystems for **T**ransportation (DynusT). DynusT is a mesoscopic dynamic traffic simulation *(17)* and assignment model *(18)* that has been developed for years and has been applied to various region-wide traffic simulation modeling applications including mass evacuation *(1, 19-21)*.

As shown in Figure 10, within DynusT the traffic assignment process involves the interplay of the simulation model and the time-dependent shortest path and flow redistribution component. DynusT can be used to compute the equilibrated route selection for travelers departing at different times. This capability is primarily used to assign the evacuees to the evacuation network. The modeler can choose to perform one-shot simulation or simulation-assignment procedure depending on the modeling requirement. During the iterative computational process, the time-dependent link travel time and intersection delays are input into the time-dependent shortest path algorithm. Based on the shortest path results, the new flow distribution and routing policies are computed in a time-dependent traffic assignment procedure based on the Method of Isochronal Vehicle Assignment (MIVA) *(22, 23)*. The vehicles with updated routes are then input into the traffic simulator to assess the performance. The process is repeated until some convergence criteria are satisfied or the maximum number of iterations is reached.

FIGURE 2 HERE

The vehicle simulation mechanism follows the anisotropic mesoscopic simulation (AMS) logic *(17)* in that individual vehicles are generated with individual attributes such as departure time, origin, destination, occupancy, vehicle types, and the route that each vehicle is taking for evacuation. During the simulation, a vehicle’s movement follows a speed-density relationship – a widely known relation between speed and density that describes the traffic flow – to ensure that as a vast amount of vehicles are simulated, they exhibit realistic traffic flow characteristics at the macroscopic level. Furthermore, individual vehicles have decision rules in response to traffic conditions as well as information *(21)*.

For this research, additional fuel consumption logics were built alongside with the AMS simulation method in order to properly capture fuel consumption under various congestion situations. This permits a more detailed estimation of fuel consumption than traditional static or analytical approaches. At each simulation instance t for each vehicle n, the fuel consumption is expressed as:

$$f_n^t = \frac{1}{\delta_k(u_n^t)}(u_n^t \cdot \Delta) \tag{1}$$

where Δ is the simulation interval, u_n^t is the running speed of vehicle n at time instance t, $\delta_k(u_n^t)$ is the mile-per-gallon (mpg) fuel economy for vehicle fuel economy type k at running speed u_n^t. The term $(u_n^t \cdot \Delta)$ means the distance traveled by vehicle n at time instance t at running speed u_n^t. The fuel economy at running speed u_n^t is $\delta_k(u_n^t)$, thereby the fuel consumption at time instance t over the simulation interval can be calculated by Equation (1). The vehicle fuel economy type k corresponds to a specific fuel economy-speed profile that can be applied to passenger cars, light-duty trucks, heavy duty trucks or even trailer trucks. The number of vehicle fuel economy types that can be included in the modeling also depends on the available data in vehicle stream composition and the fuel economy data.

As shown in Figure 11, for a typical vehicle at low speed, the fuel economy is at 10 mpg. The fuel economy increases to 30 mpg when speed is in the range of 45 to 55 miles per hour (mph). The fuel economy however starts to decrease at a linear rate when speed exceeds 55 mph. The fuel economy curve clearly indicates that fuel economy is sensitive to running speed; as such, it becomes clear that severe congestion during evacuation can quickly deplete an evacuee vehicle's fuel tank.

FIGURE 3 HERE

The application of Equation (1) into simulation considering other related implementation issues are briefly discussed hereafter. At the beginning of simulation, each vehicle (assuming vehicle type is known) is assigned with a random initial fuel level F_n^0. F_n^0 can be assumed to follow various distributions. One would assume that when evacuees set off their trips their fuel level may be close to full. As they travel a certain distance and arrive at the boundary of the study area, their remaining fuel level becomes random as this depends on their origin and traffic condition along the way. The research in fuel level distribution is out of the scope of this research. To this extent, we assume that the distribution follows a normal $N(\theta, \sigma)$ distribution with modeler-specified mean θ and standard deviation σ parameters. Bounds for minimal and maximum fuel levels also need to be specified. To circumvent this issue a log-normal distribution can be also be used. A uniform distribution can also be considered, if appropriate.

For each vehicle n, the remaining fuel at each simulation time instance t can be calculated as $F_n^t = F_n^{t-1} - f_n^t$. Vehicle n is marked as a fuel requesting vehicle when $F_n^t \le F_n^{\min}$, where $F_n^{\min}$ is the minimal fuel level threshold for vehicle n. $F_n^{\min}$ is also assumed a random variable. Modeling multiple vehicle types can be pursued by applying different initial fuel level distributions $N_k(\theta, \sigma)$ for each vehicle type k. The fuel economy for each vehicle type k also needs to be specified, but once it is specified Equation (1) is applicable to all vehicles regardless of their vehicle type.

