Route Stability in Large-Scale Transportation Models

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ABSTRACT

We present results from sensitivity analysis of a simulation model capturing the transportation system in a large urban setting. This system is a component of an agent-based simulation suite designed to model the effects and behaviors after a small-scale, nuclear detonation in the center of Washington D.C. In this paper we focus on how the ambient traffic density parameters affect the travel times and route choices of the individuals of the population in our model. These parameters are not easily estimated, particularly in the given context, and they directly influence travel times and routes which in turn impact the health and the behavior of the individuals and vice versa. This work is the first in a planned series of sensitivity analyses, with future extensions incorporating network structure and the detailed coupling with other system modules.

Our sensitivity analysis shows that the ambient density parameters clearly impact travel times and route choices for broad ranges. The results indicate the existence of a threshold point beyond which the delay and changes in route are significant, showing that the appropriate range of density parameters needs to be carefully determined.

Keywords

Transportation, routing, constraints, sensitivity, stability

1. INTRODUCTION

Considerable efforts have gone into planning & response to natural and human-initiated disasters affecting populations in urban areas. Clearly, it is important to consider the effects of geography and physical damage (when applicable) when modeling such scenarios. Perhaps more important, however, is the effect of human behavior and interdependencies between critical infrastructures such as transportation, power and communication.

The work that we present here is a part of a project employing disaggregated agent-based simulation methods to model the collective behavior in the aftermath of a large-scale nuclear detonation in an urban setting [19, 10]. In the past, there have been several such attempts at modeling the effects of nuclear disasters [9, 24, 11, 15, 14], focusing on the effects of the detonation on human life based on static geographic distribution of population and evacuation policies and strategies. However, they do not capture in detail the role of behavioral responses and their influence on infrastructures.

Urban traffic flow is an extensively studied topic. Both theoretical formulations as well as simulation models have been used to understand traffic congestion. Simple game theoretic models were used to demonstrate surprising outcomes. For example, Pigou [21] demonstrated that selfish routing need not produce an optimal outcome. Braess's paradox [8] showed that the intuitively helpful action of adding a new road can increase congestion. There are many technical and scientific discussions based on these examples [1, 5, 23, 22]. Even though such studies are relevant and helpful, they are highly inadequate for understanding urban traffic flow, even more so in the context of disasters. In recent years, transportation simulation systems (TRANSIMS [2] for example) have been developed which take in to account the geographic distribution of urban population, traffic density and related factors in great detail. Fujimoto, et al. [12] provide an overview of such systems.

There have been several studies that concern and involve modeling transportation system in the event of failures and disasters. Some have explored various evacuation strategies taking into account population distribution, behavior and transport network [24, 20, 17, 7] while others have looked at human initiated cascading failures in critical infrastructure [3, 18]. However, in most of this research the human behavior and its effects are not modeled adequately. For example, most disaster management strategies are based on "shelter in place" vs. "evacuation" policies. Behavioral responses of individuals such as reaching for family members, following a leader, aiding and assisting incapacitated people are seldom taken into account.

Our overall model is constructed from a collection of models capturing elements such as human behavior, health evolution, communication, transportation, and infrastructure damage & restoration. The simulation model as a whole is constructed through composition of all these models. In our scenario, the detonation directly damages the transportation system and causes power and communication failures. Additionally, it impacts peoples' health which in turn impacts their behavior and mobility. Also considered is the human reaction to the unusual event which includes panic, efforts to reach family members and evacuation policies. This in turn may lead to traffic congestion in certain routes, which in turn may have an adverse impact on the health conditions due to continued radiation exposure and effects of blast. Analysis so far has considered the impact of for example emergency broadcasts and their timing on health and the number of lives saved [19, 10].

In this paper we consider the transportation model and conduct a sensitivity analysis for this system in the case of evacuation in a large urban area. Sensitivity analysis of mathematical models is a key part in ensuring that their predictions are reliable. However, for realistic models of large, complex systems, such analysis is highly non-trivial. Validation with respect to their intended use will cover many aspects such as that of initial data, ability to reproduce known outcomes, and preservation of functional/structural invariants. Validation covers several dimensions and it is often useful to break it up into fidelity (features represented), resolution (amount of detail in

Appears in: *Proceedings of the Workshop on Multiagent Interaction Networks (MAIN 2013), held in conjunction with AAMAS 2013*, May 7, 2013, Saint Paul, Minnesota, USA.

features), precision (consistency of forecasts) and accuracy (ability to predict the true system outcome).

