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A Simulation-Based Approximation Algorithm for Dynamic Marginal Cost Pricing

by Ampol Karoonsoontawong, Satish Ukkusuri, S. Travis Waller, and Kara M. Kockelman

This work offers a simulation-based approximation algorithm for dynamic marginal cost pricing (MCP) congestion pricing that is a direct extension of its static counterpart. The algorithm approximates the time-dependent marginal costs, and is incorporated into the inner approximation dynamic user equilibrium algorithm to evaluate the results of dynamic MCP, which are then compared to static assignment results with MCP from previous study. The status quo and dynamic MCP-on-freeways scenarios are simulated (and then compared) on the Dallas-Fort Worth 35,732-link network. Due to computational requirements for such a large-scale dynamic traffic assignment application, the dynamic MCP scenario is simulated without feedback, and only route choices are permitted to vary. When prices are imposed on freeway users, some minor system benefits are observed, including a delay in the onset of congestion. Dynamic prices vary substantially over the three-hour period of analysis, reflecting changes in freeway congestion. Reasons for any inconsistencies between dynamic and static results are discussed, along with important enhancements to future implementation.

INTRODUCTION

It is well known in the literature that two broad methods to combat traffic congestions are supply improvement and demand management. The supply-side solutions include capacity expansion, managed lanes and ramp metering to name a few. According to the Pigou-Knight-Downs paradox (see Arnott and Small 1994), increasing capacity actually allows latent demand to consume much of the travel time savings. Clearly, demand management is key, emphasizing behavioral modification in order to shift and shorten car trips and reduce their frequency and peaking over certain times of day (Kockelman 2004). One rather obvious option is the tolling of congested roads, or congestion pricing (CP).

This paper presents a simulation-based approximation algorithm to calculate dynamic tolls under the dynamic marginal cost pricing (MCP) scheme, which is a direct extension of the static MCP (Kockelman 2004). The contributions of the paper include the proposed dynamic MCP toll approximation and the incorporation of the proposed MCP computation to the Inner Approximation Dynamic User Equilibrium (IADUE) algorithm, which is implemented in the dynamic traffic assignment (DTA) module of the Visual Interactive System for Transport Algorithm (VISTA) (Ziliaskopoulos and Waller 2000). The DTA module employs RouteSim (Ziliaskopoulos and Lee 1996), which is a mesoscopic simulator¹ based on an extension of Daganzo's (1994) cell transmission model,² to propagate traffic while accounting for traffic realisms such as link capacity, queue spillbacks³ and shockwaves.⁴ The static model requires the strict guarantee of first-in-first-out (FIFO) condition, which can be relaxed in the dynamic model. For example, vehicles approaching an intersection may not satisfy the FIFO condition. Thus, it overcomes the weakness of using link performance functions⁵ as is typical in the literature.

The first section of this paper focuses on a review of the literature, followed by the description of the simulation-based approximation algorithm for the dynamic MCP. Our computational experience is then presented, and the limitations in our approach are discussed. Finally, the major conclusions are summarized and possible directions for future research are given.

LITERATURE REVIEW

The concept of road space rationing is not new and dates back to the early 20th century (Pigou 1920 and Knight 1924). Early work in CP includes Vickrey (1963), who observed that an effort was underway to differentiate between peak and off-peak demand in several markets, and something similar for transportation would be useful. There are numerous works on static traffic assignment (STA)-based CP, which essentially assumes steady-state traffic conditions such as Zhao and Kockelman (2006) and Dial (1999). Given the time-varying nature of traffic flow on a transportation network, to truly assess the traffic and economic impacts of CP, one should seek a dynamic traffic assignment based CP. The advantages of a dynamic CP over the static CP are as follows: 1) more realistic marginal costs are calculated at various time slices, and 2) better representations of traffic flows as traffic dynamics and spatial and temporal vehicular interactions can be captured. Moreover, the recent commitments by municipal, state and federal governments to construct and operate roadways with dynamic toll pricing, which is a toll pricing method that changes prices based on traffic conditions to maximize the performance of the tolled facility, have crucially motivated the need for dynamic CP models (Friesz et al. 2007).

The literature on dynamic traffic assignment-based congestion pricing is very limited, and may be classified based on three criteria: 1) simulation-based/non-simulation-based approaches, 2) within-day/day-to-day dynamic models, and 3) first-best/second-best CP schemes. First, the simulation-based approach employs a traffic simulation procedure, whereas the non-simulation-based approach employs link performance functions (also known as the Bureau of Public Road formulation). Second, the within-day dynamic models simulate certain important traffic realisms, which cannot be captured by the day-to-day dynamic models, including demand peaks, temporary capacity variations, temporary over-saturation of road supply elements, and formation and dispersion of queues (Cascetta 2001). The day-to-day dynamic models simulate the evolution of the system over a sequence of similar periods and the possible convergence of the system to a stable condition, while the traffic condition within each day is assumed stationary. Third, under the first-best CP, every portion of the road system is charged a MCP toll, while under the second-best CP, only certain portions are tolled.