When a vehicle is in need for fuel (i.e. $F_n^t \le F_n^{\min}$, it would search for fuel at the immediate downstream refueling location i. If this location has sufficient fuel (e.g. $c_i > 0$) when the vehicle requests fuel, then the remaining fuel for that station c_i is reduced by the fuel tank capacity of that vehicle β_n until the station runs out of fuel. The demand for the station b_i is incremented by one unit. For a vehicle, if the nearest station i has no fuel, the vehicle will look for the 2nd nearest station downstream along the travel direction until it is refueled or it runs out of fuel. In the event that a vehicle runs out of fuel, it becomes a stalled vehicle. A certain roadway capacity reduction (5% as an example) is applied for each stalled vehicle. The reduced roadway capacity will in turn affect the traffic condition at the site starting when the vehicle is stalled and onward. In other words, the stalled vehicle could decrease the roadway capacity and further aggravate the congestion situation. The reduced capacity can be partially restored at a later time to consider the situation of moving the stalled vehicles out of the traffic lane.

3.2 Optimization Model

The Optimal Refueling Station Location and Capacity Planning problem is formulated as a mixed-integer program (MIP). The problem is formulated as follows.

Data:

- I Set of potential refueling stations
- i Subscript for refueling station, $i \in I$
- β Average vehicle fuel tank capacity (gallons)
- C Total available fuel supply (gallons)
- N Maximum number of stations that can be operated
- b_i The number of vehicles which demand fuel from station i estimated by simulation.

Decision variables:

- x_i (Binary) $x_i = 1$ if station i is operated during evacuation, $x_i = 0$ otherwise
- y_i Fraction of station i demand met
- ε_i Amount of fuel supply provided to station i

Model

$$\max Z = \sum_i b_i y_i \tag{1}$$

Subject to:

$$0 \le y_i \le 1, \qquad \forall i \tag{2}$$

$$y_i \le x_i, \qquad \forall i \tag{3}$$

$$b_i y_i - \frac{\varepsilon_i}{\beta} \leq 0, \qquad \forall i \tag{4}$$

$$\sum_i \varepsilon_i \leq C \tag{5}$$

$$\sum_i x_i \leq N \tag{6}$$

The objective function (1) maximizes the total number of vehicles that can be refueled with a maximum of N opened stations. The maximum number of opened stations can be determined by the emergency management agency considering the staffing and contract issues with the gas stations. Constraints (2) restrict y_i to be a fraction of demand met by station i. Constraints (3) force y_i to zero unless x_i is nonzero. If x_i is zero, station i will not be operated, so y_i has to be zero. In other words, if $x_i = 1$, y_i can be nonzero. Constraints (4) indicate that the assigned fuel supply for station i divided by average vehicle fuel tank capacity, given by $\frac{\varepsilon_i}{\beta}$, needs to be greater or equal to the total amount of fuel requesting vehicles, given by $b_i y_i$. Constraints (5) require that the total station supply not exceed the total available fuel supply C. The total fuel supply C can be estimated from the petroleum terminal operators based on the number and capacity of gasoline terminals in a feasible distance to the study area. Constraints (6) bound the maximum number of stations to operate.

3.3 Convergence Criterion

The overall model convergence criterion could be set based on objective function or estimated demand. The algorithm will terminate once the change in objective function value Z or the change in demand b_i is less than a pre-set threshold. The reason that we choose not to use the solution per se as the stopping criterion is because this MIP problem may not have a unique solution; the model may be oscillating between two different solutions with the same objective function value.

4 NUMERICAL EXAMPLE

4.1 Network Descriptions and Model Setup

This section provides an illustrative example to highlight the performance of the proposed modeling approach. The network is a 200-mile section of interstate 45 from North Houston to South Dallas. This network is extracted from a central Texas regional network with all the lane geometry configuration carefully coded as part of a prior modeling effort in DynusT *(1)*. All evacuation vehicles were extracted from the same study to form new trajectories pertaining to the extracted network shown in Figure 12. A total of about 70,000 evacuation vehicles were generated over the period of 24 hours. The initial fuel level follows the normal distribution *N*(10,3). The mean fuel level appears to be seemingly less than what a typical passenger car can hold. This is because vehicles' actual origin is outside the modeled network. After driving for a certain distance, their fuel level upon arrival at the network should be lower than the actual capacity. Therefore, 10 gallon was chosen as the mean starting fuel level. The average travel distance is 90.6 miles and average travel time is 333 minutes, equivalent to an average speed 16.3 mph.

