TRAFFIC ASSIGNMENT USING ITERATED ROUTE-BASED SIMULATION

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ABSTRACT

When a portion of a network infrastructure is to undergo a scheduled upgrade, whereby a “work zone” is introduced in the network, or when a capacity reduction takes place due to external interventions, traffic operators and planners are interested in the effect on traffic patterns. This paper proposes a procedure to track and predict traffic patterns based on an accelerated version of the Method of Successive Averages (MSA) for obtaining traffic equilibrium. The model does not use a volume-delay function such as the BPR function, but rather keeps track of the travel times experienced by the travelers impacted by a work zone or, in general, by a network intervention. Notes that the experienced travel time incorporates driver responses to, and effects of, lane changing and gap acceptance, intersection control strategies, start-up loss times, vehicle headways, turn avoidance, pedestrian traffic, driver interactions, etc. Furthermore, this iterative process may represent the equilibration process that takes place in actual settings.

The approach was tested on a route-based microsimulation model, where drivers’ experiences in one period were used as the input to the MSA-type algorithm to provide traffic assignment for the next period. To test the validity of the approach, traffic assignment was based on travelers choosing routes that minimize travel times experienced in the simulation, and the network loading was examined for the level of equilibrium in the network. Analysis of the results from the assignment/simulation model showed that routes most used for each OD pair had nearly equal travel times and that the assignment/simulation process tends to converge to a traffic equilibrium as the number of periods increases.

Keywords: Traffic Assignment, Traffic Equilibrium, BPR Functions, Method of Successive Averages, Traffic Simulation, CORSIM
1. INTRODUCTION

Consider the following scenario, which is very applicable, for example, to cities like Tucson, Arizona, that have several sections within a “work zone” to upgrade network infrastructure. Work zones invariably lead to changes in traffic patterns providing a challenge to traffic management and planning departments to minimize the disruption caused to motorists. In particular, one needs to estimate the re-routing and resulting traffic loading for this purpose. Similar concerns are also raised by major traffic incidents whose impacts last for several days, local flooding and, in general, when a portion of network infrastructure is damaged to the point where some motorists avoid it. In order to forecast the network load, several issues arise: (1) Which routes will carry the displaced loads? (2) Will there be some sort of traffic equilibrium among the routes? (3) If so, how long will it take to reach this equilibrium? (4) What is the role of traffic measurements, such as detector data and travel times from probe vehicles? These are some of the issues addressed in this paper.

2. EQUILIBRIUM MODELING

To estimate current and future use of traffic networks, planners use what is referred to as static traffic assignment, where, for given origin-destination predicted flow volumes, an equilibrium concept is utilized to assign routes and load flows on these routes. The most accepted equilibrium condition is the so-called Wardrop’s First Principle [1952], or the user equilibrium, where it is assumed that minimizing travel time is the only attribute of concern and any traveler cannot unilaterally decrease his/her travel time at equilibrium by choosing an alternative route.

There are two categories of issues that arise in the use of a static traffic assignment (STA) model: behavioral modeling and analytical modeling issues. With respect to the former category, we note that it is difficult to develop a mathematical model that replicates all the human decision processes in route choice and encompasses various factors about the trip and possible choices. The major behavioral approximations made in STA are that (B1) each traveler knows the state of the network at all times, (B2) the state does not change during the trip, (B3) the traveler computes the travel times on all possible routes and (B4) the traveler chooses one of the routes that gives the shortest travel times. Some of these assumptions have been relaxed in models that have appeared in the literature, such as each traveler has some measurement errors in his/her knowledge of the state of the system and chooses a route that is perceived as being the shortest [Daganzo and Sheffi, 1977], or each traveler perceives the network as having random travel times with known distributions and chooses the route that minimizes the expected disutility of travel time where the traveler’s disutility function is given [Mirchandani and Soroush, 1987].

