# TOWARS A COMPLETE EVACUATOIN DEMAND AND SUPPLY MODELING AND MANAGEMENT PROCESS

*Hossam Abdelgawad, Ph.D. Candidate, Toronto ITS Centre and Testbed, Department of Civil Engineering, University of Toronto*

*Baher Abdulhai, Ph.D., P.Eng., Canada Research Chair in ITS, Director, Toronto ITS Centre and Testbed, Department of Civil Engineering, University of Toronto*

## ABSTRACT

In this paper, we introduce a complete set of integrated tools for modeling and managing transportation systems under emergency evacuation scenarios. The main contributions of the proposed system are 1) it comprehensively models evacuation *trip generation*, *mode split*, *evacuation schedule*, *trip distribution* and *trip assignment* in a systematic and integrated fashion 2) it generates an optimized multimodal evacuation plan by combining transit-evacuation and auto-evacuation. The proposed model is applied to a hypothetical large-scale evacuation of the City of Toronto and selected results from the implementation are presented for each mode to illustrate the capabilities of the full system. This paper focuses on the <u>integration</u> of the different demand and supply modeling aspects of the system. Detailed presentation of the individual components of the system and their corresponding results are beyond the scope of this paper for space limitations. However, proper references to the necessary details are provided.

## INTRODUCTION

Day-to-day travel patterns are typically modeled using conventional urban transportation planning models. These models, in a variety of ways, assess trip generation, trip distribution, mode split and trip assignment either sequentially or concurrently (e.g. combining destination and mode choice for instance). Under emergency evacuation scenarios the behavior of the transportation system is vastly different from day-to-day travel patterns. Such emergency situations are characterized by sudden sheer non-discretionary demand, vulnerable supply (infrastructure), and poor system performance in the form of longer travel times, chaos, severe congestion, uncertainty, and destination vulnerability, to name a few. Moreover, travellers

themselves may act differently in emergency situations compared to their regular daily travel. For instance, evacuees may more likely follow directions from officials as to which route to use instead of their habitual routes (Fu and Wilmot, 2004). Also, in daily travel, trip makers decide upon their trip start times to maximize their utility of travel; however, in case of emergency evacuees might be urged to follow an evacuation schedule and or get directed to safe shelters that are not necessarily their pre-planned destination choices.

Despite the above unique characteristics of travel under emergency situations, a complete set of integrated tools for assessing demand generation, distribution, mode choice, destination choice and route choice is still lacking. For instance, a tremendous body of recent literature on evacuation planning, although extremely useful, assume that demand is known or given, or focus on one mode of evacuation (predominantly cars) with little attention to multi-modal evacuation using both cars and mass transit (Sbayti and Mahmassani, 2006; Mitchell and Radwan, 2006; Chiu *et al.* ,2006). Although widely used transportation planning approaches comprehensively cover all aspects of travel starting from the generation of demand all the way to dynamic travel assignment and link travel times, this is not the case yet in emergency evacuation planning which motivates us to close this gap.

In this paper, we therefore introduce a complete set of integrated tools for modeling and managing transportation systems under emergency evacuation scenarios. The main contributions of the proposed system are 1) it comprehensively models evacuation *trip generation*, *mode split*, *evacuation schedule*, *trip distribution* and *trip assignment* in a systematic and integrated fashion, and 2) it generates an optimized multimodal evacuation plan by combining transit-evacuation and auto-evacuation. The proposed model is demonstrated on a large-scale evacuation of the City of Toronto and selected results from the implementation are presented for each mode to illustrate the capabilities of the full system. This paper is the culmination and integration of our research of different aspect of emergency evacuation optimization over the past several years. In the current paper we expand our work to cover evacuation demand assessment and _integrate_ the different demand and supply aspects of the system. Detailed presentation of previously published components of the system and their corresponding results are not repeated here for space limitations and to avoid duplication. Readers interested in further detail are referred to Abdelgawad and Abdulhai (2009); Abdelgawad *et al.* (2010); and Abdelgawad and Abdulhai (2010).

The remainder of this paper is structured in three main parts. The first part emphasizes the uniqueness of emergency evacuation planning and compares the state-of-the-practice emergency evacuation planning to typical comprehensive transportation planning models. The second part proposes a multimodal comprehensive evacuation planning system and its implementation on a large-scale evacuation of the City of Toronto. The third part extends the vision to include a _closed loop_ optimization of the evacuation process in real-time while continuously monitoring the system. Finally, a summary and conclusions are presented.

# EMERGENCY EVACUATION DEMAND MODELING METHODS

## Trip Generation

Several natural disasters occurred in North America in the past decade.  A side product of those events is a new body of data on system performance and users' response during the events. The increased development of trip generation models for emergency evacuation in general and for hurricane evacuation in particular is closely related to the availability of such new data on evacuation and behavior of evacuees. Most of the post hurricane surveys and behavioral studies were conducted after the late 1980s. In a post survey structured by Mei (2002), the following data were collected: number of people evacuated, factors affecting evacuees decision, type of destination, home departure time, vehicles available, and socioeconomic and demographic characteristics. Analysis of such yields insights into people's reaction to and behavior during emergency events. Analysts and evacuation planners can then use this knowledge to estimate demand, anticipate behavior and properly plan for future emergencies that require evacuation.

In transportation planning in general, statistical analysis methods are used in trip generation models, this includes: zonal or household trip rates (based on historical data) estimated using either regression or cross-classification models (sometimes also referred to as category analysis) (Stopher and McDonald, 1983). Several methods can be utilized in cross-classification analysis; these include analysis of variance, factor and cluster analysis, contingency tables, and discriminant analysis (Oppenheim, 1995). Artificial Neural Networks (ANN) were also used to model trip generation by Faghri and Hua (1991) and Faghri and Aneja (1996).

In evacuation planning, evacuation demand is estimated in two steps: 1) the estimation of total evacuation demand, i.e. the total number of people that need to be evacuated, and 2) the estimation of the temporal profile of evacuation, i.e. departure times of batches of evacuees.

These steps are typically conducted using oversimplified methods and relationships such as mean demand generation, participation rates and assumed temporal profiles rather than rigorous estimation of demand using comprehensive urban transportation planning models and demand profile optimization (Mei, 2002). For instance, participation rates (proportion of households in an area who will consider evacuation) of geographic subdivisions is the most widely used method in estimating the evacuation demand. The household composition and the severity of the disaster are the major factors affecting the participation rates. Participation rates are subjectively established based on past behavior and therefore not amendable to different emergency situations. Wilmot and Mei (2004) conducted a comparison of alternative trip generation models for hurricane evacuation, where conventional participation rates, logistic regression, and various forms of neural network models were estimated and tested using a data set of evacuation behavior collected in southwest Louisiana following Hurricane Andrew. The study showed that the logistic regression and neural network models were able to predict evacuation more accurately than the participation rate models.

