A Comparison of Static and Dynamic Traffic Assignment Under Tolls: A Study of the Dallas-Fort Worth Network

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ABSTRACT

There is great interest in developing pricing models for congestion relief. However, most of the work in the literature uses static transportation models for analysis. The benefits of accounting for traffic dynamics under congestion pricing are unclear. This research performs a systematic comparison of static traffic assignment with the VISTA model, a simulation-based dynamic traffic assignment approach, and with an approximation to DTA using an add-in for TransCAD software. A novel demand profiling algorithm based on piecewise linear curves is developed, and a method to enable reasonable comparisons of static traffic assignment and the TransCAD add-in is provided. The results indicate that traditional static models have the potential to significantly underestimate network congestion levels in traffic networks, and the ability of DTA models to account for variable demand and traffic dynamics under a policy of congestion pricing can be critical.

INTRODUCTION AND BACKGROUND

As the number of drivers increases in urban areas around the world, the search for policies to counteract congestion continues in earnest, as does the search for models to reliably predict the impacts of these policies. One such policy is congestion pricing, which assesses users a fee for traveling certain links at certain times, in an effort to efficiently allocate space on the network. While the idea of congestion pricing has existed for some time (see, for instance, (1), (2), and (3)), it has gained considerable acceptance in practice as technological advancements address various implementation issues.

Techniques for finding first- and second-best pricing schemes under a variety of scenarios have been developed, as in (4, 5, 6, 7, and 8), and different versions of congestion pricing has been tested or implemented in a number of locations around the world (9).

Techniques for predicting the impact of such policies also have improved in recent years. Dynamic traffic assignment models have attracted recent attention, due to their ability to account for time-varying properties of traffic flow (10). However, these formulations generally lead to extremely complicated solution procedures. Nevertheless, progress has been made using techniques such as simulation for solving large networks (11 and 12).

In particular, many state agencies are currently evaluating pricing as a potential congestion relief policy, and the Texas Department of Transportation (TxDOT) is exploring the value of using DTA models to predict the impact of such policies. This paper investigates the difference in results obtained from using static and dynamic traffic assignment (STA and DTA) to evaluate congestion pricing policies on a real traffic network, and its contributions of this paper are twofold. First, an algorithm is proposed that quickly and reliably generates a time-varying demand profile from aggregate demand data (static OD trip tables). Such profiles are a required input to perform the DTA analysis. Second, this investigation compares the results from a DTA approximation, a simulation-based DTA approach, and traditional static assignment when applied to the Dallas-Ft. Worth (DFW) network, where TxDOT is considering implementation of congestion pricing on selected links.

This paper is organized as follows. First, the TransCAD add-in and the VISTA model, which were used to perform the DTA analysis, are described. Following this is a description of key issues that arise when attempting to compare static and dynamic assignment, and a method to facilitate comparison between the approximator and static assignment. Next, an algorithm is presented that creates time-varying demand data from aggregate data, followed by the DFW network results. Finally, the contributions are summarized and the principal findings reiterated.

DTA APPROXIMATION USING TRANSCAD'S ADD-IN

The add-in to TransCAD, developed by Caliper Corporation, approximates DTA by utilizing an algorithm developed by Janson and Robles (13) which converges to a dynamic user equilibrium solution. This algorithm approximates the variability in travel demand and link flows by dividing the analysis period into smaller, discrete time intervals, over which demand is assumed to be uniform. The procedure employs the notion of a node-time interval $\alpha_{r,i}^{d,t}$, a binary variable which is set to unity if the last unit of flow leaving origin *r* during a particular time interval *d* passes through node *i* during time interval *t*, and set to zero otherwise. Intuitively, the node time intervals trace the paths of the last vehicles leaving each origin at each time interval.