Major analytical modeling approximations include (A1) the traffic network can be modeled as a directed network, where (A2) the travel time on each directed link is a known (or calibrated from data) function of only the traffic volume on the link, (A3) the travel time on a route is simply the summation of the travel times of the links on the route and (A4) the origin-destination demand is distributed uniformly over time. Approximation A4 is a physical rationalization for approximation B2, which in turn translates to the network being “static” in the sense that instantaneous link travel times are always the same and therefore the travel time on the route is sum of these link travel times leading to approximation A3.

A major weakness in the use of STA models is approximation A2. In such models, volume-delay or BPR (Bureau of Public Roads) functions, also referred to as impedance functions, have been developed to model congestion dynamics. They represent link travel times as non-linear, convex functions of traffic volume on the link. These functions provide nice convergence properties to the equilibrium assignment models and have found favor universally with modelers.

Notwithstanding their popularity, volume-delay functions have certain modeling limitations. These functions take a simplistic view of congestion and do not incorporate network or traffic characteristics such as lane changing and gap acceptance behavior, intersection control strategies, start-up loss times and...
vehicle headways, pedestrian traffic, different driver types and modes of transport, etc. Further, such models make a simplifying assumption that the volume-delay function of a link is independent of other links, which is not necessarily true, especially for urban networks.

The other major weakness in the use of STA is the implication of behavioral approximations B1, B3 and B4 that result in the network always being in user equilibrium. For one, there are always some capacity changes in the network, so that travelers would find difficulty in adjusting daily to an equilibrium. In other words, the state of the traffic at any point in time is a transient condition that is tending to an equilibrium. Moreover, with the availability of traffic information systems and advisories, based on, for example, work-zone activities and temporary loss of traffic capacity due to a major incident, travelers could decide to switch routes during the prevailing traffic situation, or even not travel. Consequently, the traffic forecasts obtained from the assignment models may not be as realistic as anticipated and could struggle to match the observed data.

This paper, in fact, attempts to present an approach to respond to the above two weaknesses – the assumption that a calibrated volume-day function is available and that the network is always in an equilibrium – so that STA model may be used for short-term traffic planning of a locally impacted area due to, for example, work-zone activities. In the sequel we will refer to the locally impacted area as an Impacted Neighborhood Network (INN).

The approach presented also responds to the limitation of approximation A4, which has been already addressed by researchers in the context of wide-area traffic prediction and management using Advanced Traveler Information Systems like Dynamic Variable Message Signs and In-Vehicle Route Guidance. Planners consider “peak demands” in order to design the network. Hence, to use STA, approximation A4 translates to a uniform peak period during which there is a constant demand per unit time, and the static equilibrium, or more appropriately steady-state conditions, are based on this uniform demand. Since the ’70s, researchers [e.g., Merchant and Nemhauser, 1978] have realized that during a traveler’s trip the state of the network changes and the travel time is not simply the sum of instantaneous link travel times, but rather the sum of link travel times that are dynamically changing. To model the route travel times and the speed profiles during the trip actually experienced by the traveler, researchers have developed the so-called Dynamic Traffic Assignment (DTA) approaches; both based on analytical optimization [e.g., Jenson, 1991, Ran and Boyce, 1996] and based on simulation [e.g., Mahmassani et al. 1993, Jayakrishna et al 1994 and Ben-Akiva et al., 1997a,b]. In this scenario, if all drivers optimize their own travel times, one comes up with the Dynamic User Equilibrium, the counterpart to the Static User Equilibrium, where, as before, a traveler cannot unilaterally decrease his/her travel time by switching to another route. The richness of DTA models allow one to include, besides route choice, (i) departure time choice, (ii) en-route decision making in cases where en-route traffic advisory and/or route guidance is available, and, in simulation-based models, (iii) a large variety of traveler behavior assumptions.

Most of the available DTA models, especially the analytical optimization ones, still need calibrated volume-delay functions and assume that the network operates at a deterministic equilibrium. Versions of some prototype simulation DTA models claim that they do not need explicit volume-delay functions, but these are not commercially available.