Our transportation network is constructed from NAVTEQ road data, metro and bus lines. The underlying routing methodology is an extension of Dijkstra's algorithm with constraints on travel modes that also includes dynamic network loading. Information about the impact of the detonation is used to modify the transportation network. Highly damaged road segments are removed, and moderately damaged segments are assigned reduced speeds, or equivalently, increased travel delays. Additionally, the population used in our study only captures those directly in the downtown area that is impacted (the study region, or DSA). To account for the load on the transportation system caused by individuals not in our population, our traffic models consider *ambient traffic densities*. Specifically, we have density parameters ρ_{in} and ρ_{out} accounting for external traffic inside and outside the study area, respectively. Both parameters are assumed to be constant over the entire simulation duration.

Summary of results. We conducted sensitivity analysis of the transportation model with respect to ρ_{in} and ρ_{out}, and compared the results for different combinations of $(\rho_{\text{in}}, \rho_{\text{out}})$ with $\rho_{\text{in}} \in [0.1, 0.3]$ and $\rho_{\text{out}} \in [0.3, 0.9]$. The input was a set of route requests which was decided by the behavior model. We used two criteria to compare the routes generated for a route request across different $(\rho_{\text{in}}, \rho_{\text{out}})$ pairs: (1) The delay to traverse the route and (2) whether the paths differ. In all the experiments, we did not employ dynamic network loading. Our analysis shows that the density parameters clearly impact travel times and route choices. Some choices of $(\rho_{\text{in}}, \rho_{\text{out}})$ seem to be more critical than others especially with respect to route changes. This prompts careful study in determining their values. However, these are preliminary results and need to be strengthened in the future work by taking several other factors into account such as multiple instances of damage to the network, dynamic network loading, variation in density over time and the extent to which routes differ.

Paper outline. We first describe the overall model in Section 2 and the scenario it is capturing. The transportation model is presented next in Section 3 covering the network construction, the regular-expression constrained routing, dynamic network loading and the description of the ambient traffic. The experiments and findings are described in Section 4 before we finish with comments and open questions in Section 5.

2. MODEL DESCRIPTION

In this section, we give a brief description of the study scenario, the individual components of the system and the way they interact.

2.1 Scenario

A hypothetical nuclear detonation occurs at ground level on a working day at 10 a.m. in the heart of Washington DC on the corner of 16th and K Street NW. The effects of the blast covers a circular area from ground zero. The radioactive fallout cloud spreads mainly eastward and east-by-northeastward. The simulation model focuses on the population inside the *detailed study area* (DSA). Figure 1 shows the DSA and the fallout path. The blast affects all the people present in the DSA at that time. Human casualties occur due to thermal burns, trauma from blast and falling structures and high radiation exposure. Health conditions deteriorate, and as a result casualties continue to occur after the blast effects have tapered off. The entire simulation model, where the transportation module is one of the components, seeks to answer questions such as how human behavior and various policies affect the number of lives saved.

2.2 Overall system description

The simulation uses a synthetic population of the Washington

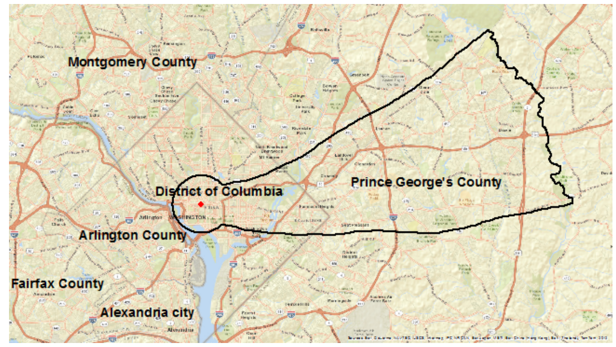


Figure 1: The detailed study area (DSA).

DC Metro Area as described in [3, 6]. The synthetic population is a data set capturing the actual population present in the DSA at the time of impact, and is created based on statistical samples and distributions of relevant demographic variables. The total size of the population in this region is over four million. However, we limit our attention to the people in the DSA at the time of impact. Our synthetic population for this has $730,833$ agents who are either residents of the DSA, people with activities in the DSA, dorm students or transients such as tourists or business travelers. The details of the synthetic population generation including the data sources and methodology are described in [19].

The simulation process is a composition of several modules which include transportation, human behavior, health, communication, infrastructure damage & restoration. The interaction between modules is illustrated in Figure 2. The simulation proceeds in time steps where each time step is referred to as an *iteration*. The first six iterations correspond to 10 minutes of simulated time, that is, the first hour is simulated with a resolution of 10 minutes. Each of the remaining iterations cover 30 minutes.