While the mixed integer program developed by Janson and Robles is non-convex over all possible node time intervals, for a fixed set of node-time intervals, the problem is convex. Thus, the algorithm employs an iterative procedure whereby a set of node time intervals is assumed and then the traffic assignment problem is solved. A new set of node time intervals is calculated from the traffic assignment results, which are used to generate another traffic assignment. This iterative process converges to a dynamic user-equilibrium solution within a given tolerance, defined as sufficiently few node-time intervals changing from one iteration to the next.

Constraints in the mathematical program guarantee that FIFO conditions are satisfied, and the algorithm also includes procedures to resolve problems with spillback queues that may occur due to incidents or other changes in link capacity. However, since the approximator in its current state only uses Bureau of Public Roads-type (BPR) link performance functions in TransCAD to calculate travel times, this feature cannot be used.

SIMULATION-BASED DTA USING VISTA

VISTA (Visual Interactive System for Transport Algorithms) is a network-enabled software that integrates spatio-temporal data and models for a wide range of transport applications: planning, engineering, and operational (14). VISTA can be accessed via a cross-platform JAVA client or a web page. In particular, VISTA can perform dynamic traffic assignment using a cell transmission model (CTM).

The cell transmission model was developed by Daganzo (15) as a discrete version of the hydrodynamic traffic flow model. The CTM can be thought of as a simulation-based model which divides network links into shorter "cells," which then tracks the number of vehicles in each cell through a series of discrete time steps on the order of five seconds. Limits on the maximum number of vehicles in each cell and the maximum number of vehicles that can move from one cell to the next between iterations correspond to maximum densities and capacity for links in the network.

A key feature of the CTM is that flows are explicitly prohibited from exceeding capacity. This is in contrast to static assignment methods, or the DTA approximator, where it is possible to have link volumes exceed capacity. In the CTM, if demand for a cell exceeds the available capacity, queuing forms to maintain flows less than capacity. This ability to model queues in a somewhat realistic manner is one of the prime attractions of the CTM.

The simulator used in VISTA is an extension of the basic CTM. The main enhancements over the basic cell transmission model are the concept of adjustable size cells that improves the flexibility, accuracy and computational requirements of the model, and a modeling approach to represent signalized intersections. The basic cell transmission model along with the enhancements yields a model that can simulate integrated freeway/surface street networks with varying degree of detail.

ISSUES IN COMPARING STA AND DTA RESULTS

The question of how to compare static assignment to DTA is a nontrivial one. Typical measures of comparison, such as volumes on individual links or total system travel time (TSTT), cannot be applied in a naïve fashion due to fundamental differences between the modeling approaches. Moreover, the behavioral assumptions are so different that parameter assumptions are not really comparable.

With regard to the DTA approximator, the need for a more sophisticated way to compare results arose from preliminary investigations into a smaller test network, where, contrary to intuition, the DTA approximator predicted a lower total system travel time than a static assignment. The cause of this phenomenon was determined to be the presence of clearance intervals in DTA after the assignment periods, which continue to model vehicles in the network until they reach their destinations, even though no additional trips are loaded. Since this results in some links having volume for a longer period of time than in static assignment (which has no need for clearance intervals), the result is an effective increase in link capacities. Fundamentally, this occurs because STA has no concept of arrival or departure times; thus, the issue of trips departing late in the peak period is not relevant.

For this reason, a procedure was sought to make the results of static and dynamic assignment commensurable. The procedure used here first assigns vehicles with DTA; then, for each link, the number of clearance intervals needed before the last vehicle leaves is noted. Finally static assignment is performed, with the capacity of each link altered based on the number of clearance intervals needed in DTA. For instance, for a link with a two-hour capacity of 2000 veh/hr, if the last vehicle departed this link 15 minutes after the end of the assignment period, STA link capacity was increased by (2000)(15/120) = 250 veh/hr (for a total of 2250 veh/hr). Essentially, this procedure provides the same additional capacity that clearance intervals provide in DTA, on a link-by-link basis. Capacities were only increased using this method (that is, if the last vehicle on a particular link left before the end of the assignment periods, no capacity reduction was made).