3. RESEARCH OBJECTIVES AND APPROACH

The primary goals of this paper are (1) to propose an analytical traffic assignment approach to monitor an INN when count detectors and traffic probes are available and (2) to demonstrate the feasibility and applicability of the model, which considers implicitly the actual dynamics of traffic and congestion rather than the use of explicit BPR functions. The idea is to re-engineer the traffic assignment process for an INN to make it more responsive to behavioral aspects and inherent randomness of the transportation system in the presence of new interventios, such as work zones. Moreover, the rapid deployment of Advanced Traveler Information System (ATIS) technologies has resulted in a shift in the way individuals choose their routes in such situations.
To demonstrate the proposed approach, a widely-used commercial simulation package was used, although any micro-simulator that assigns and loads vehicles on specified routes can be used. We chose to use the commonly available CORSIM simulation package that was appropriately modified to load vehicles on user specified routes (we refer to this as Route-based CORSIM). Of the currently available simulators in the market, AIMSUM 2, PARAMICS and VISSIM claim to also allow route-based loading [see, e.g., Oh et al., 1999].

We propose a simple approach that can be depicted as shown in Figure 1. We will assume that the INN is constantly monitored with count detectors and vehicle probes that provide trip times. This information is available to travelers that use the INN. After each period, for example a day, each traveler experiences a trip time and chooses another route if he/she has current knowledge of some trip times. We refer to the modeling of the route choices of traveler population as traffic assignment. The travelers’ trips are then loaded on the network where, because of transportation supply-demand congestion effects, each traveler experiences a trip time. This is repeated in the next period and the process continues. Note that rather than assume a volume-delay function, the traveler makes his/her decision based on the actual experience on the previous trip and, hence, can account for whatever factors that influence his/her decision such as aversion to left turns, avoidance of traffic signals, lane blockages due to buses, etc.

![Figure 1 Schematic for on-line traffic assignment and loading](image)

To test this approach, we replaced the “Real-World” block with a route-based simulator, in our case the Route-based CORSIM. We replaced the “traveler decision making” with a “route-choice model that seeks to minimize experienced travel times”, which is more in line with the equilibrium models that are used or are being proposed. In the evaluation of our scheme, we examined how close the travel times were with one other over time, to reflect the process of equilibration and level of equilibrium in the network. If, in fact, travelers did choose routes to minimize their travel times, then it is expected that most of the experienced travel times for any given origin-destination pair would tend to a steady state where they are approximately equal.

4. REVIEW OF VOLUME-DELAY FUNCTIONS

Many types of volume-delay functions have been proposed and used in practice in the past [Branston, 1976]. By far the most widely used volume delay functions are the BPR functions, which are of the form

$$t_{BPR} = t_0 \cdot (1 + (v/c)\alpha)$$

With higher values of $\alpha$, the onset of congestion effects becomes more and more sudden. The simplicity of these BPR functions is certainly one reason for their widespread use. Unfortunately, these functions also have some inherent drawbacks, especially when used with high values of $\alpha$. These drawbacks were pointed out by Spiess [1990]. According to Spiess “While for any realistic set of travel volumes, we can assume that $v/c \leq 1$ (or at least not much larger than 1) this is usually not the case during the first few iterations of
an equilibrium assignment. Values of v/c may well reach values of 3, 5 or even more. A BPR function with \( \alpha = 12 \) and a v/c ratio of 3 has congested link travel-time equal to \( 1 + (3)^{12} \) or 531442 times the free-flow time, which means that every minute of free flow time becomes roughly equal to one year of congested time! These aberrations slow down convergence by giving undue weight (cost) to links with high \( \alpha \) value”.