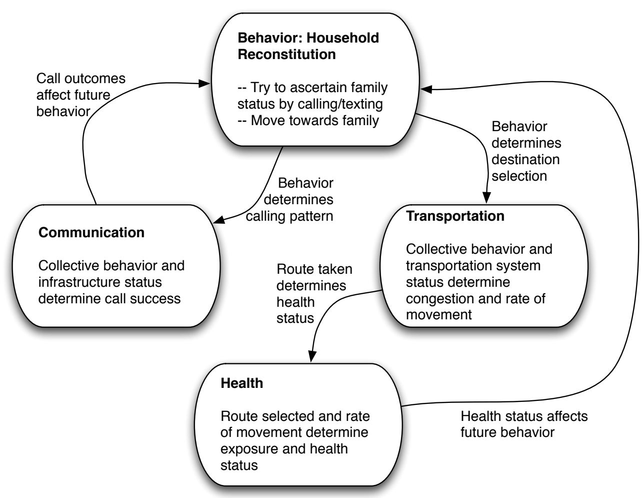


Figure 2: Interaction between models in the multi-agent simulation model (courtesy [19]).

The behavior module captures agent behavior using a decentralized semi-Markov decision process formalism [13]. An agent has several behavior options such as household reconstitution (e.g., seeking family members or information about them), evacuation and moving to a safe place, seeking shelter inside a building to avoid radiation, and health-care seeking. Each option is associated with an action. For example, if the agent chooses household reconstitution, he or she may choose to make a call to ascertain the safety of the family member or try to reach the person's location, whereas a shelter-seeking behavior will prompt the agent to move to the nearest shelter location. Collectively, agents' actions affect the infrastructural modules such as transportation and communication.

The health module captures the health of agents which in turn drive their behaviors and affect their mobility. Apart from immediate effects of the blast, an agent's health can deteriorate over time due to cumulative radiation exposure or injuries suffered while moving over the damaged landscape. Naturally, the route taken and time delays impact the agent's health. For more details of this model the reader is referred to [19]. The communication module, which governs aspects of agents' communication capabilities and calling success, is covered in [10].

This is a data- and compute-intensive simulation system. The simulations were run on a large 60 node multi-core cluster. One complete run (around 120 iterations) takes about 35 hours and requires a few TB of space.

3. THE TRANSPORTATION MODEL

For the description of the transportation model, we will be referring to the schematic shown in Figure 3. The model has two main parts, the first one being the construction of the transportation network and the second part being the routing of agents over the resulting network. The network is constructed in an offline process detailed in Section 3.1. In each iteration of the simulation, the transportation module queries the database keeping track of the current data for the agents whose current location and desired destination are different. A *trip request* is constructed for each such agent is then specified as a triple including the source, the destination, and the travel mode. The source and destination are specified as network nodes, and the travel mode specifies whether the agent has access to an automobile or not. The model permits group travel where an agent may follow a leader, in which case, the trip request for the agent will match his or her leader. Using the network and the delay information on each link, the transportation router module computes the route corresponding to the trip requested by the agent according to the permitted travel mode. The output of the transportation module is the route which consists of the sequence of nodes and links visited along with travel mode and time of visit for each node.

3.1 The transportation network

The transportation network is constructed in an offline process as a union or overlay of several networks. The networks included in this case were:

- Road data (NAVTEQ)
- Bus route data (WMATA)
- Metro data (WMATA)

From these three networks, we construct a synthetic network for walking as follows. For each road link, a bidirectional link is included in the walking network. Under normal circumstances, it may be unreasonable to permit walking on a highway, but for the scenario considered, allowing this seems like a fair assumption. Next we include a bi-directional walk link between each WMATA bus/metro node to the nearest road node to allow for travel on all networks. We note that even though one may walk on any road link, the opposite is not necessarily true. The three networks above are then combined using walk links and gives us the undamaged transportation network. The network has around 50,000 nodes and 230,000 links. At the end of this process, each network edge has the following key attributes: the physical distance between its end nodes, the mode of travel, and the speed limit of the link. In the case of an auto link, the speed limit is as given by NAVTEQ. For all other links the speeds were estimated.