FIGURE 4 HERE

Fifty three refueling stations were identified using Google map. These sites are primarily the existing gas stations. Existing rest areas on state right of way can also be included. Figure 14-8 illustrate selected sites along the I-45 corridor. In this case study, the average vehicle fuel tank capacity β is assumed to be 20 gallons. The total fuel supply for all the open stations C, is assumed to be 1.4 million gallons for all the stations and the maximum number of opened stations N, is assumed to be 40.

4.2 Results and Analysis

The first step of the analysis is to examine the convergence of the solution procedure. As previously explained, the overall algorithmic procedure invokes iterative interplay between the simulation and the optimization model. Figure 13 indicates that initially, only 70028 vehicles are served. The number increases to 70075 at the 2nd iteration. The number remains the same at the 3rd iteration, suggesting the convergence of the solution procedure.

FIGURE 5 HERE

The demand b_i obtained from DynusT at convergence is depicted in Figure 14. One can see that along the I-45 corridor, a large portion of demand concentrates between Houston to Madisonville, particularly in the area before reaching Conroe. These locations have demand exceeding 10,000 vehicles over the 24-hour period. The simulation results also indicate severe traffic congestion occurring in the same area due to lane dropping from 3 lanes to 2 lanes at Conroe. The secondary demand concentration location is at the vicinity of Fairfield, about 70 miles south of Dallas.

FIGURE 6 HERE

The solution obtained by the optimization model, as shown in Figure 15, indicate a concentrated allocation of fuel supply to stations located between Houston and Conroe. The needed fuel would be as high as 425k gallons. Others range between 140k to 280k gallons. The fuel supply would gradually decrease after passing Conroe. Stations in the vicinity of Fairfield are also allocated with fuel in the range of 10,000 gallons. The 1.4 million gallons of gasoline that is set as the constraint is found to be binding, meaning that there may be unserved vehicles.

FIGURE 7 HERE

The amount of unserved vehicles are found to be rather uniformly distributed along the corridor, on the average less than 20 vehicles per gas station, except for station 3 with more than 70 unserved vehicles (see Figure 8).

FIGURE 8 HERE

5 SUMMARIES AND CONCLUDING REMARKS

This paper documents a research effort based on the simulation-optimization framework integrating a mixed integer programming (MIP) formulation and a mesoscopic simulation model. The mesoscopic simulation model incorporates realistic refueling station selection decision for evacuees and stalled vehicles' impact on traffic flow. The MIP formulation is aimed at maximizing the served demand by deciding on which stations to operate and how much fuel to supply given the set constraints. The interplay between the simulation and optimization models continues until convergence. The case study indicates the potential of the proposed modeling approach.

Further refinement of both simulation and optimization models can be pursued to improve the realism of the model. First, the impact of the stalled vehicles was assumed in this paper, but it can be more realistically estimated from field data. The gas station searching behavior is assumed to be instantaneous, that is, there is no delay associated with refueling and vehicles are reloaded to the network without delay. The optimization model is a static model, which does not account for the time-varying demand that can be naturally output from simulation. This would lead to time-varying fuel supply decisions, which may require additional gas tanker fleet routing decisions and fuel terminal operation constraints.

6 REFERENCES

[1] Henk, R. H., Ballard, A. J., Robideau, R. L., Peacock, W. G., Maghelal, P., Lindell, M. K., Prater, C. S., Loftus-Otway, L., Siegesmund, P., Harrison, R., Lasdon, L., Chiu, Y.-C., Zheng, H., Perkins, J., Lewis, C., and Boxill, S., *Disaster Preparedness in Texas Final Report*, Texas Transportation Institute, College Station2007.

[2] Eskovitz, J., Evacuation Planning in Texas: Before and After Hurricane Rita, in *Interim News*2006n ed. vol. 79th Legislature, Texas: HOUSE RESEARCH ORGANIZATION, 2006.

[3] Fuel Economy Gov, Fuel Economy versus Speed, 2008n ed. vol. 2009: Fuel Economy Gov, 2008.

[4] Current, J., Daskin, M., and Schilling, D., Basic Facility Location Models, in *Facility Location: Application and Theory*2008n ed, H. W. H. Zvi Drezner, Ed.: Springer, 2008.

[5] Plastria, F., Continuous Covering Location Problems, in *Facility Location: Application and Theory*2008n ed, H. W. H. Zvi Drezner, Ed.: Springer, 2008.

[6] Hakimi, S. L., Optimum Locations of Switching Centers and the Absolute Centers and Medians of a Graph, *Operations Research*, vol. 12, pp. 450-459, 1964.