For highly under-utilized link conditions, the BPR functions, especially with high \( \alpha \) values, yield free flow times independent of actual traffic volume. Therefore, the equilibrium model will locally degenerate to an all-or-nothing assignment, where the slightest change (or error) in free flow time may result in a complete shift of volume from one path to another.

A different volume-delay function was presented by Davidson [1966] as a general purpose travel time formula for transport planning purposes.

\[
t = t_0 \left[ 1 + \frac{J_D}{x(1-x)} \right]
\]

where
- \( t \) = average travel time per unit distance (e.g. in seconds per km),
- \( t_0 \) = minimum (zero-flow) travel time per unit distance. (e.g. in seconds per km),
- \( J_D \) = delay parameter,
- \( x = q/Q \) = degree of saturation,
- \( q \) = demand (arrival) flow rate in vehicle/hour,
- \( Q \) = capacity (in vehicle/hour)

A critical analysis of this volume delay function was presented by Akcelik [1991]. Akcelik claims that: “Davidson derived this function from concepts of queuing theory. He modified the well-known steady-state delay equation, which, for a single channel queuing system with Poisson arrivals and exponentially distributed service rates, is

\[
d = \frac{1}{Q} + \frac{x}{Q(1-x)}
\]

where the first term is the service time (reciprocal of mean service rate) and the second term is the queuing delay. Davidson used saturation flow rather than capacity (Q) as mean service rate in his equation. These two parameters have the same value for uninterrupted traffic facilities (e.g., freeways), but capacity rather than saturation flow needs to be used for interrupted facilities (e.g., traffic signals where capacity equals saturation flow multiplied by the ratio of green time to cycle time)”. For a detailed discussion on this issue, see Tisato [1991].

5. THE METHOD OF SUCCESSIVE AVERAGES AND ACCELERATED AVERAGING

The Method of Successive Averages (MSA) has been applied to a wide variety of traffic assignment problems that arise in transportation analysis and planning. Basically, in MSA, at each iteration new flows are generated which are averaged with flows from earlier iterations to come up with a new solution at that iteration. In some applications, it can be proven to converge to a solution, whereas in others it is used as a heuristic that usually gives good results in practice. There are many cases where the MSA displays poor convergence properties. Although it begins promisingly, the initial iterations are followed by a pronounced “tail” effect, resulting in slow overall convergence.

Bottom and Chabini [2001] extensively researched various attempts at improving convergence properties of fixed point methods like the MSA. They list several interesting methods employed over the years to develop fixed point models with better convergence rates. Reporting one such effort by Cascetta and Postorino [2001] they state that:

“Cascetta and Postorino observed that in the MSA, an iteration’s estimate is affected by the results from all the previous iterations, including those from early iterations that are presumably far from the solution. Furthermore, later iterations, which are presumably closer to the solution,
receive smaller weights when computing a new estimate. Accordingly, Cascetta and Postorino propose a heuristic method that from time to time restarts the MSA. (i.e., resets the iteration counter to 1) using the last computed value as the new initial point. By restarting, the direct influence of earlier iterations is eliminated, and larger step sizes are applied to subsequent iterations. The frequency with which these restarts are carried out decrease as the number of iterations increase, via a user specified “refreshing modulus” $\eta$. The first restart is done after $\eta$ iterations, the second after $2\eta$ iterations following the first restart, and so on”.

In estimation algorithms like MSA, each successive iteration provides a new flow, or a design point, while some sort of averaging of the design points provides a new solution at that iteration. Frees and Ruppert [1990] point out the advantages of using one method to select design points, and a different method to estimate the solution. Use of the methods adapted to each purpose allows a more aggressive exploration of the feasible space and a more effective exploitation of the results generated during that exploration. These types of methods have been classified as iterate averaging.

Polyak [1990] introduced a method to implement iterate averaging. In this method one also computes, “in parallel” with and independently of the MSA’s weighted average, a running average of the design points. The effect of this additional step is that the MSA’s large step size tends to prevent the algorithm from getting stuck in an early stage, while the “offline” parallel averaging takes care of the increased noise that the larger step sizes produce. The averaging is “off-line” in the sense that the iterations of the recursive averaging process (of the MSA) make use of the weighted average and not the running average.