The damage due to the blast is quantified using *displacement* and *rubble* data estimates provided to us by project collaborators. Here displacement measures the difference in ground level before and after the detonation while rubble measures the amount of debris present after this. We remark that the displacement d varies roughly in the range $-54m \leq d \leq 0.3m$. Based on the combined values of displacement and rubble, an affected link is either completely or partially damaged. The impact on travel speeds and link delays are specific to the mode of transportation (e.g., auto or walk) and the damage level modulates the mode-specific speed on the link. If a link is sufficiently damaged, it cannot be used for any travel. We remark that the sensitivity analysis in this paper does not involve travel on bus or metro lines. Also, a sensitivity analysis involving network damage parameters is being planned.

3.2 Routing

The routing is based on a *regular language constrained shortest path algorithm* developed in [4]. The *free flow speed*, or alternatively, the *delay* on a link in the absence of load depends on the travel mode (auto or walk), speed limits and number of lanes [16]. Additionally, the model incorporates ambient traffic density and dynamic link delays reflecting the current loads on the links.

Regular-expression constrained route construction.

Given an alphabet Σ, the router takes as input (1) a network whose edges have weights or delays and are σ-labeled, (2) a regular grammar $L \subseteq \Sigma^*$ and gives the shortest path p between source and destination complying with the additional constraint that the word obtained by concatenating the labels of the path in their natural order belongs to L. The algorithm is an extension of the classical Dijkstra's algorithm on an appropriately defined product network.

A trip request consists of the triple (source, destination, travel mode). The source and destination correspond to two nodes on the transportation network. In the current study there are two modes (or regular grammars) for travel: auto and walk. Assume that there is at least one route from the specified source to destination. If an agent requests a trip with "walk" mode, then the router assigns a route with only walk links. If the agent requests "auto" mode, the router can assign routes involving both auto and walk links. However, the following restriction is applied to the route assigned for this mode: The route links should follow the regular expression $w^*a^*w^*$ in their natural ordering from source to destination. This means for example, the routes $(waaaww)$ or $(aaaaa)$ are valid while $(waawa)$ is not. This is under a fair assumption that in a trip, after abandoning or leaving an automobile, an agent will not have access to the same or a different automobile until he or she reaches the destination. These restrictions on routes are specified as *non-deterministic finite automata* (NFA) and are a part of the input to the router module. The NFAs corresponding to the two modes described above are illustrated in Figure 4. There are two other possible modes – bus and metro – that are not used because we assume that those services come to a halt inside the DSA region after the blast.

Ambient traffic density.

For the DSA surrounding region there are several million people that are not accounted for but that will be present on the transportation network inside and outside the DSA. To capture this effect we use the notion of *ambient traffic density*. In our model, it thus corresponds to the background automobile traffic of individuals out-

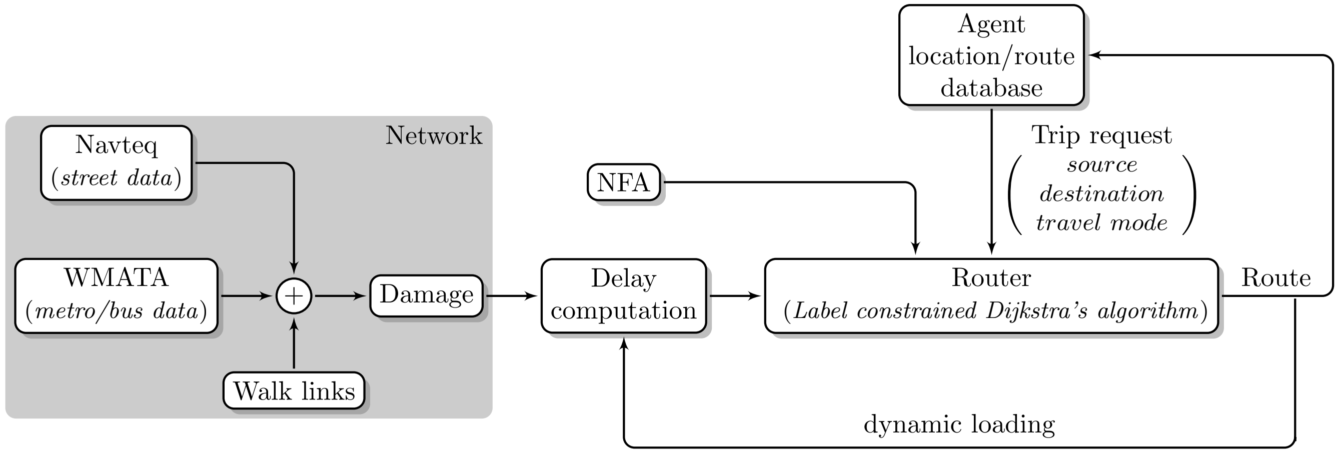


Figure 3: The transportation model encompasses network construction and the impact of the detonation (left) and regular expression constrained route construction over this network (right). In the general model, the routes take into account the load on the network links and also includes follow-the-leader behavior.