In many cities (e.g. City of Toronto) hurricanes rarely occur due to the geographic and environmental characteristics of the area and consequently there is no historical data to help develop trip generation models for potential hazards. Therefore, the total demand has to be estimated on the basis of where people are by time of day when a disaster strikes. This requires tools for assessing the spatial and temporal profiles of demand across a region. Moreover, in the event of a disaster, it is more effective to optimize the mobilization of evacuation (evacuation schedule or temporal profile) as opposed to assuming such profiles on the basis of past behavior in other cities or other evacuation contexts. In such a case, the demand release temporal profile is normative (optimized) as opposed to descriptive (what people did during past events), which requires rigorous large-scale optimization methods and dynamic traffic assignment tools.

## Evacuation Departure Curve

The departure curve (know as: loading or mobilization curve) has significant impact on traffic operations, congestion, and therefore the network clearance time in emergency evacuation. Loading the evacuation demand in stages has the potential to better utilize the existing capacity of the transportation system as opposed to simultaneous evacuation which potentially gridlocks the network (Abdelgawad and Abdulhai, 2010). Generation of evacuation departure curves can be achieved using one of three broad methods: (1) response curves based on previous post

evacuation surveys, (2) development of mathematical models using data from surveys, and (3) evacuation demand scheduling optimization (staging).

The US Army Corps of Engineers (2000) conducted post-evacuation surveys and behavioral analyses that provide useful information on evacuation departure time. Three different response curves were proposed (see Figure 1); slow, medium, and rapid responses. The zero time point in the figure is when the evacuation order is issued. The value of % evacuated at time zero reflects the average proportion of the population who elected to evacuate before the order is given (a.k.a. "shadow evacuation") as observed from past behavior. The advantage of this approach lies in its simplicity. On the other hand however, the transferability of such profiles to other evacuation events is questionable and the insensitivity of such profiles to the dynamics of the evacuation process is an issue.

The second approach uses the planners' knowledge and judgment and the collected data to produce more general functions for departure time estimation. Mitchell and Radwan (2006) used a logistic curve to model the loading time of trips into a highway network during an evacuation event. The cumulative percentage of evacuees is estimated as a function the public response rate and the loading time. Tweedie *et al.* (1986) consulted several experts to determine the mobilization time parameters. The study concluded that the time required for a given percentage of the evacuating population to be mobilized can be approximated by a Rayleigh probability distribution function.

The above two approached as obviously descriptive as they mimic observed behavior. The third approach is normative as it is concerned with determining the optimal or "near-optimal" evacuation schedule that achieves a certain objective (e.g. minimizing network clearance time). However, solving this problem is mathematically and computationally demanding and requires the interaction between an optimization model and a dynamic model of the transportation system. This approach has received increasing attention over the past decade due to the maturing and mainstreaming of Dynamic Traffic Assignment (DTA) tools. Chiu *et al.* (2006) presented an evacuation scheduling simulation and assignment model. They simultaneously optimized evacuation time and route choice while interacting with a Cell Transmission simulation model. Sbayti and Mahmassani (2006) also solved the evacuation staging problem using a hill climbing iterative optimization procedure and DYNASMART-P, a mesoscopic simulation-based dynamic traffic assignment model. Abdelgawad and Abdulhai (2009) proposed an optimal spatio-temporal evacuation strategy that combines evacuation scheduling, destination choice and route choice using the interaction between DTA and evolutionary optimization algorithms.
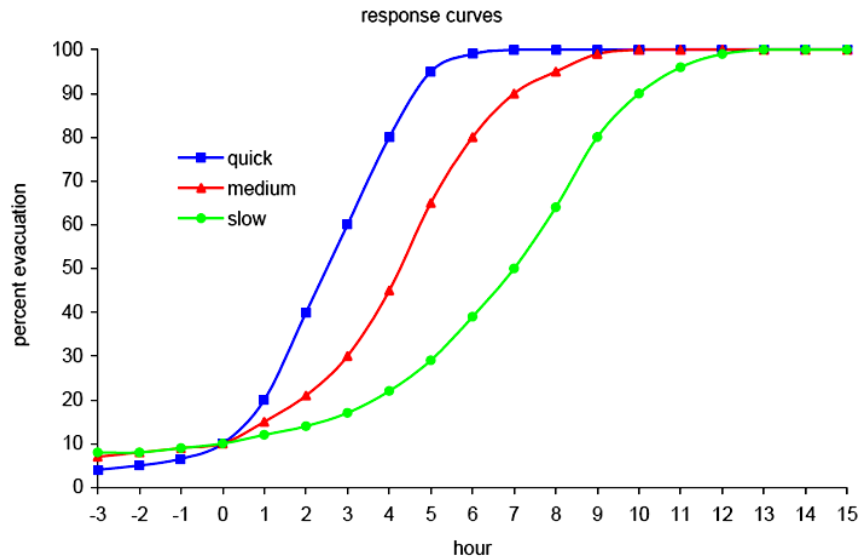
Figure 1 Three different loading curves (The US Army Corps of Engineers, 2000)

## Evacuation Trip Distribution

Evacuees' destination in emergency evacuation is typically one of the following options (Southworth, 1990): nearest safe destination, typical default destinations such as home, relatives or well known shelters (if any), or recommended destinations according to an evacuation plan. The distribution of choices depends on factors such as current location, home location, location of friends and relatives, hazard characteristics, and the transportation network conditions.

Almost all hurricane evacuation behavioral studies analyzed the destination type of the evacuees. In a review conducted by Wilmot and Mei (2004) it was found that relatives or friends are the most commonly sought destinations during hurricanes (50-70%) followed by hotels or motels (15-25%) and the least attractions are found to be public shelters (5-15%). It is noteworthy that hurricanes are notice events (known in advance) and the trip origins are typically evacuees' homes. This is different from non-notice events in which case evacuees can be anywhere at the onset of the event (e.g. at work) and may choose to head home as a destination or at least as an intermediate stop before going elsewhere.

Hurricane-related evacuation trip distribution has been widely studied in the past few decades due to frequent hurricane evacuations. Most of these studies use historical and post survey data in order to predict the distribution pattern for future hurricanes. Such data may not be readily available in all cities because of the lack resources to collect such data or due to the infrequent (or scarcity) occurrence of such natural disasters. A different modeling approach utilize the well-

established Newtonian gravity models to capture destination selection, in which case the destination choice depends solely on the cost of travelling from hazard zones to shelters. The cost function typically consists of negative exponential function with a suitably calibrated origin-destination time-decay parameters. However, this approach has some limitations in the case of emergency evacuation, these include: 1) no evidence available to decide the time-decay parameter which has significant impact on the model performance 2) the cost is not solely function of the destination chosen but also depends on the routes chosen by evacuees to reach the destinations. In case the impedance function is set to account for distance-decay parameter only, setting the parameter to a very large number will increase the sensitivity to the distance as opposed to the time spent in the network; this will direct evacuees to the nearest destination. Moreover, existing models are incapable of capturing the effect of time-dependant congestion levels in the network. In other words, both the spatial (destination location) and temporal (time-dependant travel times) dimensions are significant which is beyond the capabilities of the typical static gravity models. We believe a DTA based optimization approach can address this issue and produce optimized destination recommendation which take into account prevailing congestion conditions.