Bottom and Chabini applied the Polyak and MSA averaging to a variety of problem instances and analyzed the resulting convergence behavior. They report that

“In most cases considered, accelerated averaging can significantly outperform the MSA in terms of both the noise at convergence as well as the number of iterations needed to converge.

This performance can be obtained at a modest incremental cost to the MSA”.

They observed that the application of the Polyak method to dynamic traffic assignment problems resulted in noise at convergence considerably lower than for the MSA with convergence rates four or more times faster than the MSA.

6. ITERATIVE ROUTE-BASED SIMULATION

In order to realistically model traffic assignment and the resulting loading in the network, it is essential that the model captures the dynamics of congestion formation and dissipation associated with traffic and allow for a wide-range of route-choice behaviors. This enables the evaluation of a wide array of congestion relief measures, which could include both supply-side and demand-oriented measures.

However, as discussed previously, the volume-delay or impedance functions used in analytical traffic assignment approaches have their limitations in modeling congestion and dissipation. In these models the impedance on a link is simply a function of volume of traffic, capacity of link, mean travel time on the path-link, saturation rate and some parameters obtained empirically.

Although the parameters of these impedance functions may be obtained after many empirical observations and extensive calibration, the ability of such functions to comprehensively capture all characteristics and dynamics of a specific link of a particular route is limited; especially when one needs to include a new intervention such as a work zone. The impedance of a link is not only a function of volume and capacity but should also take into account lane changing and gap acceptance behavior, intersection control strategies, start-up loss times and vehicle headways, pedestrian traffic and different modes of transport, etc.

In order to overcome the shortcomings in capturing the traffic dynamics details for modeling route-choices, an alternate traffic-loading model is proposed, which does not use volume-delay functions but, rather, uses the trip experiences from a simulation model. That is, we use iterative route-based simulation in conjunction with an averaging algorithm for traffic assignment. By avoiding the use of impedance functions and instead simulating the traffic on the network, we can expect more realistic traffic loading
where network and traffic characteristics, which have a significant impact on network congestion, can be included in the model. Further, the efficiency of the assignment procedure is improved by avoiding limitations of the volume-delay functions in highly congested or under-utilized link conditions and by introducing accelerated averaging for route assignment. Note that the Frank-Wolfe algorithm cannot be used in this model because calculation of the step-size requires a one-dimensional search to determine the step-size that minimizes the objective function. This line search requires evaluation of volume-delay functions, which are not available for on-line traffic assignment and loading.

7. EVALUATION APPROACH

As discussed in Section 3, the ideal way to evaluate the proposed traffic-assignment approach would be in the field, where one sets up a data collection system that includes detector counts and travel time probes. This test would be quite expensive and extensive given the scope of the research. Hence, the traffic assignment approach was tested using a route-based simulation model as the “field”. Specifically, the procedure was tested on a small network (INN) to examine if the traffic assignment results in nearly equal travel times when travelers are made to choose routes that minimize their experienced travel times.

For the assignment procedure, at each iteration a minimum path tree is constructed for each specified origin node to all its destination nodes, using a shortest path algorithm. However, unlike conventional assignment models, this model does not calculate link impedances using BPR or Davidson functions. Instead, at each iteration, the route costs are found by simulating the traffic network using the flows and paths generated by the assignment algorithm. The network is simulated such that traffic loads between origin-destination pairs follow exactly the paths generated in that iteration. This is accomplished by using route-based simulation (PF-CORSIM). The iterative procedure continues until a defined convergence criterion is attained or when the number of iterations reaches a pre-specified upper bound. Figure 2 presents a flowchart for traffic assignment and loading on a route-based simulation.