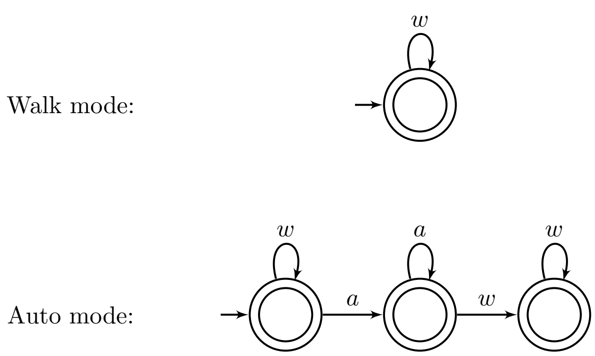


Figure 4: The two NFAs used to constrain travel modes for agents.

side our synthetic population, and in the simulation it affects only the "auto" links. We assume that this density is a constant over the iterations. However, we use separate ρ-values for the links inside the DSA (ρ_{in}) and the links outside the DSA (ρ_{out}). The ambient density of a link e is denoted $\rho(e)$ and equals either ρ_{in} or ρ_{out}, respectively. Both ρ_{in} and ρ_{out} are between 0 and 1. We expect ρ_{in} to be smaller than ρ_{out} as most of the ambient traffic is expected to occur outside the DSA region – the synthetic population covers the DSA, and people from outside the DSA are likely to try to avoid the hazardous region if possible.

Dynamic network loading.

For each iteration there are time invariant parameters such as physical distance between the link end points, the mode of travel (auto or walk), maximum speed possible and ambient traffic density. However, the load on a link varies with time, and the load will impact the delay of travel across the link. The load impacts the walk and auto modes differently. Denoting the load, length and *free flow* speed on the link e by $\lambda(e)$, $l(e)$ and $v(e)$, respectively, the delays taking into account the ambient traffic density and dynamic network loading is computed as follows:

Delay on an "auto" link.

Let the free flow delay on a link e be denoted by $t_f(e) = l(e)/\text{speed}(e)$. The link is divided into cells, each of size equal to the average distance around an automobile of 7.5 meters as done in the TRANSIMS model [2]. Let cells(e) and lanes(e) denote the number of cells and number of lanes on e. The effective car count during the current iteration is computed as

$$\text{cars}(e) = \text{cells}(e) \times \rho(e) \times \text{lanes}(e) + \lambda(e) \times \frac{t_f(e)}{T_{\text{prev}}}, \quad (3.1)$$

where T_{prev} is the duration of the previous iteration. In the above equation, the first and second terms correspond to the ambient traffic density and dynamic network loading respectively. The factor $\frac{t_f(e)}{T_{\text{prev}}}$ denotes the fraction of time an automobile would have traveled on e during the previous iteration under free flow conditions. The effective background density is computed as:

$$\rho_{\text{eff}} = \frac{\text{cars}(e)}{\text{cells}(e) \times \text{lanes}(e)} \; . \quad (3.2)$$

Finally, the delay on the link is computed as

$$t(e) = \frac{t_f(e)}{1 - \rho_{\text{eff}}} \; . \quad (3.3)$$

Delay on a "walk" link.

In our model we bias walking links with many travelers to capture the "follow-the-leader" phenomenon. We have minimal and maximal walk speeds $v^w_{\min}$ and $v^w_{\max}$, respectively. On a walk link with no other travelers, an individual will walk with speed v^w_{min}. As the linear density of walkers increase, the walking speed will increase slightly and is capped at $v^w_{\max}$. The detailed computation to determine the delay on a walk link is done by first estimating the fraction $f(e)$ of time spent on the given link as

$$f(e) = \min\left\{1, \frac{l(e)}{v^w_{min} T_{prev}}\right\} \; ,$$

and then by determining the linear traveler density along the walk link as

$$\rho_{\text{lin}} = \frac{N_e(t-1)}{l(e)} \times f(e) \; .$$

Here $N_e(t-1)$ is the number of walkers on the link in the previous iteration. Next, the walking speed is computed as