## EVACUATION PLANNING VS. TRANSPORTATION PLANNING MODELS

In this section we attempt to compare evacuation planning models to the more mature and well established transportation planning models. In a variety of ways, traditional planning models capture four main processes: trip generation, trip distribution, mode split and trip assignment as show in Figure 2. Those planning models reasonably capture the typical daily origin-destination patterns; however, they are not applicable to emergency evacuation modeling due to the vastly different spatio-temporal travel patterns.

Figure 2 State-of-the-Art Four Staging Model

Figure 3 illustrates our summary of the *five* stage evacuation modeling process in a manner analogous to the well known four stage transportation planning process. A fifth layer is added to the process to account for the departure pattern during evacuation, i.e. evacuation schedule. In emergency situations, the mobilization pattern of evacuees plays a paramount role in the performance of the system and in the success or failure of the evacuation process. Despite this importance, mobilization curves are typically assumed as previously discussion and shown in Figure 1. Only in recent years, efforts emerged that focus on optimizing the mobilization pattern for evacuees so as to minimize or maximize an objective (Sbayti and Mahmassani, 2006; Abdelgawad and Abdulhai, 2009). Trip distribution is typically assumed on the basis of past emergency events. Recent research started to address the potential of optimizing the evacuees' destination (Chiu *et al.* ,2006; Yuan *et al.* 2006) . Most evacuation modeling studies focus on automobile-based evacuation. Therefore, Mode split is rarely modeled or even realistically assumed and is certainly not optimized (TRB, 2008).
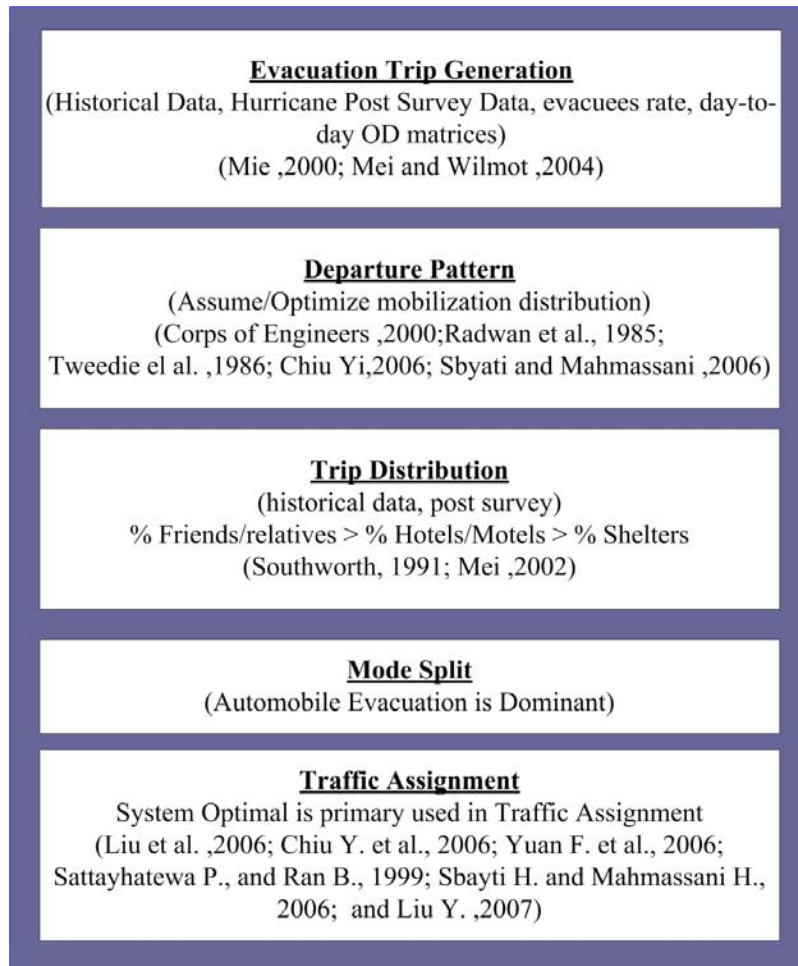
Figure 3 State-of-the-Practice Evacuation Planning Models

## PROPOSED EVACUATION PLANNING MODELING PROCESS

Despite the traditional transportation planning models and the state-of-the practice evacuation models that significantly contributed to improving the evacuation process, an integrated evacuation model is still largely missing. Most evacuation planning models deal with each layer (stage) separately, while evacuees' decision making stages are closely interrelated. For example, the departure time of evacuees may influence their destination choice and their destination choice maybe affected by congestion on the routes to the chosen destination. This is after assuming that the mode choice is known apriori, i.e. how many evacuees own and/or have access to cars and how many are transit-captives. It is indeed clear that more effort is needed to synergistically integrate some or all of these decision elements to further improve the efficiency of the evacuation process. Our approach combines evacuation scheduling (departure curve),

destination choice (trip distribution) and route choice (trip assignment) into a single comprehensive solution.

Also, an accurate representation of the spatial distribution of population, by time of day and mode of travel is essential to realistically address major population evacuation. Unlike day-to-day travel patterns, emergency evacuation has unique non-recurrent demand distribution that depends on the time an emergency strikes and how the population is distributed at that time. Our approach attempts to carefully assess evacuation demand based on knowledge of people's likely location at different times of the day, which is important  for the model to produce accurate evacuation management measures.

Furthermore, automobile evacuation has received the most attention; consequently multimodal evacuation is still largely missing in most emergency evacuation studies. A significant portion of the population in cities like Toronto use public transit particularly within, towards, and out of the downtown core. This portion of the population does not have access to their automobiles during the day, regardless whether the own one. Utilizing the readily available transit capacity is therefore essential to not only shuttle the transit captives to safety but to also expedite the overall evacuation process and reduce network clearance time by moving people in masses. Therefore, our approach explicitly optimizes mass transit based evacuation.

In summary, our approach considers the following elements to be essential to realistically plan for emergency evacuation:

- Accurate estimation of the spatial and temporal distribution of population (***trip generation***).
- Accurate identification of available modes and captive population to certain modes (***mode split***).
- Integrated framework that accounts for various evacuation strategies such as evacuee scheduling, destination choice, and route choice simultaneously (***departure curve, trip distribution, and trip assignment***).
- Multimodal evacuation strategies that synergize the effect of multiple modes.
- Robust and extensible optimization and solution algorithms that can tackle such multi-dimensional non deterministic problem.

The following paragraphs highlight the components of our system.

As shown in Figure 4,  the platform utilizes two optimization modules; an Optimal Spatio-Temporal Evacuation (OSTE) module for optimizing the auto-evacuation side of the problem and a Multiple Depot Time Constrained Pick and Delivery Vehicle Routing module (MDTCPD-VRP) to optimize the transit-evacuation side of the problem (Abdelgawad *et al.*, 2010) with

travel time estimates from the first module. The process starts by estimating the evacuation demand using a regional demand survey and a representation for the traffic analysis zones (implementation in Toronto is discussed later in the paper). The output of which is a representation of the spatial and temporal distribution of population and their modes of travel, which represents the *Trip Generation and Mode Split* stages simultaneously.