Route-based CORSIM Model (PF-CORSIM)

The evaluation of the proposed traffic assignment model requires a mechanism to simulate traffic loads on user-defined paths. Currently, most of the commercially available microscopic simulation models do not have an option to load traffic on paths. A route-based implementation of the CORSIM microscopic simulation [FHWA 1998] called PF-CORSIM has been developed by ITT Industries (which maintains CORSIM) with support from The ATLAS Research Center at The University of Arizona.

The Path-Following implementation (PF-CORSIM) works with CORSIM releases 4.32 and 5.0 and retains all the features of the original simulation package while providing additional features like path-assignment and vehicle-injection at user-defined times.

The following is a brief description of the test network model.

- A 40-node, 104-link network (including entry/exit nodes and links), modeled using CORSIM Version 4.32.
- Ten Origin-Destination (OD) pairs with a cumulative flow of 720 vehicles.
- A pre-timed, four-phase signal control strategy for all nodes (intersections). The signal duration interval for all through movements is 30 seconds and for all left turning movements is 15 seconds.
- Traffic is loaded only through the PF-CORSIM tool, i.e., there is no background traffic.
- The mean values of start–up loss time and queue discharge headway are 2.5 and 1.7 seconds, respectively, and they are the same throughout the network.
- Right turns on red are allowed.
- The free flow speed is 45 mph for entry/exit links and 35 mph for the rest of the links.

We note that this test network model was used only to evaluate the assignment procedure and does not represent an actual site.
Select the initial set of link costs, the free-flow travel times. Initialize all flows $V_a$ to 0 and number of iterations, $n=0$

Find the set of minimum cost trees with current link costs using Dijkstra’s algorithm and make $n = n + 1$

Make all-or-nothing assignments on the shortest paths obtaining a set of auxiliary flows $F_a$. Check if any new paths have been generated. For new paths set flow at previous iteration = 0.

Calculate current flows as $V_a^n = (1 - \Phi) V_a^{n-1} + \Phi F_a$ where $\Phi = 1/n$. These flows are the design points.

Calculate “off-line” running average for each route, $\bar{V}_a^n = \frac{1}{n} \sum_{i=1}^{n} V_a^i$

Are convergence criteria satisfied?

Yes

STOP

No

Simulate (with PF-CORSIM) the network using the routes and their $V_a^n$'s. Obtain new link travel-times.
8. ANALYSIS AND RESULTS

Several traffic assignments and loadings were performed using different random seeds for the CORSIM simulation. The different random seeds result in stochastic variations in lane-changing and car-following behavior, as well as queue discharge and start-up loss time characteristics. For standard CORSIM models, a random seed is also used to stochastically generate the vehicle entry headways at origins; routes are not explicitly specified for each vehicle -- they result only from the intersection turning ratios as pre-specified by the user. In PF-CORSIM an external agent (e.g., our traffic assignment procedure) specifies the traffic routes and loads while a random seed stochastically generates the vehicle entry headways.

The fact that stochastic attributes are incorporated in the traffic assignment/simulation model makes the network loading model significantly more realistic than the case where these characteristics are assumed to have been modeled by a simple volume-delay relationship. However, a definitive statement regarding the representativeness of the results obtained from the simulation of traffic assignments can only be made once the output has been tested for effects of random processes in the simulation model.