[7] Hakimi, S. L., Optimum Distribution of Switching Centers in a Communication Network and Some Related Graph Theoretic Problems, *Operations Research,* vol. 13, pp. 462-475, 1965.

[8] Church, R. and ReVelle, C., The maximal covering location problem, *Papers in Regional Science*, vol. 32, pp. 101-118, 1974.

[9] Hodgson, M. J., Developments in Flow-Based Location-Allocation Models, in *Econometric Advances in Spatial Modeling and Methodology*, 11998n ed, C. G. A. Daniel. A. Griffith, Jean-Marie Huriot, Ed.: Springer, 1998.

[10] Hodgson, M. J. and Rosing, K. E., A network location-allocation model trading off flow capturing and p-median objectives, *Annals of Operations Research,* vol. 40, pp. 247-260, 1992.

[11] Berman, O., Larson, R. C., and Fouska, N., Optimal Location of Discretionary Service Facilities, *Transportation Science,* vol. 26, 1992.

[12] Bapna, R., Thakur, L. S., and Nair, S. K., Infrastructure development for conversion to environmentally friendly fuel, *European Journal of Operational Research,* vol. 142, pp. 480-496, 2002.

[13] Goodchild, M. F. and Noronha, V. T., Location-allocation and impulsive shopping: the case of gasoline retailing, in *Spatial Analysis and Location-Allocation Models*1987n ed, A. G. a. G. Rushton, Ed., New York: Van Nostrand Reinhold, pp. 121-136, 1987.

[14] Kuby, M. and Lim, S., The flow-refueling location problem for alternative-fuel vehicles, *Socio-Economics Planning Sciences,* vol. 39, pp. 125-145, 2005.

[15] Birge, J. and Louveaux, F. (1997). Introduction to Stochastic Programming. Springer-Verlag.

[16] Haghani, A. and Yang, S.,Real-time Emergency Response Fleet Deployment: Concepts, Systems, Simulation and Case Studies, in *Dynamic Fleet Management*, 1 ed, C. D. T. Vasileios Zeimpekis, George M. Giaglis, Ioannis Minis, Ed.: Springer, 2007.

[17] Chiu, Y.-C., Zhou, L., and Song, H., Development and Calibration of Anisotropic Mesoscopic Simulation Model for Uninterrupted Flow Facilities, *Transportation Research Part B,* vol. forthcoming, 2009.

[18] Chiu, Y.-C. and Bustillos, B., A Gap Function Vehicle-Based Solution Procedure for Consistent and Robust Simulation-Based Dynamic Traffic Assignment, in *The 88th Annual Meeting of Transportation Research Board*, Washington, D.C., 2009.

[19] Noh, H., Chiu, Y.-C., Zheng, H., Hickman, M., and Mirchandani, P., An Approach to Modeling Demand and Supply for a Short-Notice Evacuation, *Transportation Research Record,* vol. Forthcoming, 2009.

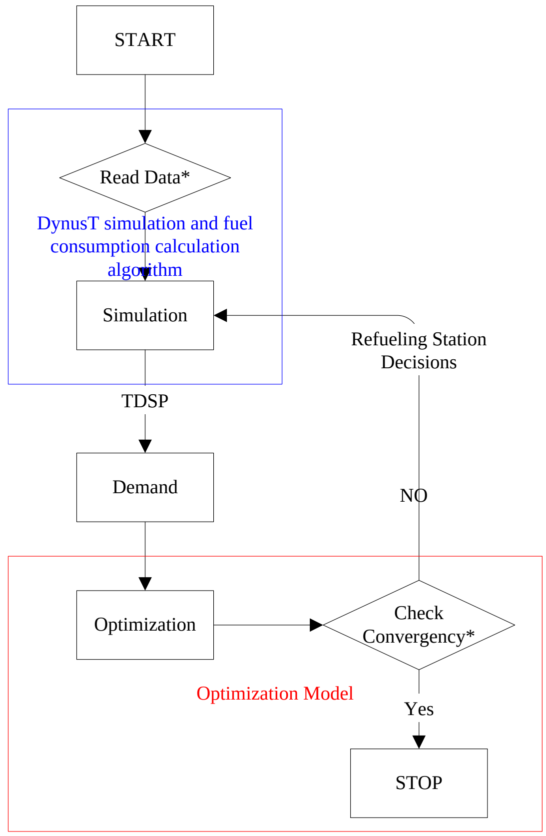
[20] Chiu, Y.-C., Zheng, H., Villalobos, J. A., Henk, R., and Peacock, W., Evaluating Regional Contra-Flow and Phased Evacuation Strategies for Central Texas Using a Large-Scale Dynamic Traffic Simulation and Assignment Approach, *Journal of Homeland Security and Emergency Management,* vol. 5, 2008.