This method was chosen for several reasons. First, it is a fairly straightforward way to accommodate the effective increase in capacity provided by clearance intervals in DTA, and is specific to each link in the network. Additionally, it avoids manipulation of DTA results, thereby preserving arrival times, departure times, and all the other time-varying properties of the network which make DTA attractive in the first place. Furthermore, the additional computational burden imposed by this method is negligible.

The issues in comparing DTA with STA are further compounded when attempting to compare STA with VISTA results. While clearance intervals are a major issue in comparing results from the DTA approximator, the approximator still uses the same BPR link performance functions that static assignment used. VISTA, on the other hand, uses no link performance functions at all, but instead uses the simulation-based cell transmission model to propagate traffic.

For this reason, global measures of comparison were chosen to compare the two assignment procedures. Individual link flows are not directly comparable because of the vast differences between the assignment procedures, and measures such as *v/c* ratios have different meanings (flow-to-capacity in VISTA, demand-to-capacity in static assignment). For each of five functional classes of roadways (freeways, arterials, etc.), the total travel time was compared, as was the total system travel time for the entire network.

DEMAND PROFILING

Problem Description

One issue in using DTA is the need for a time-dependent OD demand. While a single OD matrix for the entire peak period suffices for static assignment, for DTA one needs to know how this demand changes during the peak period. Many DTA routines approximate this by requiring an OD matrix for each of many small intervals, for instance, five or ten minutes in length. Unfortunately, such detailed data on travel demand is not readily available. While loop detectors or observed traffic counts can possibly be used to extract these time-dependent demand matrices, for now one must often make do with demand data only for very coarse time intervals, such as AM peak, PM peak, and off-peak times. The problem then becomes how to create time-dependent demand at a much finer resolution from the aggregate data. This is known as the *demand profiling problem*. Much of the literature focuses on estimating profiles from observed traffic counts using techniques such as least squares; see, for instance, (16). In this work, however, profiles are created using existing demand data used for static assignment.

One rather naïve way to create a profile is to assume that demand is distributed uniformly throughout the period if interest. For instance, if the demand for an OD pair in a two-hour peak period is 2,400 vehicles, and an OD matrix is needed for every five minutes, one approach is to simply assign a demand of 100 vehicles for each of those five-minute intervals, for a total of 2,400 in the two hours. This approach has some drawbacks, namely that the demand will not be “smooth.” In general, between two abutting time intervals the demand will jump. This is unlikely to be a realistic model of this demand profile, since one would not expect an instantaneous decrease from one time period to the next.

An approach used by Kockelman et al. (9) uses quadratic programming to minimize the sum of the squares of the difference between successive time intervals, such that the total demand constraints over the coarse periods (e.g. peak and off-peak periods) are satisfied. Although this creates smooth curves, quadratic optimization is computationally expensive.

Piecewise Linear Demand Functions

An alternative approach developed here involves the use of piecewise linear functions to approximate demand profiles. These functions are completely defined by the points at which they are not differentiable; that is, where the linear "pieces" intersect; thus, the aim of these procedures is determine the locations of these so-called "defining points" in an expedient manner.

Once the defining points, and thus the function, are determined, it is easy to obtain the demand for the small time intervals to be used in DTA, as the area under the demand function between the endpoints of the time interval.

It is important to keep in mind that the piecewise linear function E that we seek is a rate of demand and that its units are vehicles per some unit of time. Thus, integrating E over a time interval will produce the total vehicular demand for that time interval. Since E is piecewise linear, the area under any portion of the curve can be readily computed using the formula for the area of a trapezoid.