OSTE optimizes vehicular evacuation demand using parallel (multi-deme) distributed (multi-processors) genetic algorithms as a global optimization technique and a DTA tool. OSTE explicitly accounts for the dynamic interaction between the loading and evacuation curves in emergency evacuation and the area between them (total travel time encountered by all evacuees) (see Figure 5). OSTE searches for the departure curve (evacuation schedule) and destination choices (optimal destination) that minimize the total system evacuation time (i.e. areas $A_1 + A_2$ Figure 5) in a DTA environment. OSTE generates optimal evacuation schedule, optimal destination choices (trip distributions) if requested and optimal user routes to destinations (dynamic traffic assignment).

OSTE also produces link travel times that are used as input to the mass transit routing and scheduling module. The routing and scheduling problem of transit vehicles is then solved using constraint programming and local search techniques.

The problem is modeled as a variant of the VRP that includes: (i) *Multiple Depots* (MD) to account for the dispersed presence of transit vehicles in a city and to account for the availability of different types of buses at different depots such as municipal transit bus depots, commuter bus depot, school buses etc., (ii) *Time Constrained* (TC) to ensure optimal use of the transit vehicles within the evacuation time window, and (iii) Multiple p*ick-up and Delivery* (PD) locations for evacuees to allow for picking up evacuees from dispersed stops to avoid excessive walk distances. Further technical details of the solution algorithm are presented in Abdelgawad *et al.* (2010). The auto OSTE plan and the transit optimal routing and scheduling plan are finally combined for dissemination to evacuees.
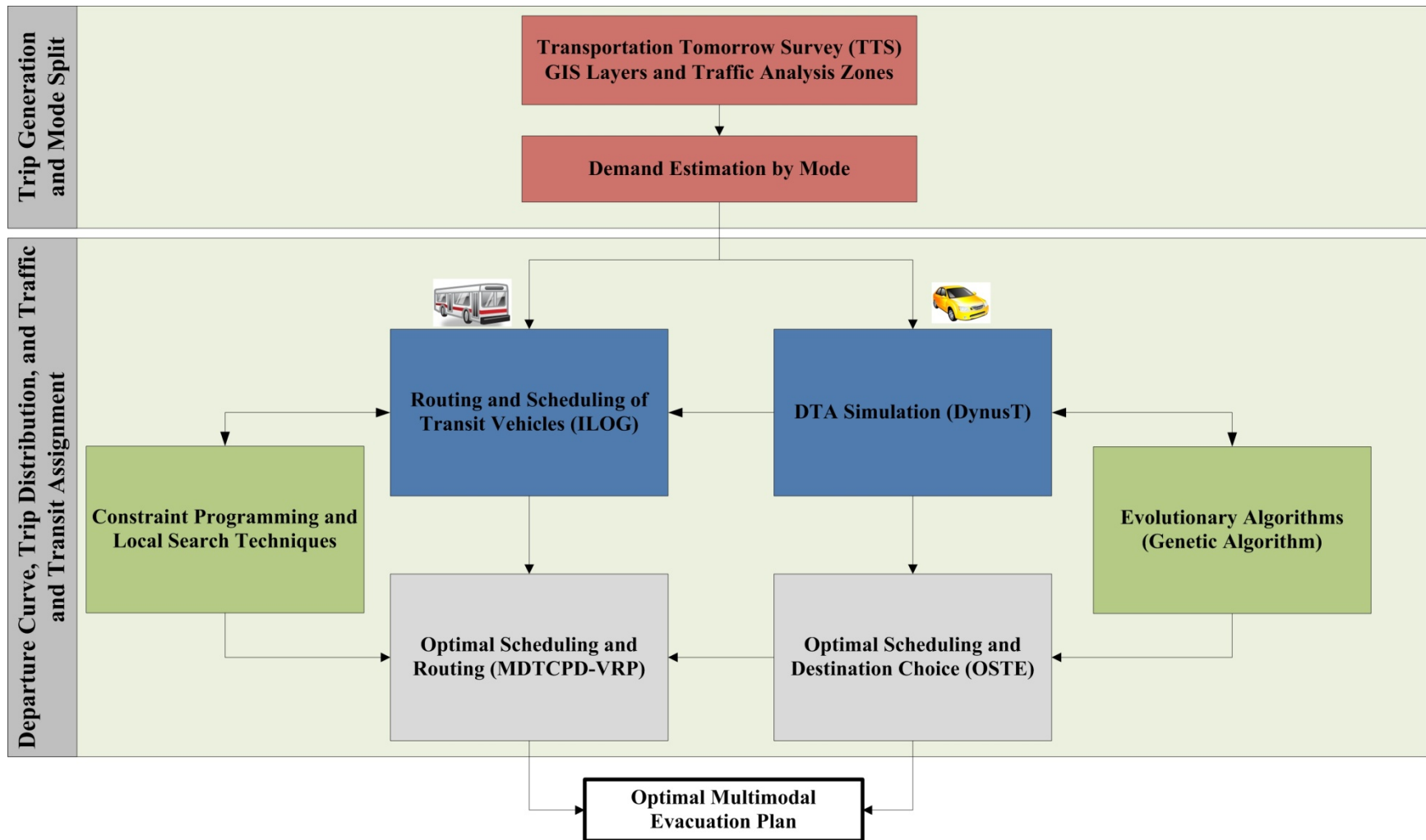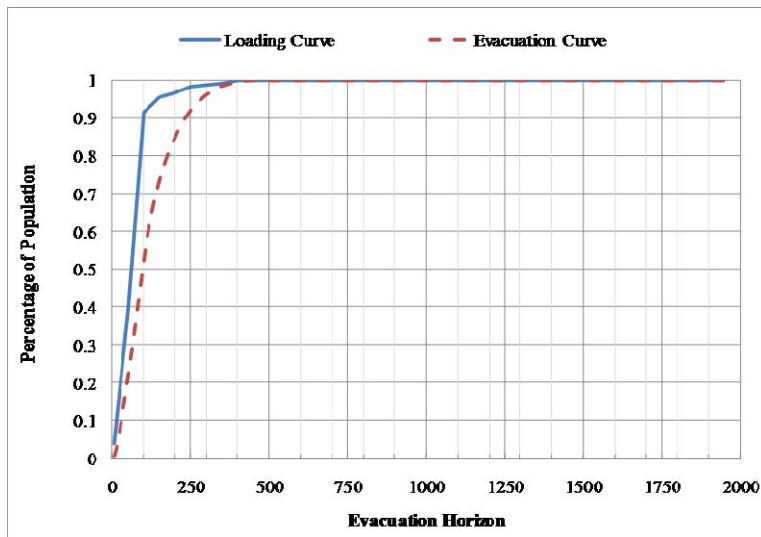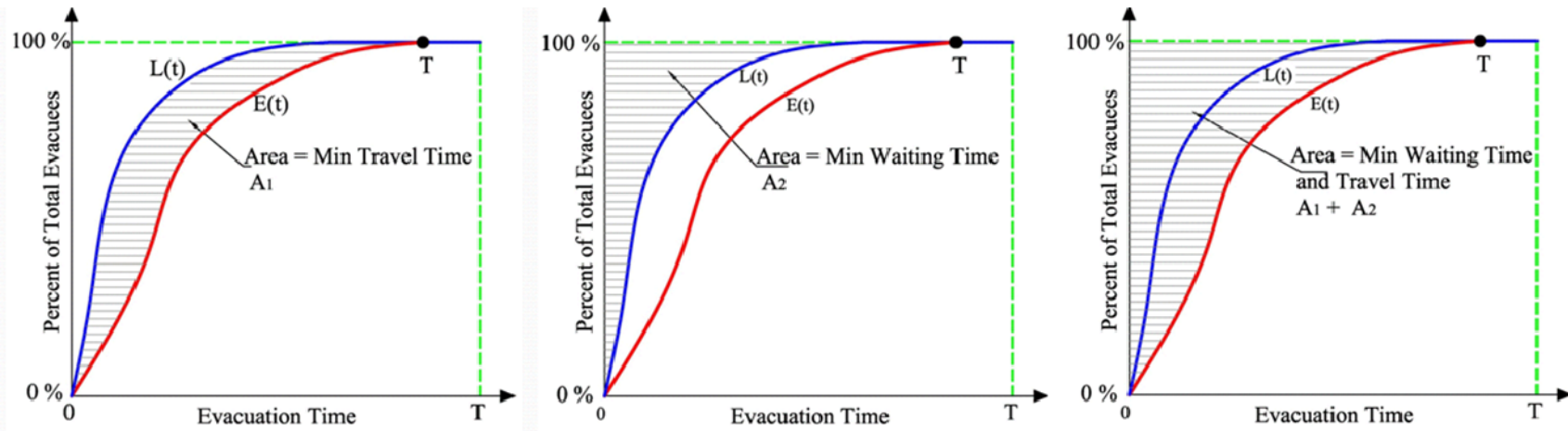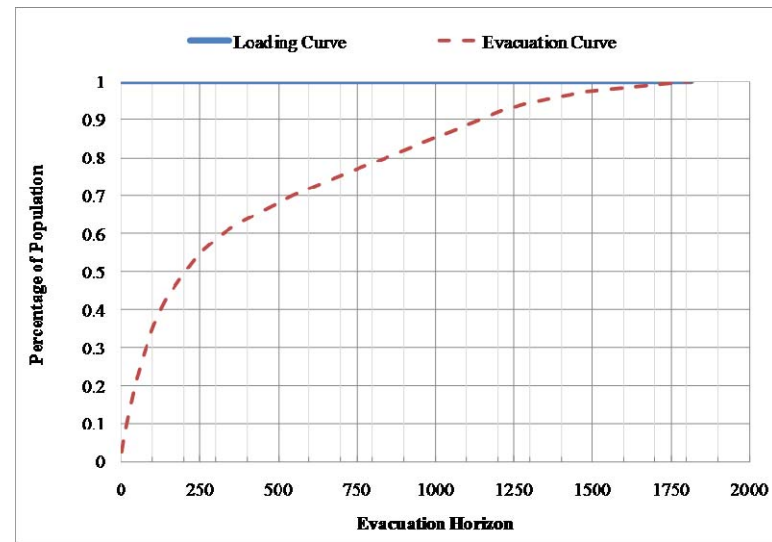
Figure 4 Proposed Emergency Evacuation Planning Model