[21] Chiu, Y.-C. and Mirchandani, P. B., Online Behavior-Robust Feedback Information Routing Strategy for Mass Evacuation, *IEEE Transaction on Intelligent Transportation Systems,* vol. 9, pp. 264-274, 2008.

[22] Chiu, Y.-C. and Nava, E., The Method of Isochronal Vehicle Assignment for Large-Scale Long-Period Scalable Dynamic Traffic Assignment, in *The 88th Annual Meeting of Transportation Research Board*, Washington, D.C., 2009.

[23] Chiu, Y.-C. and Nava, E., Method of Isochronal Vehicle Assignment for Simulation-Based Dynamic Traffic Assignment, *Transportation Research Part B: Methodological*, vol. Under review, 2009.

List of figures:



(*Data includes network configuration, locations of gas station and initial fuel level for every vehicle.

*Convergence criteria include either demand or objective function value.)

Figure 9 Research Framework

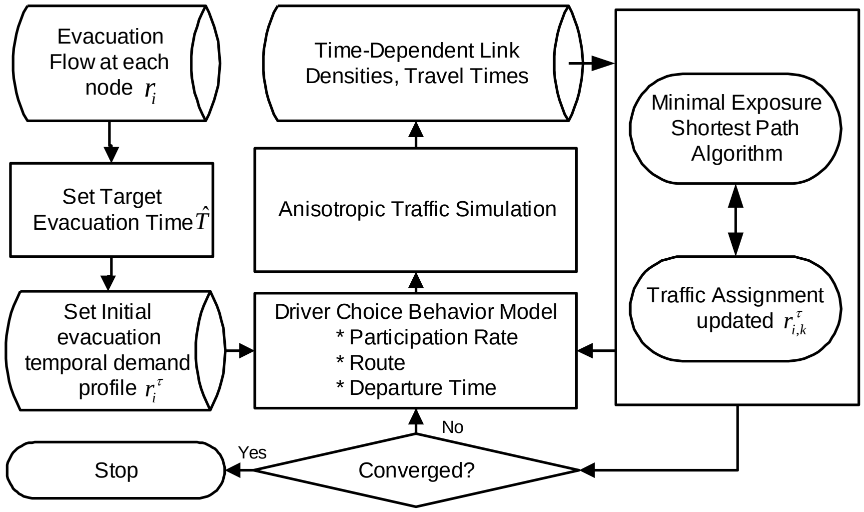


Figure 10 General Algorithm Structure of the DynusT Model *(21)*

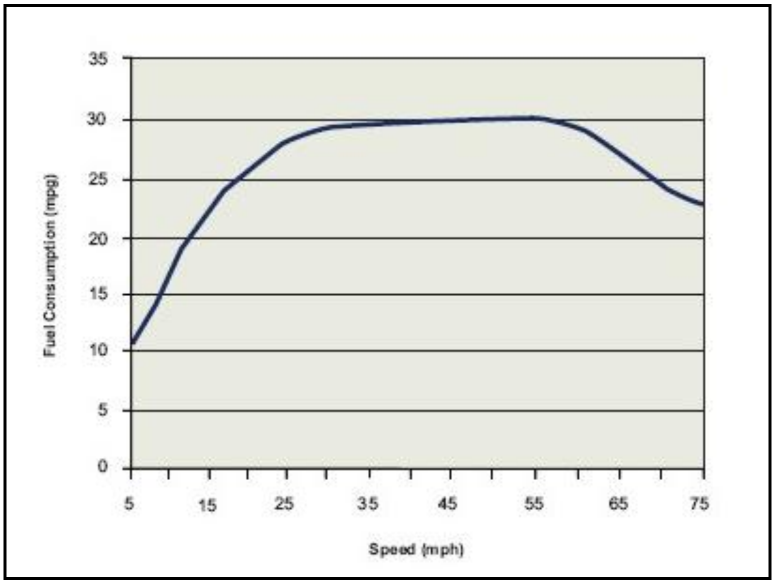


Figure 11 Relationship of vehicle speed and fuel consumption *(3)*

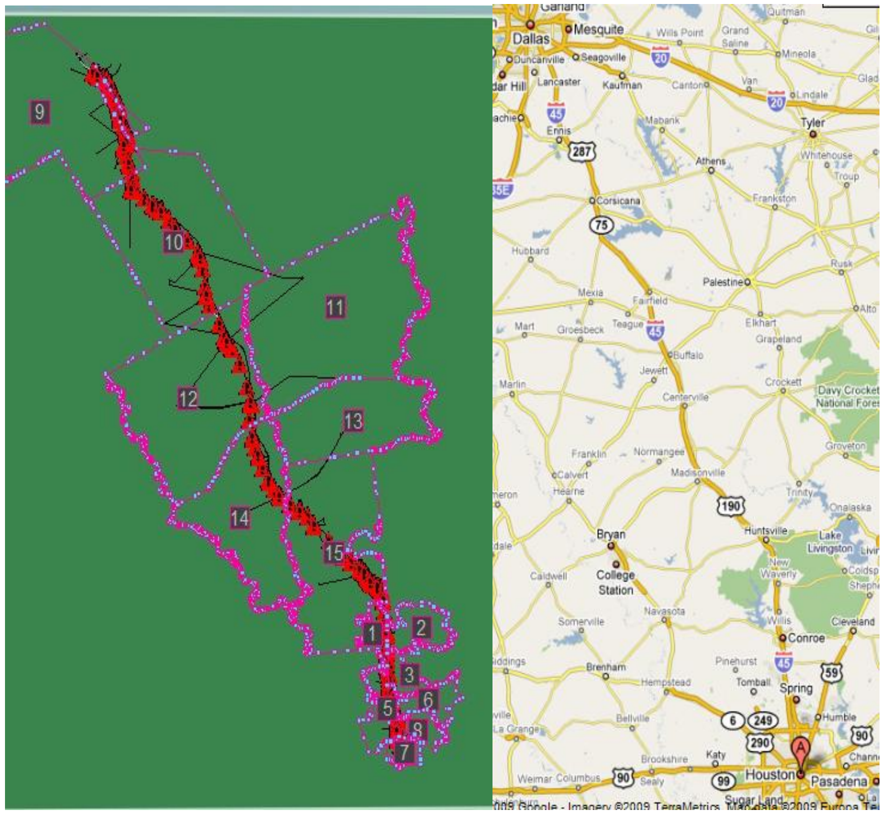


Figure 12 Case study network