The most general framework for this approach would be to choose defining points that optimize some objective function, taking as constraints the requirement that the total demand in the longer periods is the same as that given in the input (e.g., if given peak hour demand of 50,000 for 7 AM to 9 AM, the demand function generated by the defining points should reveal the same thing.) Since these constraints are linear, a linear objective function seems a natural choice, although it is not immediately clear what form this function should take to form a "smoothest" curve. One option is to use a quadratic function, where the sum of the squares of the slopes of each line segment (possibly weighted according to length) is minimized, which can still be solved with relative ease because of the convex/concave nature of quadratic functions, and the relatively small number of decision variables involved, compared to the more general quadratic programming formulation mentioned above. Another option would be to sum the absolute value of the slopes of each segment, and minimize this.

A Quick Approach for a Specific Case

An alternative method was developed that primarily uses basic geometric relations, involves only linear programs that can be trivially solved (or possibly none at all), and thus, is extremely fast. This method applies when given n consecutive coarse time intervals as input (e.g., AM Peak, Midday, and PM Peak time intervals), and the total demand for each is known. Initially, the defining points will be established at the endpoints of each of the coarse intervals, although, if necessary, more will be created to ensure that the curve is everywhere non-negative.

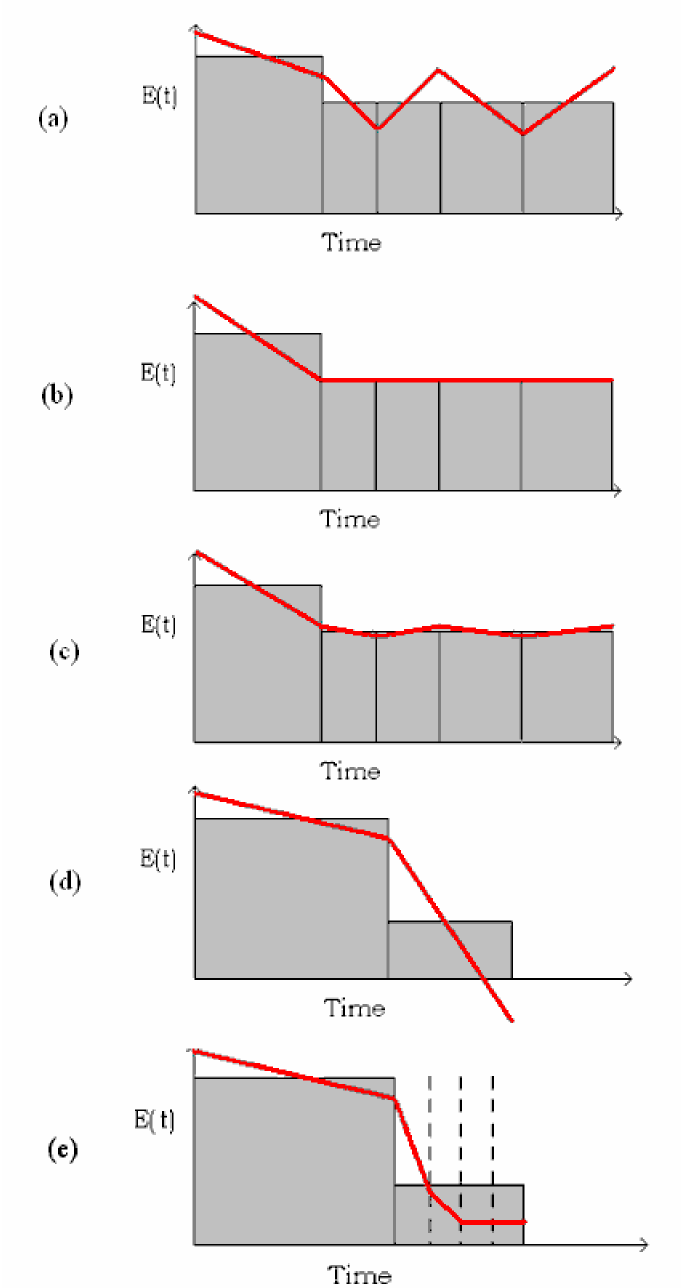
This method involves calculating successive defining points based on the value of the previous one. Consider, for instance, an interval of length L_0 whose endpoints correspond to defining points x_0 and x_1, with given demand D_0. Let $E_0^* = D_0/L_0$ (one can think of E_i^* as the average rate of demand for time period i, or the value of the function $E(t)$ on this interval using the naïve approach described above). If x_0 is fixed, then there is only one possible value for x_1 that satisfies the requirement that total demand in this interval equal D, and this is readily found using geometry ($x_1 = 2E_0^* - x_0$). Now that x_1 is known, we consider the next interval defined by x_1 and x_2 and proceed to calculate x_2, and so forth. The initial value x_0 can be calculated using a formula that produces a reasonable seed value; for instance, $x_0 = E_0^* - (E_1^* - E_0^*)/2$ considers the first two time intervals to generate a seed. From here, knowing x_0 fixes $x_1 = E_0^* + (E_1^* - E_0^*)/2$, and so forth.