$$\mathrm{speed}(e) = v_{\min}^w + (v_{\max}^w - v_{\min}^w) \times \min\left\{1, \frac{\rho_{\mathrm{lin}}}{\rho_{\mathrm{crit}}}\right\} \quad (3.4)$$

where ρ_{crit} is the density parameter value at which maximal walking speed is realized. This is illustrated in Figure 5. Finally, the delay is determined as

$$t(e) = \frac{l(e)}{\mathrm{speed(e)}} . \quad (3.5)$$

Again, the overall goal of this is to slightly bias walk links with many walkers to capture the follow-the-leader behavior. In the simulations, $v_{\min}^w = 3$ miles/hour and $v_{\max}^w = 3.5$ miles/hour.

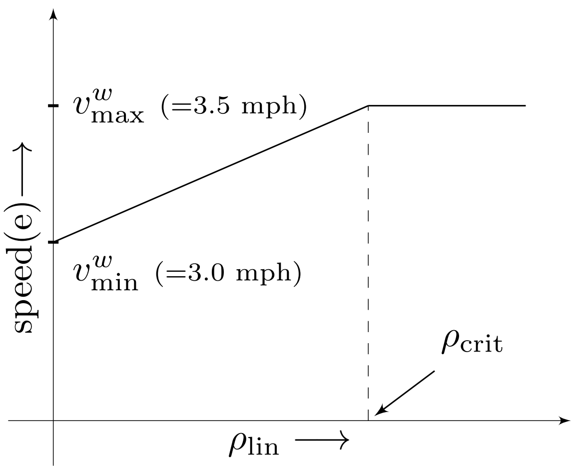


Figure 5: Effect of "follow the leader" phenomenon on the walking speed on a link (see equation (3.4)).

4. EXPERIMENTS AND RESULTS

The goal of the experiments described was to assess the sensitivity of travel times and routes on the ambient density parameters. For the experiment we did not consider dynamic network loading, but we expect that incorporating this would have resulted in a larger impact on travel times and route changes.

We compared the output of the router for several $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}})$ pairs. In each experiment, the input to the router was a set of trip requests which consists of a list of (source, destination, travel mode) triples, one for each individual. In each iteration of the simulation, depending on the behavioral option chosen by the individual, the trip request is subject to change. Any such change is reflected in the subsequent iteration. Therefore, we considered two sets of trip requests, one corresponding to the first iteration (time elapsed 0 minutes after detonation) and another for the 14th iteration (time elapsed 4.5 hours). We chose this particular iteration because of the fact that a large number of individuals who initially choose the "shelter in place" option change their option to "move to evacuation location" around this time.

We analyzed the effect of ambient traffic density with respect to delay and route choice. For this, we considered several combinations of $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}})$ for $\rho_{\mathrm{in}} \in [0.1, 0.3]$ and $\rho_{\mathrm{out}} \in [0.3, 0.9]$. In each case, the set of routes was restricted to those individuals who used at least one "auto" link; routes with all "walk" links would have the same delay. The consistency of the results was verified by performing 4 such independent simulation runs.

Some notations.

Henceforth, let $S_{\rho_{\mathrm{in}},\rho_{\mathrm{out}}}$ correspond to the set of $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}})$ pairs considered in an experiment. Let $(\rho_{\mathrm{in}}^{\min}, \rho_{\mathrm{out}}^{\min})$ be the minimum pair in $S_{\rho_{\mathrm{in}},\rho_{\mathrm{out}}}$, i.e. for every $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}}) \in S_{\rho_{\mathrm{in}},\rho_{\mathrm{out}}}$, $\rho_{\mathrm{in}}^{\min} \leq \rho_{\mathrm{in}}$ and $\rho_{\mathrm{out}}^{\min} \leq \rho_{\mathrm{out}}$. Similarly, we define $(\rho_{\mathrm{in}}^{\max}, \rho_{\mathrm{out}}^{\max})$. In general, these minimum and maximum elements need not exist, but in our experiments they do.

Delay plots.