OSTE

SE

Figure 5 Loading and Evacuation Curves: Concept and Sample Output

# SIMULATED EVACUATION OF THE CITY OF TORONTO

The proposed integrated modeling system is applied to a hypothetical large-scale evacuation of the City of Toronto in case of emergency. The City of Toronto is a typical example of fairly large North American cities with a population of 2.37 million. The City of Toronto is located in the center of the Greater Toronto Area (GTA), the overall population of which is 5.368 million. It is the oldest, densest, and most diverse area in the region. Toronto's financial and business district is the highest concentration of economic activity in Canada.

## Trip Generation and Mode Split

A demand estimation model is developed to quantify where people are at the time crisis hits and what mode they used up till that point (auto driver, auto passenger, transit user etc). This determines the auto and non-auto evacuation demands which are the inputs to the OSTE and the variant VRP modules, respectively. The demand estimation model utilizes a regional demand survey (the Transportation Tomorrow Survey, TTS, in this case) and a representation for the traffic analysis zones. At different times of the day the population moves around. For instance, through the night and till early in the morning, the majority of people are at their homes. During the morning peak, people are on the road heading to work. By mid-day, most people are at work, and so on. The output of this analysis is a representation of the spatial and temporal distribution of population and their modes of travel, i.e. at each half-hour interval, how many people are in each zone (including residents and commuters) and which mode they used to get there (driving, transit etc).(see Figure 6).

The total peak demand within the bounds of the City of Toronto is found to be 2.56 M people and occurs at the 11:30 AM- Noon interval, which constitutes the worst case scenario for evacuating City of Toronto. It is important to note that total trips in the GTA that are processed by the demand estimation model sums up to the total population in the GTA of 5.368 M, 2.56 M of which are found to be present in Toronto around noon time and the rest are outside of the bounds of the city (DMG, 2003).

The demand estimation process resulted in two main categories of trips that are modeled in evacuating the City of Toronto:

- **At Home Evacuees (**1,107,353)**:** Number of people located at their homes in the subject zone at the onset of the evacuation if occurs at noon. These trips include trips that are

not yet started and trips that started and ended at home at the time of the evacuation event.

- **Not-At-Home Evacuees**
    - Non-Drive Users (791,264): Number of people starting from any zone and ending at the subject zone in the 11:30-noon interval using "*NonDrive*" mode. These trips include trips made by the following modes: passenger, transit, walking, cycling.
    - Auto Drivers (663,209): Number of people starting from any zone and ending at the subject zone in the 11:30-noon interval using "*Drive*" mode. These trips include trips made by auto-drivers.