Two problems with this approach become apparent:

First, the functions formed by defining points calculated in this way may oscillate or exhibit other bizarre behavior. For instance, if $E_0^* = 500$, and $E_1^* = E_2^* = ... = E_n^* = 400$, we obtain defining points $x_0 = 550$, $x_1 = 450$, $x_2 = 350$, $x_3 = 450$, $x_4 = 350$, ... in sort of perpetual oscillation (see Figure 1a). One possible solution to this problem is to take advantage of its speed by calculating the defining points starting with different intervals as seeds, and averaging the results. (When starting with an interval that is neither the start nor end interval, we calculate defining points both forwards and backwards. Initial x_n and x_{n+1} values are chosen in a way similar to that described above). For instance, taking the same example, although starting with the first interval produces oscillation, that is the only interval in which this is seen. For instance, starting with the interval defined by x_2 and x_3 we obtain defining points $x_0 = 600$, $x_1 = 400$, $x_2 = 400$, $x_3 = 400$, ..., $x_n = 400$ (Figure 1b). Repeating this process for the other n intervals and averaging the curves, we see that the oscillation is significantly reduced (Figure 1c). Intuition suggests that other anomalies from this approach can be controlled in a similar way, although this certainly is not guaranteed.

The other immediate problem is that there is no guarantee that the defining points calculated in this way will be nonnegative. For example, if $x_5 = 600$, and $E_6^* = 200$, then we would calculate $x_6 = -200$ which clearly is meaningless for modeling purposes (see Figure 1d).

A straightforward approach to dealing with the second problem is to subdivide the problematic interval into several smaller intervals and choose defining points, all of which are positive, such that the total area under all subintervals is equal to the demand in the original area (see Figure 1e). More generally, suppose that instead of simply being non-negative, we require a defining point x to satisfy $x \geq T \geq 0$, where T is a user-specified lower bound for the defining points in a time interval (possibly a function of D or E^*).



(a) An example of problematic oscillation.
(b) No oscillation is present when starting from a different seed interval.
(c) Averaging the curves produced from different seeds reduces oscillation.
(d) An example of a nonnegativity violation.
(e) Solving the nonnegativity issue by subdividing the interval

FIGURE 1 Potential Problems with Demand Profiles

Consider some interval $[t_0, t_1]$ (again, let $L = t_1 - t_0$) with demand D, and an associated lower bound T. Assume that the defining point x_0 associated with the endpoint t_0 is known, and is such that $2D - x_0 < 0$. As before let $E^* = D/L$. We consider the possibility of dividing this interval into n equal subintervals, so there will be a total of $n + 2$ defining points associated with this interval (x_0 with t_0; x_i with $(t_0 + t_1)i/n$ for $i = 1, \ldots, n$; and x_{n+1} with t_1). We now construct a linear program to solve this problem.