In order to justify the claim that the route flows provided by this traffic assignment/simulation model represent reasonable values and are not biased by the use of a particular random seed, the model outputs were studied for all aspects that could be influenced by the randomness of the model. The convergence criteria for this particular network and scenarios included: (i) travel times of all routes of an OD pair should be similar, and (ii) the flows assigned to a route should not vary by more than 0.5 vehicles for two successive iterations. We specify 0.5 vehicles as the acceptable upper limit on the absolute difference in flows for consecutive iterations because most assignments generally have a few routes with fractional flows assigned to them. When modeling congestion effects using simulation, we cannot use a fractional number of vehicles. Hence, if the difference in flow is fractional, it will not impact the link travel times obtained at the end of simulation, and consequently the flow assignments in subsequent iterations. Continuing, the other convergence criteria include: (iii) no new routes are generated, and (iv) more than 90% of the trips should have excess travel time less than δ% of the average trip travel time or τ seconds. Excess travel time of a route is defined as the difference between its route travel-time and the travel time of the shortest route for that OD pair. In this test case, the average trip time ranges from 326 seconds to 360 seconds for different random seeds. Therefore, τ = 10 seconds of excess travel time is approximately δ = 3% of the average trip time. We chose the statistic “percentage of trips with excess travel time less than ten seconds” because it appeals as a reasonably good indicator of the state of convergence. This statistic can have different excess travel time (cut-off) values depending on the nature of the network under consideration.

To gain insight into the effect of random seeds on the route travel-time distributions for all the routes and for a given OD pair, the routes and their travel times were plotted against random seeds to observe the variations induced by randomness in the travel-time profiles. Figure 3 presents route travel-time distributions of OD Pair 8 for different random seeds. Each bar represents the travel time of a route. We can see from the figure that the number of routes generated and the distributions of route-travel times for different random seeds do not show much variation. In fact, the profiles of the distributions for different seeds are remarkably similar.
Validation of Assignment/Simulation Process

To further validate the assignment/simulation process, we examined if the results provide a reasonable representation of the system, given the particular objectives of the travelers. Therefore, for this model, we felt the output data should satisfy the following condition: “When the model achieves convergence, the travel-times of all routes for a given OD pair must approach a consensual value”. However, in case the values differ widely, the routes with the lowest travel times should be assigned almost all the flow. The reason would be that there is no real alternative to these “minimum-cost” routes even when all of the flow for that OD pair is loaded on them. Figure 4 shows distributions of route travel times for OD Pairs 1 through 10, using random seed 99999. The distributions of route flows for this traffic assignment are presented in Figure 5, where the route flows are given as the total number of vehicles for that period, on each route for each OD pair. We can make the following observations from this figure:

- The number of routes for each OD pair ranged between 1 (Pair 2) and 10 (Pair 10).
- The two routes for OD Pair 3 showed perceptible difference in route travel-times; the shorter route had 94 vehicles (out of 100) assigned to it, while the larger had 6.
- The two routes for OD Pair 5 showed significant variation in travel-times. As expected almost 97% of the trips were assigned to the shorter path.
- Of the 6 routes for OD Pair 8, two had somewhat longer in travel-times. The total flow on these two long routes was only 7 vehicles (out of 160).
Figure 4. Route travel time distributions for all OD pairs with random seed 99999

Figure 5. Route flow distributions for all OD pairs with random seed 99999
Excess Travel Time Analysis

To provide further proof of convergence, excess travel-time analysis was carried out. Figures 6 and 7 give the excess travel time distribution of 720 OD trips for random seed 99999. In this distribution the horizontal axis is the excess travel time in seconds, and, for each excess travel time, the number of trips that have excess travel time greater than this is represented by the y coordinates. Figure 6 shows the distribution at convergence (15th iteration) and Figure 7 gives the distribution midway (31st iteration) through the assignment.

The following observations can be made from Figure 6: at the end of 15 iterations,

- 58% of the trips have excess travel time of less than 10 seconds.
- About 50% of the trips have zero excess travel time.
- Approximately 22% of trips have excess travel-time of more than a minute and just above 3% of the trips have excess travel time more than 2 minutes.
- The average excess travel time per trip is 2.29 seconds.

According to Figure 7, at the end of 31 iterations,

- 90.5% of the trips have an excess travel time of less than 10 seconds.
- About 63.2% of the trips have zero excess travel time.
- Less than 7 or 0.96% of the trips have excess travel-time of a minute or more. No trip has excess travel time greater than 79 seconds.
- The average excess travel time per trip is 0.9 seconds.