In case of evacuation, it may be harder to persuade drivers to abandon their cars and take any other mode (although maybe possible). Also transit users and non-drivers are captive to transit modes because their choices are limited. Therefore, we assume that evacuees will use the same mode of transport while commuting to City of Toronto, i.e., the Not-At-Home drivers will evacuate using their cars and the Not-At-Home non-Drive users will evacuate using transit modes. Available transit modes in this implementation include the Rapid Transit system (Subway Lines) and surface street buses used as shuttles. For At-Home evacuees, trips are assigned to modes based on the mode split reported by the TTS for the trips made by residents of City of Toronto (DMG, 2003). The overall results are 1,216,886 evacuation trips by auto and 1,344,942 evacuations trips by transit. The auto trips form the input origin-destination matrix to the simulation-based DTA model; while the transit trips are distributed between buses and subway as discussed next.
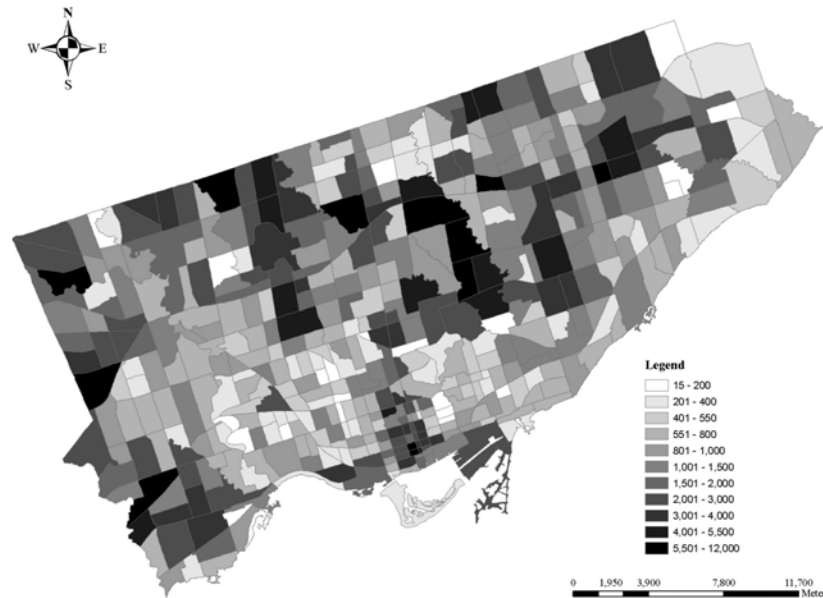
Figure 6 Drive Population Spatial Distribution for the City of Toronto [1]

## Departure Curve, Trip Distribution and Traffic/Transit Assignment

### *Automobile Evacuation (OSTE)*

In this effort, the GTA and the City of Toronto road networks are developed in DynusT© (Dynamic Urban System in Transportation), a mesoscopic DTA model that is well suited for dynamic traffic simulation and assignment on a regional scale. The OSTE platform is built on the interaction between DTA and genetic algorithms (GA). Each solution (e.g. an evacuation schedule vector) is a chromosome in the GA platform. A population of solutions or chromosomes constitutes a generation. The GA evolves the optimal solution by going through multiple generations while performing genetic operations such as cross over and mutation. The fitness of each chromosome throughout the genetic optimization process is evaluated using the traffic assignment model. The mesoscopic representation of the traffic assignment simulation model provides sufficient details for the analysis of departure time, destination choice (shelters), and routing plan for each vehicle.

In this implementation, we give special attention to the dynamic interaction between the loading and evacuation curves and the area between them. Figure 5 shows the conceptual relation

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[1] Numbers in the figure represent the number of people starting from any zone and ending at the subject zone in the 11:30- 12:00 period using "*Drive*" mode. These trips include trips made by auto-drivers.

between the loading and evacuation curves and how it is translated to different objective functions. For illustration, a sample output of OSTE is also shown in Figure 5 where the optimal loading and evacuation curves for OSTE are compared to the do-nothing scenario (simultaneous evacuation-SE) in which evacuees receive no guidance regarding their departure time and seek their pre-defined fixed destination. Significant improvement is achieved in OSTE as a result of optimizing the departure curve, destination choice while accounting for dynamic routes travel times in one shot.

The resulting optimal departure time, which is the process of allowing vehicle to enter the network so as to minimize the congestions effects and clear the network promptly, is interesting from several perspectives. First, it replicates the *network breathing* concept, which is an analogy for the breathing process where vehicles are inhaled by the network and dissipated by the network (Dixit and Radwan, 2009). This is clearly shown in Figure 7 in the network departure time pattern where vehicles are released in *optimal steps* to allow for network breathing. Second, it captures the concept of *reserve capacity*, which defines the additional demand that a network can accommodate without changing its physical characteristics (Yang and Bell, 1998). This phenomenon is captured when comparing the actual number of vehicle that a network can accommodate under different demand patterns. Overloading the network as in the SE strategy, results in very critical transportation network with no room for additional demand, in other words it results in early grid-lock in the network that lasts for long periods to be released. This is clearly evident in Figure 8 when comparing the number of vehicles in the network with time for OSTE and SE strategies. Although in SE 100% of the demand is released at time zero, it took almost 12 hours to be completely released in the network meaning that traffic was backed up because the network capacity cannot accommodate such demand surge. On the other hand, in OSTE, the same number of vehicles entered the network with the last vehicles being released after almost three hours which resulted in more room for routing options and less congested transportation network. The same conclusion can be drawn from Figure 9 by comparing the density levels of the transportation network for SE and OSTE at the onset of the evacuation. One can easily identify which scenario has more room for additional demand if it necessities. Thirdly, it captures the *network breathing* at the destination level where destination choice is dynamically changing with the evolution of the evacuation process depending on the capacity of the routes leading to safe destinations. This can be illustrated by displaying the paths from an origin zone (e.g. Zone 229 in the middle of downtown Toronto) to the optimal destination with

the corresponding departure time for OSTE (see Figure 10). It is shown that OSTE assigns traffic to different destinations and different routes depending on network.
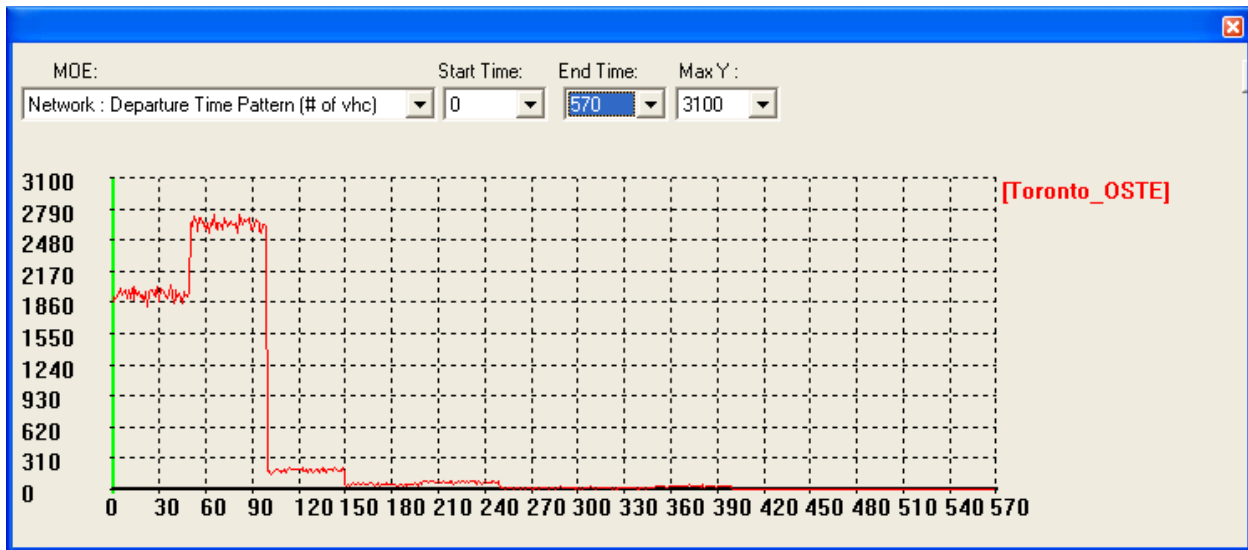