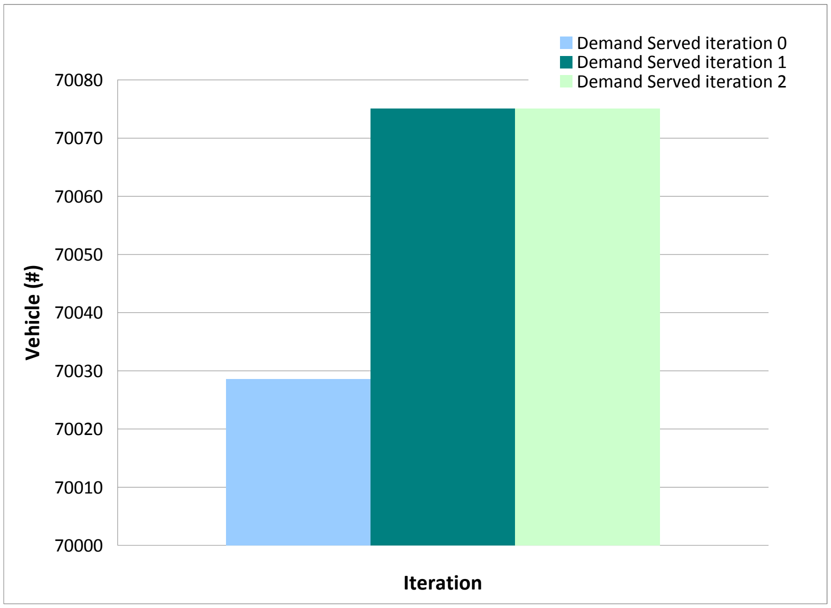


Figure 13 Objective Function Value (Served Demand) Over Iterations

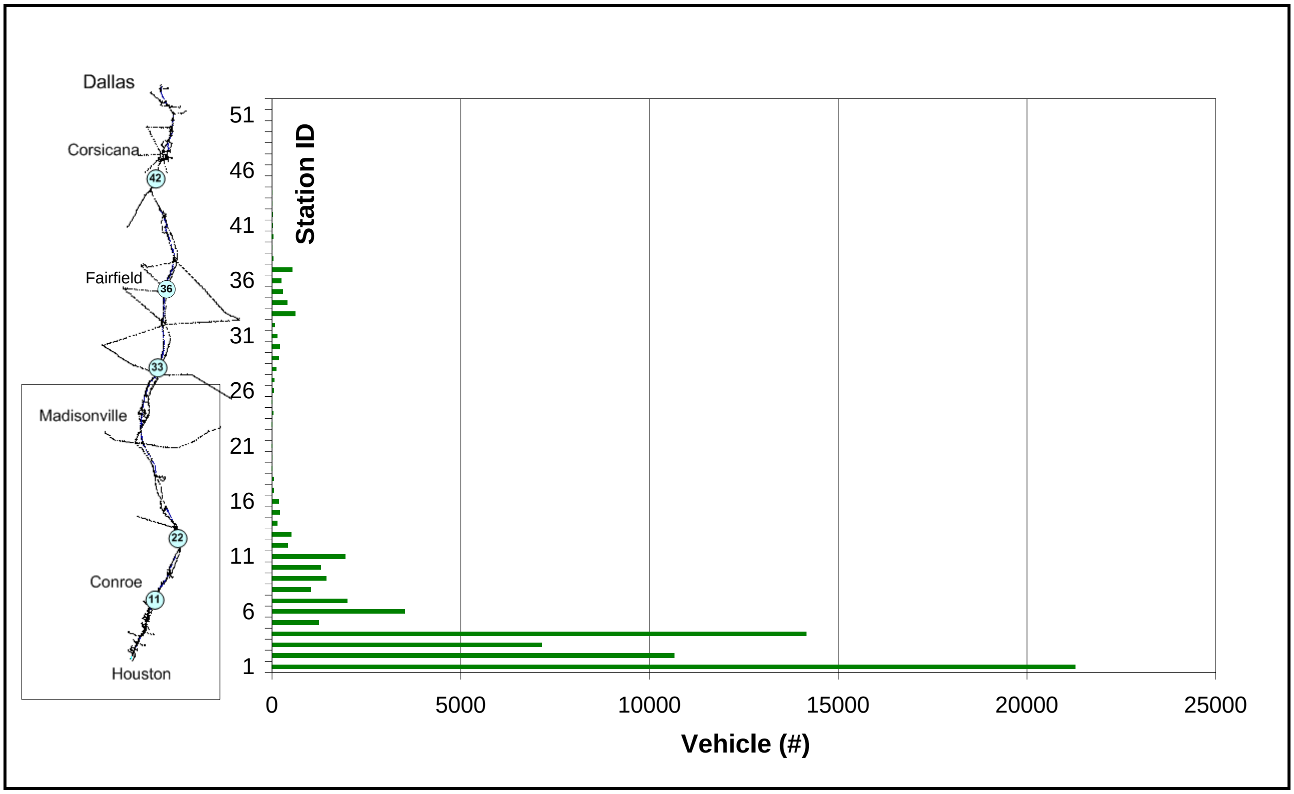


Figure 14 Demand Spatial Distribution

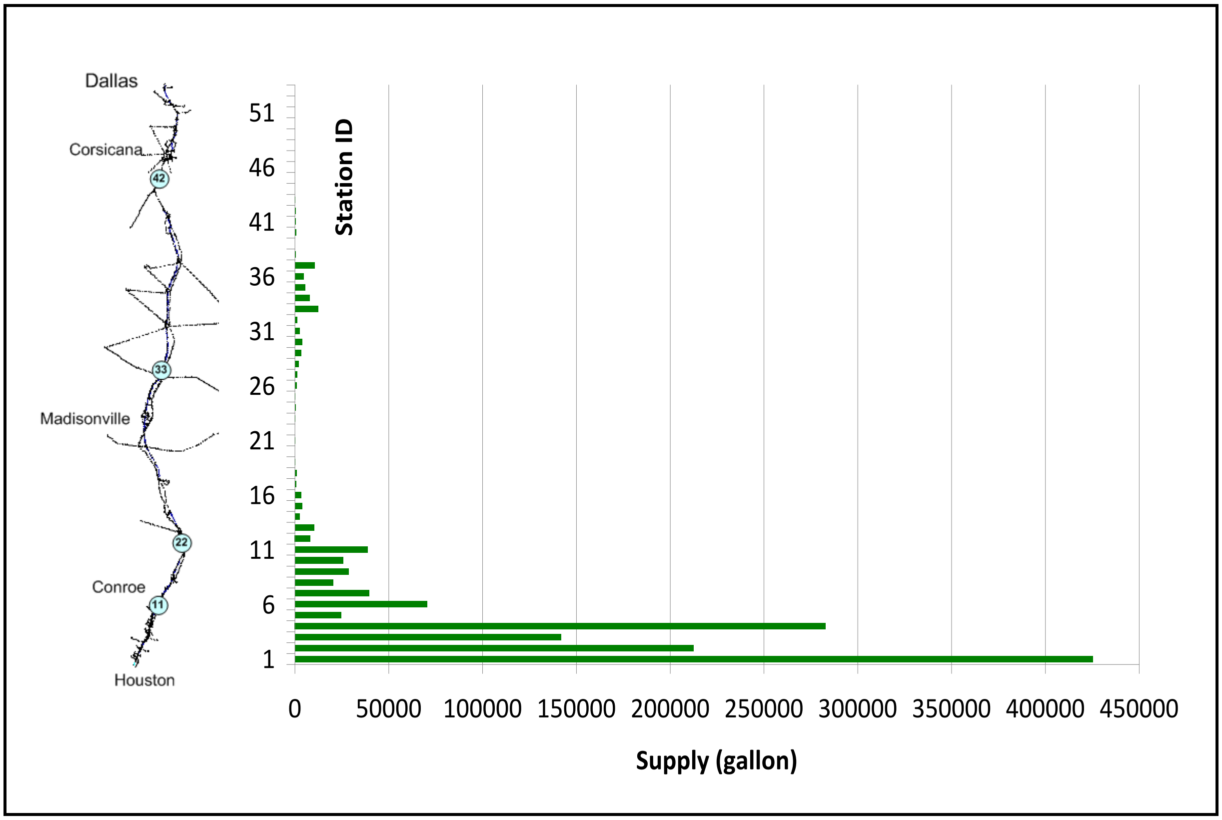


Figure 15 Planned supply (model solution) for each station

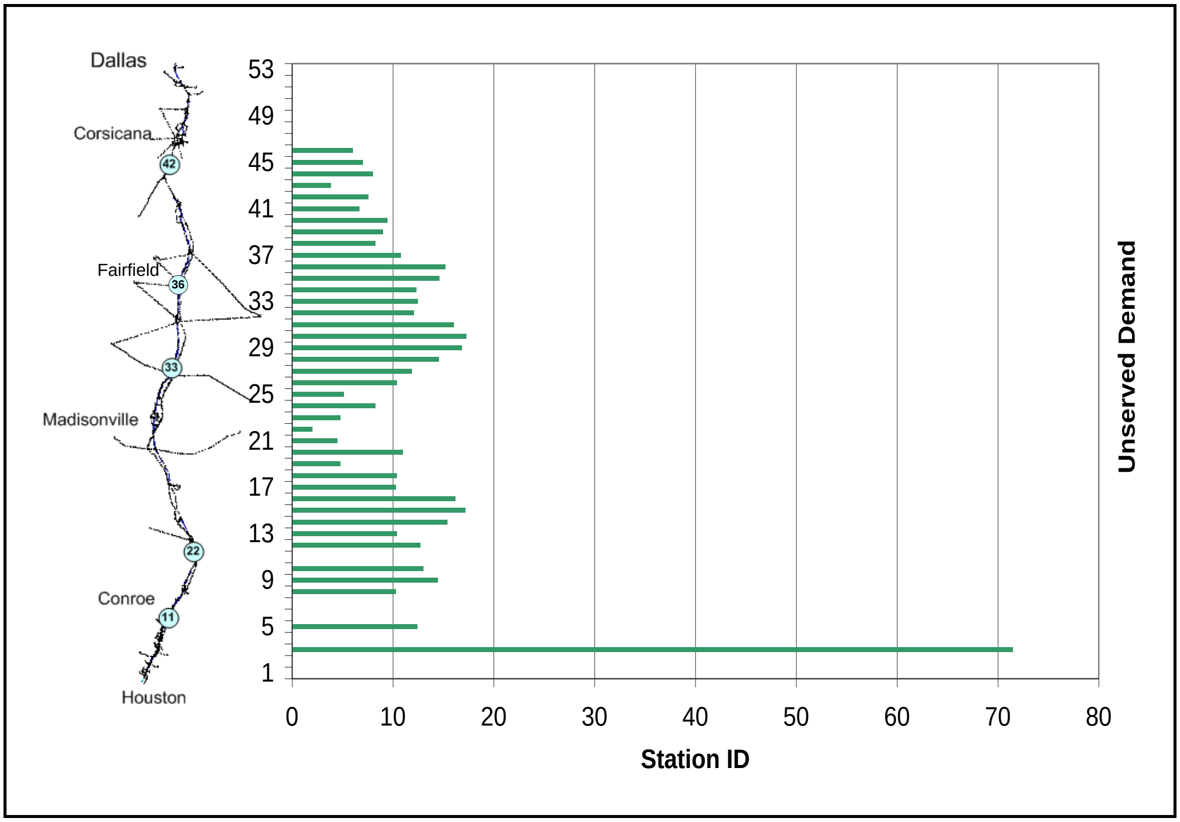


Figure 16 Unserved demand by station