We want to choose $x_1, \ldots, x_{n+1}$ such that the area under this portion of the curve will equal D; that is,

$$\sum_{k=0}^{n-1} \frac{L}{n} \cdot \frac{x_k + x_{k+1}}{2} = L \cdot \frac{x_0 + 2x_1 + 2x_2 + \cdots + 2x_{n-1} + x_n}{2n} = D.$$

Simplifying, this constraint becomes

$$2x_1 + 2x_2 + \cdots + 2x_{n-1} + x_n = 2E^* - x_0 \tag{1}$$

Likewise, we have constraints $x_1, \ldots, x_n \geq T$ (2)

Now we need to choose an appropriate objective function. One simple choice is to maximize x_1, since the demand in the previous interval is greater than the demand in this interval. Thus, intuitively a large x_1 would tend to create a "smoother" demand profile.

This program can be solved easily: because the coefficients on all decision variables are positive in constraint (1), and our objective is to maximize x_1, the optimal solution has $x_2 = x_3 = \ldots = x_{n+1} = T$, assuming the program is feasible and the resulting x_1 is at least T. Solving the program, we find $x_1 = E^*n - x_0/2 - T(n - 3/2)$, which is feasible if

$$E^*n - \frac{x_0}{2} - T\left(n - \frac{3}{2}\right) \geq T \Leftrightarrow n \geq \frac{x_0 - T}{2\left(E^* - T\right)}$$

Thus we see that this program is always feasible for sufficiently large n, and we have derived an analytical expression that shows the minimum value of n needed for feasibility.

So, this method is complete and can be expressed as follows: Choose the first interval, pick x_0 as described above, then starting with this seed value proceed to calculate x_1, x_2, and so forth using the formula $x_n = 2D_n - x_{n-1}$. If any of these are negative, subdivide the interval into the minimum number of subintervals needed (choose n to be the least integer satisfying $n \geq (x_0 - T)/2(E^* - T)$, and calculate defining points for the endpoints of each subinterval using the analytical formulas described above. Once this is done, repeat the procedure using the second interval as a seed, and so forth, until the procedure has been done for all intervals. Take the average of the defining points from each run of the procedure, and let these be the defining points used to generate the final demand profile (interpolating where necessary, since the number of subintervals intervals are divided into need not be the same for all runs).

Implementation

The above procedure was coded in VisualBASIC, and runs external to TransCAD. To create the time-dependent OD matrices, the OD matrices for the coarse intervals were exported into a text format, and the procedure was run to generate similarly-formatted text files representing the matrices for each of the finer time intervals used for DTA. These matrices were then imported back into TransCAD for use with the approximator.

Since demand profiling also was required to generate DFW demand inputs to VISTA, the program generated a second demand file in the proper format for VISTA, in addition to the one needed for TransCAD.

Typical run times to generate a 24-hour profile for the 919-zone Dallas network (844,561 origin-destination pairs and five aggregate times of day) at five minute resolution was on the order of one day. The output files generated were quite large, on the order of 500-1000 MB depending on the required precision. All runs were performed on a 2.8 GHz machine running Windows XP with 1 GB RAM.

Extensions

Although the method described above works for the specific case demand in each of the separate periods is known, it also would be useful to have a procedure that can work in a more general setting. For example, if one is given data that contains total demand in the AM peak, PM peak, and off-peak times, but no information about how the off-peak demand is distributed between midday and nighttime traffic, the method in §5.6.3 cannot be directly applied.

One possible approach for such a case is to use a quadratic programming approach on a few randomly-selected OD pairs, and to calculate how that approach divides the off-peak demand between midday and nighttime for those pairs, generating a distribution of this split among different OD pairs. Ideally, this distribution will be fairly tight, and one can safely assume the same split across all OD pairs, divide them accordingly, and proceed to use the algorithm described above.

If the distribution does not indicate that one midday/nighttime split is suitable for most OD pairs, another possibility is to try to find all defining points at once, rather than sequentially as done in this approach. While the sequential approach runs very quickly, this speed comes at the cost of foresight: the algorithm is myopic and never considers any time intervals beyond the immediate one where defining points are being found. As such, it is impossible to capture a more general constraint such as that mentioned above.