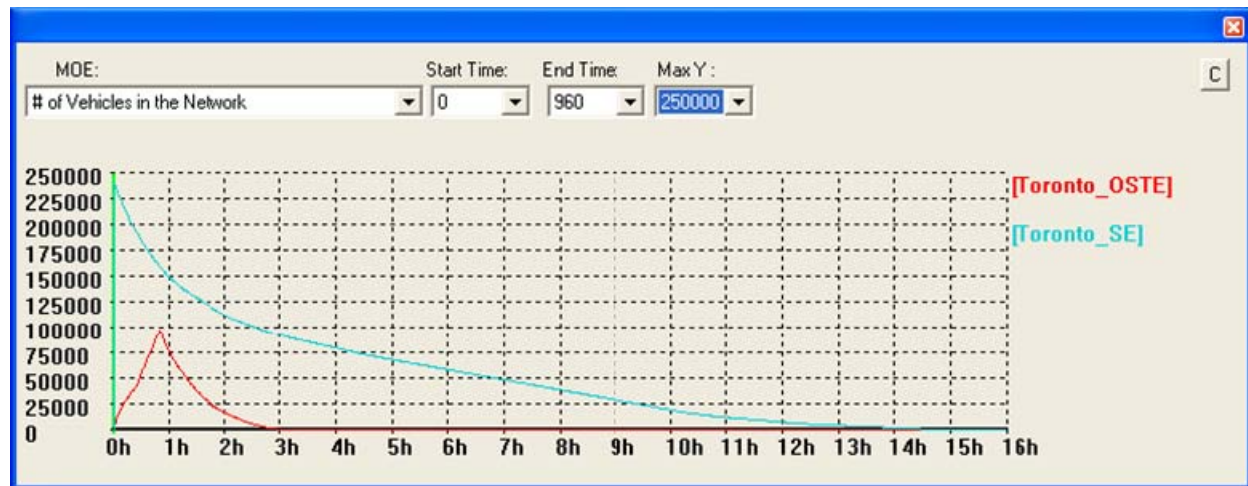Figure 7 Network Breathing Effect



Figure 8 Number of Vehicles in the Transportation Network for SE and OSTE Strategies

Figure 9 Density Levels in the Transportation Network for SE and OSTE Strategies

Figure 10 Example for Optimal Destinations with the Corresponding Departure Time

## Optimal Routing and Scheduling of Transit Vehicles

The output of the MDTCPD-VRP is the optimum routing and scheduling of each transit vehicle. In addition to the optimized routing plans, the model provides extensive vehicle by vehicle detailed output for each scenario; which is beneficial in many ways. The analyst can examine the scheduling of transit vehicles through the reported data at the transit *stop level*; individual bus level or route level. For instance, at the stop level, the analyst can identify stop ID, bus arrival times, departure times, onboard passengers upon the arrival, onboard passengers upon the departure, alighting passengers, and boarding passengers. At the vehicle level, the analyst can observe and asses the fleet capacity requirements by examining vehicle ID, total number of passengers transported by that vehicle, travel distance, and travel time. In addition, at the route level, the analyst can construct the route that a given transit vehicle takes by examining vehicle ID, first stop ID, sequence of nodes that construct a route, pick-up points along that route, and destination stop ID.

As an example from the Toronto application, one bus (*Vehicle 401*) is scheduled to start from the depot (*location of the bus at the onset of the evacuation*) at *time 0*, picks up 90 passengers (*visit 6075*) and travels along the optimal *route* as shown in Figure 11. The vehicle then drops off the evacuees at *shelter1* and continues to pick up evacuees located at *visit 5826* and drop off them at *shelter2*. The routing and scheduling plan continues until all vehicles accomplish the assigned tasks. At the end of the evacuation, all vehicles return back to the shelter (terminal) as in the case of bus #401 shown in the last row of Figure 11.

[1]

Visit 6075

[2]

Visit 5826

[3]

Visit 5761

[4]

Visit 4786

[5]

Visit 2270

[6]

Visit 1268

[7]

Visit 1082

| Visit | Arrival Time (min) | Departure Time (min) | Evacuees on Board | Travel Time (min) | Travel Distance(m) | Route from pickup point to shelter to next pickup point (sequence of nodes) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| visit6075 | 0.4 | 1.15 | 90 | 0.4 | 328.6 | Depot -Visit 6075 | 10447 | 13116 | - | - | Shelter1 | 10090 | 13021 | 10091 | 13023 | 10095 | . | Visit 5826 |
| visit5826 | 34.3 | 35.06 | 90 | 33.9 | 29009.3 | Visit 5826- Shelter2 | 10441 | 10433 | 11589 | - | Shelter2 | 10090 | 13021 | 10091 | 13023 | 10095 | . | Visit 5761 |
| visit5761 | 67.7 | 68.37 | 90 | 33.3 | 28779.2 | Visit 5761- Shelter3 | 10433 | 13021 | 10091 | - | Shelter3 | 10090 | 13021 | 10091 | 13023 | 10095 | . | Visit 4786 |
| visit4786 | 103.2 | 103.90 | 90 | 35.5 | 30412.9 | Visit 4786- Shelter4 | 10336 | 13233 | 10330 | - | Shelter4 | 10001 | 10018 | 13002 | 10019 | 10020 | . | Visit 2270 |
| visit2270 | 149.1 | 149.84 | 90 | 45.9 | 41710.0 | Visit 2270- Shelter 5 | 11013 | 11012 | 10494 | - | Shelter5 | 11258 | 11257 | 11265 | 11255 | 13058 | . | Visit 1268 |
| visit1268 | 189.8 | 190.52 | 90 | 40.7 | 32650.0 | Visit 1268- Shelter 6 | 11674 | 11689 | 11690 | - | Shelter6 | 11241 | 11477 | 11476 | 10242 | 11475 | . | Visit 1082 |
| visit1082 | 197.0 | 197.68 | 90 | 7.2 | 6906.0 | Visit 1082- Terminal | 10236 | 10235 | 11475 | 11476 | 11477 | 11241 | Terminal | | | | | |

Figure 11 Example of Routing and Scheduling for Transit Vehicle

# OPEN VS CLOSED LOOP EVACUATION MANAGEMENT: FUTURE DIRECTIONS

Although planning for emergency evacuation is paramount to ensure public safety from man-made and nature disasters, prediction of evacuation scenarios is challenging due to the highly dynamic and stochastic nature of emergency situations.  No matter how well an evacuation plan is scrutinized or optimized, actual evacuation patterns will almost definitely deviate from plans. Therefore, actual system behavior will need to be monitored and managed in real time and evacuation plan will need to be re-optimized in accordance with the measured state of the system in a rolling-horizon closed-loop control fashion.  Very few studies have addressed real time traffic management in emergency evacuation in real time (Liu *et al.*, 2007; Chiu and Mirchandani, 2008) . Numerous factors can contribute to considerable deviation of evacuation evolution from the *offline optimized* evacuation plans. For instance, potential chaotic behavior of evacuees, transportation network vulnerability to any disruption (e.g. incidents), and evacuees' potential incompliance with announced plans can all cause such deviations. Therefore there is a strong need for closing the evacuation control loop via feeding back actual system conditions measured in real time into online evacuation optimization engine. The closed loop evacuation control system can guide and drive the transportation network towards optimal performance despite any unexpected disturbances or deviations from original plans.