The studies on the non-simulation based dynamic congestion pricing includes Joksimovic et al. (2005), Wie and Tobin (1998), Friesz et al. (2004), Yang et al. (2007), and Friesz et al. (2007). Joksimovic et al. (2005) formulated the second-best toll design problem in the within-day dynamic traffic network as a bi-level optimization problem, considering elastic demand. They only used a small hypothetical network and solved it by complete enumeration, and their DTA scheme is an extension of the static traffic assignment that employs certain link performance functions. Wie and Tobin (1998) proposed two within-day dynamic congestion pricing models based on the first-best marginal cost pricing. Their DTA scheme employs a link performance function to estimate link travel time. Friesz et al. (2004) and Yang et al. (2007) considered the day-to-day dynamic first-best congestion pricing, which forces the traffic condition to system optimum. They considered the steady-state traffic condition within each day, and employ a typical link performance function. Friesz et al. (2007) introduced the dynamic second-best optimal toll problem with user equilibrium constraints. They considered both within-day and day-to-day DTA models that employ link performance functions. A common drawback of these non-simulation-based approaches is the lack of realistic traffic representations, so these models cannot capture traffic interactions across adjacent links and other traffic flow phenomena. This drawback can be addressed by the simulation-based approach.

The works on simulation-based dynamic congestion pricing includes Lu et al. (2006) and Lu and Mahmassani (2007). They proposed a within-day dynamic model, namely the bi-criterion dynamic user equilibrium model, and a solution algorithm. Their model and algorithm can be used to evaluate any given congestion pricing scheme; however, the dynamic optimal tolls are not calculated in their work.

This paper presents a simulation-based approximation algorithm to explicitly calculate dynamic tolls under the dynamic marginal cost pricing (MCP) scheme. The underlying traffic simulation model can better represent realistic traffic phenomena when compared to the link performance function-based model. The proposed approach charges dynamic MCP tolls on only freeway links (i.e. the second-best CP) since it is not practical to toll every link in the network. The proposed approach is a within-day dynamic model that can better calculate time-varying MCP tolls during the peak period, whereas typical day-to-day dynamic models cannot. The next section describes the proposed approximation procedure.

SIMULATION-BASED APPROXIMATION ALGORITHM FOR DYNAMIC MARGINAL COST PRICING

Our approach does not attempt to solve for the truly optimal marginal-cost dynamic pricing policy because it is a highly complex problem. Instead, an approximate method is used, employing each link's marginal cost estimate to compute time-dependent tolls, updating these every 10 minutes. This approximation method assumes that a vehicle entering a tolled link imposes marginal costs only on vehicles that use the same link, rather than impacting travel times (and thus costs) on other links. The approximation algorithm for computing dynamic MCP tolls is shown first. Then, the modified IADUE algorithm that incorporates the proposed dynamic MCP computation is discussed.

Approximation of Dynamic MCP Toll

When a vehicle enters a transportation network, it imposes two types of costs: the average cost experienced by the vehicle and a marginal cost (experienced essentially by those following the new vehicle, under very slightly reduced speeds) (Liu and McDonald 1999). In this study, an approximation for calculating the marginal costs on tolled links is considered. The assumption is that a vehicle entering a tolled link imposes marginal costs only on all following vehicles using this same link. Thus, it is assumed that this vehicle does not impact vehicles using other, upstream (or downstream) links.⁶ This assumption simplifies the computations for time-dependent link tolls, but assumes that delays imposed on vehicles using other links are relatively insignificant (as compared to costs imposed on those using the same link). While this is generally true, highly congested networks result in backups that affect upstream links and users that were not destined for the bottleneck point.

The time-dependent link toll is the product of the time-dependent link marginal cost (in seconds) and the value of travel time (VOTT, in \$ per second). Peeta and Mahmassani (1995) proposed the following computation of a link's approximate time-dependent marginal cost, t^{ta} , for all time periods t and links a in terms of travel time:

$$(1) \quad t^{ta} = T^{ta}(x) + x^{ta} \frac{\partial T^{ta}(x)}{\partial x^{ta}}$$

where $T^{ta}(x)$ represents the travel time experienced by another vehicle entering link a at time t , x is the vector of time-dependent vehicle counts on all links (x^{ta} , $\forall t, a$), and dT/dx equal the link's marginal cost (in seconds).

The spatial interactions and n^{th} order temporal interactions (global marginals) are ignored in this computation. These effects may not be significant compared to the direct effect on link a at time t , $\frac{\partial T^{ta}(x)}{\partial x^{ta}}$ (i.e. local marginals). Under such conditions, the solutions obtained using the

global marginals and the local marginals will be relatively close. However, if the interactions are significant, the solution obtained using the local marginals may deviate from that obtained using the global marginals.