To compare delays between routes from different $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}})$ pairs, we considered $(\rho_{\mathrm{in}}^{\min}, \rho_{\mathrm{out}}^{\min})$ as the reference point. For each pair $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}}) \in S_{\rho_{\mathrm{in}},\rho_{\mathrm{out}}}$, we computed the average delay incurred by all routes. Let this be denoted by $T(\rho_{\mathrm{in}}, \rho_{\mathrm{out}})$. In Figure 6 (a) and (b), we have plots of the ratio $\frac{T(\rho_{\mathrm{in}},\rho_{\mathrm{out}})}{T(\rho_{\mathrm{in}}^{\min},\rho_{\mathrm{out}}^{\min})}$ (which we henceforth refer to as "delay ratio") for the first and second sets of trip requests, respectively. Note that the delay ratio plot has a monotone response to density, i.e., if $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}}) \leq (\rho'_{\mathrm{in}}, \rho'_{\mathrm{out}})$, then, $T(\rho_{\mathrm{in}}, \rho_{\mathrm{out}}) \leq T(\rho'_{\mathrm{in}}, \rho'_{\mathrm{out}})$ since the delay on the every link in the case of $(\rho'_{\mathrm{in}}, \rho'_{\mathrm{out}})$ is at least as much as $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}})$.

In Figure 8, we have plotted the average route length traveled by individuals in each iteration. However, the plot should be interpreted carefully. Since the first 6 iterations are of 10 minutes duration, the average route length traveled turns out to be commensurately smaller. After the first hour, the iterations are of 30 minutes duration. Hence, the sudden jump in the plots. Besides, in these plots, while taking the average of the route lengths we have also considered individuals who travel by walk alone. The curve for the pair $(1, 1)$ corresponds to the worst-case scenario when all individuals are forced to travel by walk while $(0, 0)$ is the idealized scenario in which ambient traffic is absent. The peak at the 3rd hour is due to evacuation efforts. Another point to notice is the relatively small gap between the two curves. Two factors contribute to this: (1) damage to the network forcing individuals to travel mostly by walk and (2) low speeds in the downtown area.

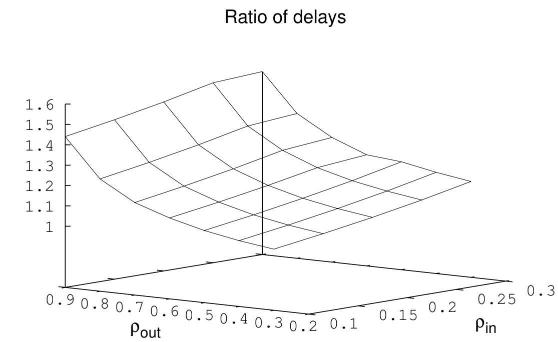
Route change plots.

To observe the effect of ambient traffic density on the route choice, we computed for each $(\rho_{\mathrm{in}}, \rho_{\mathrm{out}}) \in S_{\rho_{\mathrm{in}},\rho_{\mathrm{out}}}$, the fraction of routes which changed with respect to the $(\rho_{\mathrm{in}}^{\min}, \rho_{\mathrm{out}}^{\min})$ (Two routes are different if their node sets are different). The results are summarized in Figures 7.

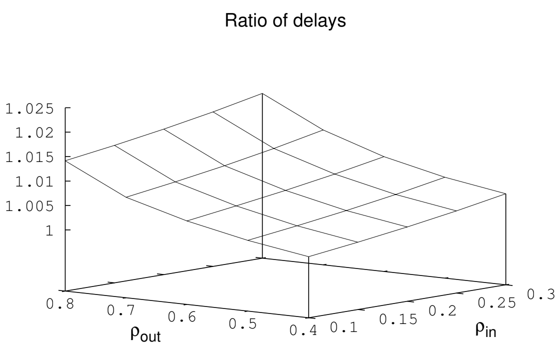
An observation.

From Figures 6 (a) and 7 (a), we observe that at $\rho_{\mathrm{out}} \approx 0.6$, there is a phase transition. Both the delay and route change ratios increase steeply beyond this point. We observed this phenomenon in all the 4 replicates of the simulation for iteration 1. This seems to indicate that some values of density parameters are more critical than others showing that sensitivity to traffic density needs to be rigorously analyzed and the appropriate range of values need to be carefully determined. The study should include different damage scenarios, different sets of trip requests, dynamic network loading, etc. Significant changes in route can have an impact on the traffic load when coupled with dynamic network loading.