The envisioned closed loop evacuation control system is schematically illustrated in Figure 12. The system starts with disseminating an offline optimized plan from a system such OSTE. An online monitoring system reports real-time information about the status of evacuees and the current road network conditions. The monitoring system also updates the status of the transit system in a form of current location of transit vehicles and the number of passengers already evacuated. . Numerous ITS technologies can be utilized in the process including, for instance, Global Positioning Systems (GPS), mobile devices, automatic passenger counters, etc. Once the real-time status of the system is updated, a new  time-dependant origin-destination matrix can be estimated on the basis on measured flows in the network (e.g. Kattan and Abdulhai, 2006). The estimated demand matrix is then input to the two optimization engines (OSTE and MDTCPD-VRP) to generate new plans for the next horizon.

In large-scale applications such as evacuating a large city like Toronto, the real-time implementation of such closed loop approach can challenging and will require ample computer processing power or even parallel processing. Our ongoing research is utilizing a recently

acquired High Performance Computing Cluster (HPC) at the Department of Civil Engineering of the University of Toronto that has 256 processors in an attempt to achieve evacuation optimization in a few minutes.

## SUMMARY AND CONCLUSIONS

This paper presents a novel and comprehensive set of evacuation planning modeling tools. We believe the contribution in this paper is twofold: (1) formulating the conceptual planning process framework, and (2) developing and testing the components on a very large- scale. The paper presented a review of the state-of-the-practice emergency evacuation planning models. We emphasized the need for integrating the different stages in one platform. The paper also highlighted the lack of multimodal evacuation. The envisioned complete platform includes demand assessment (trip generation), destination choice (trip distribution), evacuation scheduling, mode choice, and both traffic and transit assignment. This process structure is analogous to the stages of the widely used transportation planning processes. Our implementation of the proposed model synergizes trip generation and mode split in one layer and departure curve, trip distribution, and traffic assignment in another layer. To demonstrate the capabilities of the proposed model, we implemented it on a hypothetical evacuation of the entire city of Toronto and results are briefly presented. The results are very encouraging; for example, OSTE clears the network *four* times faster than the do-nothing strategy (SE) and evacuees travel *eight* times less than the do-nothing strategy. The observed benefits are attributed to synergizing different strategies such as departure curve, destination choice, and assignment as well as combining different modes such as rapid transit, shuttle buses and auto to expedite the evacuation process.

The study concludes with proposing a closed loop evacuation planning and management model that not only generates optimal evacuation plans but also re-optimizes the plan in a rolling horizon fashion while monitoring the evolution of the actual evacuation process. The control system would therefore be adaptive to unexpected behavior or incidents during evacuation. The success of such system would hinge on, among other factors, how fast the optimization process is in terms of computation time which will almost definitely require parallel processing.
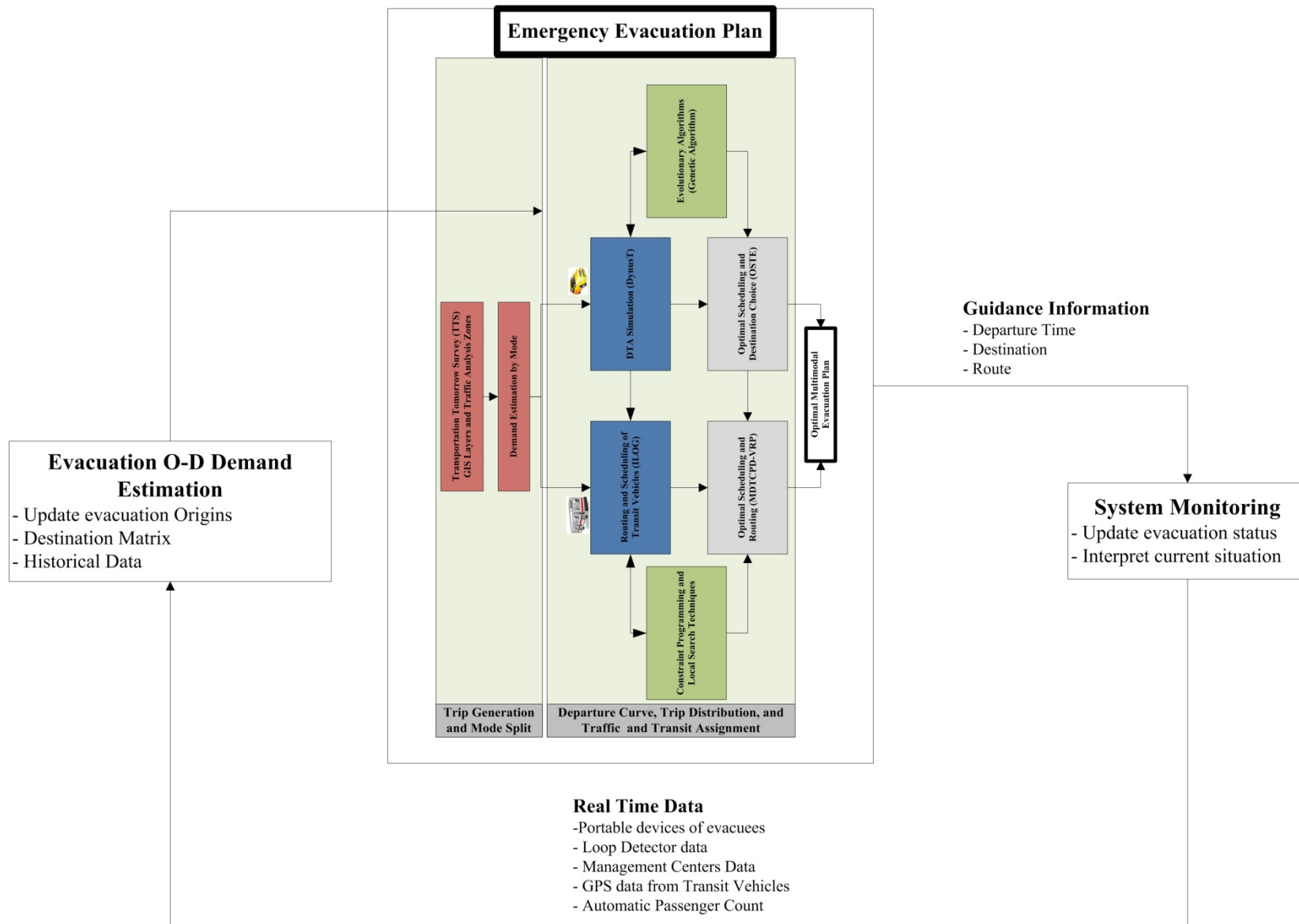
Figure 12 Closed Loop Evacuation Control System

## ACKNOWLEDGEMENTS

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