A more general mathematical programming approach could accommodate such constraints, and such an approach that preserves the notion of defining points should still run faster than an approach which attempts to set the demand values for each of the fine time intervals because far fewer decision variables would be involved. The feasibility of such an approach has not yet been studied extensively, although it appears that the mathematical programs that arise would be nonlinear.

With this method for generating the needed demand profile, and with a suitable method of comparison chosen, attention can be turned to how the results from the assignment procedures will themselves be evaluated and analyzed.

APPLICATION TO THE DALLAS-FT. WORTH NETWORK

TransCAD software was used to perform static assignment, and one of the dynamic assignment procedures for this investigation, the latter using the approximator add-in described in Section 2. Comparison was made both globally (TSTT) and on a link-by-link basis. Additionally, a global comparison was made with the results from VISTA.

The Dallas network used contains 919 zones; 15,987 nodes; and 56,574 links (92 of which are tolled in this application). A three-hour AM peak period (6 – 9 AM) was chosen for analysis. For the DTA approximator, this period was discretized into eighteen 10-minute intervals, with three additional 10-minute intervals provided for network clearance. A total of 2.56 million vehicle trips were assigned. Since the TransCAD approximator in its current state cannot directly consider tolls, in this investigation the tolls were added to the free-flow travel time for each link, using an assumed value of travel time of $10/veh-hr. Effectively, this changes the fixed-level tolls that exist in reality to marginal pricing for use in this model.

The following table summarizes the results of static assignment and the DTA approximator by showing the average *v*/*c* ratios, weighed according to vehicle-miles traveled (VMT), for each functional class of links. Additionally, a comparison was made between congested links (those with $v/c > 1$ in STA) and uncongested links. Only links with positive flow are included in this analysis.

TABLE 1 Comparison Between Static Assignment and DTA Approximator

Category	*n*	Vehicle-miles traveled (millions)		Average *v*/*c*	
		Static	Dynamic	Static	Dynamic
Freeway	6292	25.88	29.86	1.02	1.64
Principal Arterial	4936	6.46	5.39	0.72	0.86
Minor Arterial	10434	7.65	6.25	0.43	0.52
Collector	14596	2.97	2.74	0.77	1.39
Frontage Road	2783	1.56	1.44	0.60	0.96
Congested	2995	18.35	22.61	1.26	2.08
Unongested	25997	28.61	25.11	0.62	0.79

The most notable differences are seen in links that are predicted to be congested under the static analysis. For these, DTA predicts an even higher level of congestion, often significantly so. When calculating TSTT, this increase manifests itself in two ways: first, the convex nature of volume-delay functions amplifies the difference in travel times; and second, the calculation of TSTT weights links with higher VMT more than other links. Static analysis predicts a TSTT of 1.27 million vehicle-hours, while DTA predicts 2.53 million vehicle hours, nearly double the static prediction. Unfortunately, the approximator's use of BPR-type functions, which can allow arbitrarily high volumes (and thus arbitrarily high travel times) precludes taking advantage of the queue spillback features available in other DTA implementations (such as VISTA) which can provide added realism. Additionally, it should be noted that much of this increased congestion can be found on freeways, which carry far more traffic than other functional classes.

That DTA predicts increased congestion is not surprising, and is in accordance with the convexity properties associated with link performance functions, from which it can easily be shown that a nonuniform demand distribution produces a higher total travel time on individual links than would be produced by the same total volume distributed uniformly. Using the BPR parameters $\alpha = 0.15$, $\beta = 4$, and examining the congested links, we see that an increase in v/c ratio from 1.26 to 2.08 on a link increases travel times by 176%, which contributes heavily to the massive increase in TSTT seen in the approximator's results, when compared to static assignment.

As mentioned previously, vast fundamental differences exist between the cell transmission model used by VISTA, and the link performance functions used by static assignment. Thus, comparison between these two procedures was done through global measures, namely, the total travel time experienced on links of various functional classes. These results are presented in the following table, along with the proportion of the total system travel time for both approaches. Note that the network includes links not among the five functional classes listed here, such as centroid connectors and ramps; thus, the sum of the travel time values among the five classes is less than the total system travel time.