Recall that in the network construction every "auto" link has a corresponding "walk" link in the same direction. Here we determine the ambient traffic density at which the auto and walk speeds on a link coincide. Although this only considers one link in isolation, this value give a clear indication of when possible route change can occur and when we can expect large changes in the computed routes. We denote the value by $\rho_s(e)$ for a link e. If we ignore the effects of dynamic network loading, then, the first term in (3.1) vanishes and the effective ambient traffic density, $\rho_{\mathrm{eff}}(e)$ in (3.2) is $\rho(e)$. Now,

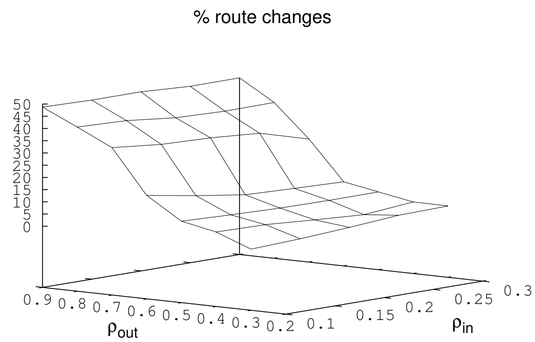


(a)

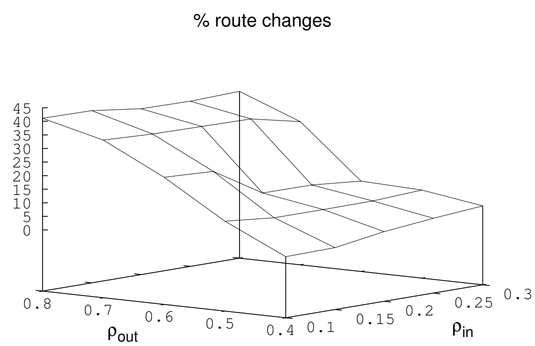


(b)

Figure 6: Effects of ambient traffic density on travel delay (a) elapsed time 0 minutes and (b) elapsed time 4.5 hours.



(a)



(b)

Figure 7: Effects of ambient traffic density on change in choice of routes (a) elapsed time 0 minutes and (b) elapsed time 4.5 hours.

equating the delays in (3.3) and (3.5), we have

$$\rho_s(e) = 1 - \frac{\text{speed}_w(e)}{\text{speed}_a(e)}\ , \tag{4.1}$$

where, the subscripts w and a correspond to walk and auto speeds respectively on that link. For example, an auto speed of 25 miles/hour, and walk speed of 3.5 miles/hour, $\rho_s(e) = 0.86$.

5. SUMMARY AND FUTURE DIRECTIONS

In our experiment we only considered the effects and sensitivity with respect to the ambient density parameters of the transportation model. As stated earlier, these are parameters that are not easily estimated in the given context. Clearly, this complex system has many parameters that warrant further investigation. Coupled with all the other models in the larger system, a validation analysis becomes challenging. This analysis is the first in a sequence, and in upcoming work we plan to conduct similar studies with respect to the network damage parameters to better understand how this impacts routing in the given scenario as well as network sensitivity in general.

A question that will also be addressed in future work is about the transitions in route changes ratios observed in Figure 7. While it seems to occur near $\rho_{\text{out}} = 0.6$, it is natural to ask if this is network specific or if it would occur for networks of other US cities.

Our work has only focused on the transportation module of the larger simulation model, and we also plan to extend our analysis to consider parameters in multiple models to study possible cascading effects.

Acknowledgments

We thank our external collaborators and members of the Network Dynamics and Simulation Science Laboratory (NDSSL) for their suggestions and comments. This work has been partially supported by the grants DTRA Grant HDTRA1-11-1-0016 and DTRA CNIMS Contract HDTRA1-11-D-0016-0010.

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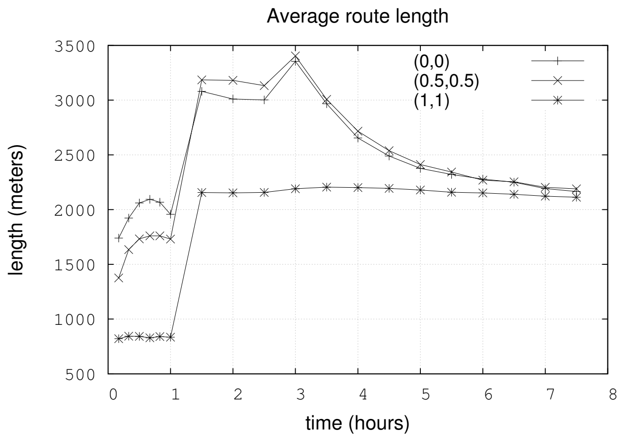

Figure 8: Average route length across iterations. Here the diagram only incorporates the portion of the route actually traveled during the respective iteration. Note that the jump that happens near one hour is largely caused by the fact that the iteration time goes from 10 to 30 minutes.

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