The above analysis clearly shows that the convergence of the assignment/simulation approach improves as the number of iterations increases from 15 to 31. The results are as anticipated, considering the fact that the model is based on a simulated network, which can induce some randomness. Table 1 shows the excess travel time statistics for six random seeds.

### Table 1. Excess Travel Time Statistics for Six Random Seeds

<table>
<thead>
<tr>
<th>Random Seed</th>
<th>11111</th>
<th>32579</th>
<th>65943</th>
<th>7798</th>
<th>95339</th>
<th>99999</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of trips with excess travel time less than 10 seconds</td>
<td>92.1</td>
<td>94.6</td>
<td>96.3</td>
<td>94.9</td>
<td>90.5</td>
<td>90.5</td>
</tr>
<tr>
<td>Average excess travel time per trip in seconds</td>
<td>0.96</td>
<td>0.59</td>
<td>0.79</td>
<td>0.71</td>
<td>1.72</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Figure 6. Distribution of excess travel time at 15th iteration with random seed 99999

Figure 7. Distribution of excess travel time at convergence with random seed 99999
9. CONCLUSIONS

The primary objectives of this study were (1) to propose an analytical traffic assignment approach to monitor an INN when count detectors and traffic probes are available and (2) to demonstrate the feasibility and applicability of the model, which considers implicitly the actual dynamics of traffic and congestion rather than the use of explicit BPR functions.

The basic goal was to re-engineer the traffic assignment process for an Impacted Neighborhood Network (INN) to make it more responsive to behavioral aspects and inherent randomness of the transportation system in the presence of new interventions such as work zones. Moreover, the rapid deployment of ATIS technologies has resulted in a shift in the way individuals choose their routes in such situations.

Our approach assumes that the INN is constantly monitored with count detectors and vehicle probes that provide trip times. This information is available to travelers that use INN. After each period, for example a day, travelers experience a trip time and choose another route if he/she has current knowledge of some trip times. This is repeated the next period and the process continues. Note that rather than assume a volume-delay function, the traveler makes his/her decision based on the actual experience on the previous trip and, hence, can account for whatever factors that influence his/her decision, such as aversion to left turns, avoidance of traffic signals, lane blockages due to buses, etc.

To test our approach, we assumed that travelers will choose routes that minimize travel times experienced by them. In the evaluation of our scheme, we examined how close the travel times were with one other, to reflect the level of equilibrium in the network. If, in fact, travelers did choose routes to minimize their travel times, then it is expected that most of the experienced travel times for any given origin-destination pair would be approximately equal.

Analysis of the results from the assignment/simulation model validated our process in that (a) routes most used for an OD pair had nearly equal travel times and (b) if a long route was chosen for an OD pair then only a very small fraction of travelers chose it. The statistics observed from excess travel time distribution graphs further support the claim that the assignment process provides reasonable network loads. One also observes that the process tends to converge to a traffic equilibrium as the number of iterations increases.

A natural extension to this research effort would be the application of this model to a real-life traffic network. This is essential to vindicate the qualitative improvements this model seeks to bring to short-term traffic planning of a locally impacted area due to situations such as work-zone activities. Further, the travel demand forecasts obtained from this model could be compared to those from a conventional assignment process and their performance against field data could be tested.

Perhaps the most important contribution of this paper is the introduction of an approach that could track the transient behavior in the process of reaching a traffic equilibrium when an intervention such as a work zone, or short-term disruption of capacity, is introduced in the network. Observe that the “iterations” in the above assignment can be a representation of time periods in the *equilibration dynamics*. By some careful, and somewhat extensive, data collection during the intervention, we may be able to fit a model that predicts the traffic loads for the next day as a function of the previous few days’ (1) trip times, (2) traffic volumes, and (3) an equilibration dynamics parameter that represents the inertia among decision makers in re-routing. This is one of our current research efforts.
REFERENCES