TABLE 2 Comparison Between Static Assignment and VISTA

Functional class	Total travel time (hr x 10^3)		Proportion	
	Static	Dynamic	Static	Dynamic
Freeways	505	325	40.6%	10.5%
Principal Arterials	174	543	14.0%	17.6%
Minor Arterials	237	715	19.1%	23.2%
Collectors	227	738	18.2%	23.9%
Frontage Roads	45	390	3.7%	12.6%
Total System	1266	3086	100%	100%

As with the DTA approximator, TSTT is much higher under the dynamic method than under static assignment. Another, perhaps more significant, result is that traffic is routed quite differently between the two procedures: static assignment tends to assign considerably more vehicles to freeways, whereas VISTA uses arterials and collectors more. This result is in contrast to the DTA approximator, where the distribution of vehicle traffic among the roadway classes was more comparable. This difference arises because the cell transmission model is a very different approach to traffic propagation than that used by static assignment or the DTA approximator, which is a link performance function-based approach.

For instance, under static assignment, freeway links had an average *v/c* ratio slightly greater than one. Since the cell transmission model explicitly prohibits flows from exceeding capacity, vehicles will route themselves differently. Additionally, in the cell transmission model, flow on links decreases as they become congested and queuing forms. This is a more realistic model than the link performance function approach, where link throughput always increases with increasing demand, even as travel times grow high. Thus, the shift from freeways to arterials and collectors is consistent with CTM's more realistic traffic flow model.

CONCLUSIONS

While congestion pricing and dynamic traffic assignment have individually attracted considerable interest in recent years, efforts at using the latter to evaluate the former on large-scale networks are relatively few. Several issues arise when trying to do this. For one, the comparison of static and dynamic traffic assignment is nontrivial due to fundamental differences between the models; however, the increase in capacity induced by clearance intervals in the DTA approximator can be accounted for by an appropriate increase in the capacities used in static assignment. With models such as the CTM, which are vastly different from static assignment, it is much more difficult to compare the results on a link-by-link basis, and in this project only global measures of system performance were compared.

Second, the problem of creating the time-dependent OD needed for DTA was addressed by creating an algorithm that uses piecewise linear functions to generate demand profiles significantly faster than previous approaches using quadratic programming.

When static and dynamic assignment models were applied to the DFW network, although TSTT was significantly higher when predicted by DTA rather than static assignment, much of this increase is due to links which showed congestion under traditional static assignment. On such links, the DTA approximator showed an even higher level of congestion, an impact which is amplified by the convex nature of delay functions. This higher level of congestion on already-congested links is not surprising, given that nonuniform demand (such as that in DTA) was shown to produce greater delay than a uniform demand (such as that assumed by static assignment). Still, this result indicates that static assignment models have the potential to significantly underpredict congestion levels due to changes in demand over the peak period. Additionally, the distribution of trips among different classes of roadways is significantly different between the cell transmission model (used by VISTA) and the link performance function-based models (static assignment and the DTA approximator), due to the CTM's more realistic model which prohibits flows from exceeding capacities. VISTA predicts significantly fewer freeway trips than static assignment or the approximator.

Further insights could be gained if the DTA approximator in TransCAD provided additional capabilities. In particular, the ability to extract path flows for each OD pair and departure time would greatly enhance modelers' ability to predict the impacts of policies at a more disaggregate level; in its current state, one is unable to show the impact of congestion pricing, or other policies, on the paths taken by various OD pairs, or on the equilibrium costs faced by each pair, and is limited to using information on the link flows. Additionally, its use of link performance functions limits its ability to model queues due to congestion, which can be captured using other formulations such as the cell transmission model. With such improvements, investigations like this one could be extended to account for traffic dynamics under congestion pricing policies in greater depth.

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