$T^a(x)$ and x^{ta} are obtained directly from simulation. Figure 1 illustrates the approach used for the computation of the derivative $\frac{\partial T^{ta}(x)}{\partial x^{ta}}$. The approach used here assumes that the time-dependence

of the derivative is due to time-varying link performance functions, which represent the link travel time as a function of the link flow. This means the performance curve in Figure 1a for link a at time t depends on the traffic flow conditions on the link at that time. This time-dependence is very significant; a link's travel time can differ significantly for the same number of vehicles at two different times, depending on the fraction of vehicles that are queued. A link's performance curve changes somewhat gradually over time. If the time interval between successive evaluations of dT/dx derivatives (marginals) is small, it appears reasonable to assume that three consecutive points in time are on the same link performance curve, as illustrated in Figure 1a. A quadratic fit using the three points results in the time-varying link performance curve at time t and the slope of this curve at time t gives $\frac{\partial T^{ta}(x)}{\partial x^{ta}}$, as shown in Figure 1b. For example, at times $t-1$, t , and $t+1$, the

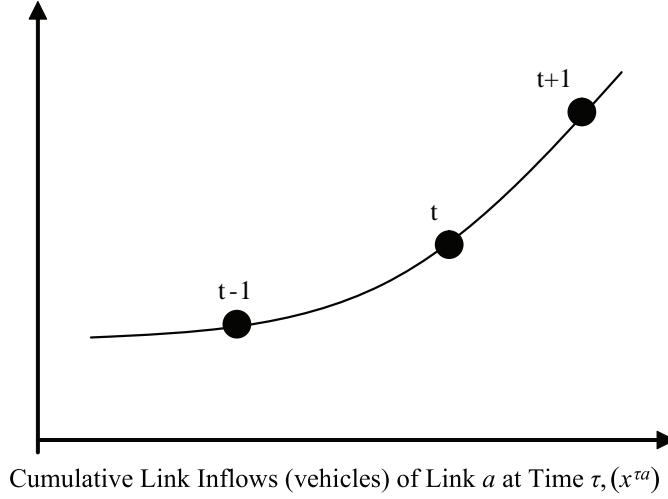
corresponding link inflows are 100, 250 and 400 vehicles, and the corresponding link travel times 1500, 2500 and 600 seconds. Following the procedure in Figure 1b, the link marginal cost at time t is 14.973 seconds/vehicle. Assuming a VOTT of \$10.00 / vehicle-hour, the MCP toll at time t is = 4.16 cents (i.e., 14.973 seconds/vehicle \times \$10/3600 seconds = \$0.0416 per vehicle) plus an existing flat toll (if any).

Peeta and Mahmassani (1995) suggested that the consideration of small time intervals (on the order of a few seconds) may cause some instability in the curves because the VOTTs and the number of vehicles in successive intervals may exhibit “jumps” at certain times. Hence, the length of the time interval between successive data points involves trade-offs between the accuracy and robustness of the curves. To achieve stability in the curves, the simulation of six-second time intervals may be too small for updating origin-destination (OD) paths, since no appreciable change takes place in the system in such a short duration. In the implementation of the solution algorithm, paths are updated every assignment interval (i.e., every 10 minutes for the DFW network). The marginal values may be computed for assignment intervals only and not for simulation intervals, thereby reducing the computational burden of the path-processing step. In the next section, this dynamic MCP computation is incorporated into the IADUE algorithm.

Modified IADUE Algorithm for Dynamic MCP

The Inner Approximation Dynamic User Equilibrium (IADUE) algorithm (Chang 2004) is a solution algorithm for the variational inequality (VI) formulation of the single-mode automobile dynamic user equilibrium problem. The algorithm estimates the equilibrium path assignment. Conventionally, vehicle assignment has been performed using the method of successive averages, which assumes that all previous solutions contribute equally to the final equilibrium, so it assigns vehicles equally among the set of past solutions. In contrast, the IADUE algorithm searches the feasible set of path assignments for the assignment that minimizes an equilibrium gap function.⁷ It searches within a subspace defined by a set or subset of the extreme points of the feasible space.

The IADUE algorithm iteratively employs the time-dependent shortest path (TDSP) algorithm (Ziliaskopoulos and Mahmassani 1994) to generate vehicle paths with the implicit assumption that drivers have perfect information and can divert to alternate paths if it reduces travel time. In this study, a minor modification in TDSP is made in order to account for tolls, under an assumption of homogeneous users (i.e., a single value of VOTT). The VOTT is used to convert tolls to a time penalty, characterized as additional time perceived by each driver. For example, with the VOTT of \$10 per hour, a \$0.33 toll charge is equivalent to two minutes of additional travel time (i.e., \$0.33/

Figure 1: Computation of Derivative for Link Marginal Cost and Time-Dependent MCP Toll**a) Graph of Link Travel Time and Cumulative Link Inflows**Link Travel Time of Link a Time τ (T^{ta})**b) Procedure to Calculate Derivative of Link Marginal Cost and MCP Toll**

Input: (X_1, Y_1) , (X_2, Y_2) and (X_3, Y_3) associated with times $t-1$, t and $t+1$
 where X_1 , X_2 , and X_3 = the cumulative link inflows at time $t-1$, t , and $t+1$, respectively.
 Y_1 , Y_2 , and Y_3 = the link travel time at time $t-1$, t , and $t+1$, respectively

Output: the gradient at point (X_2, Y_2)

Step 0: Form the system of quadratic equations:

$$AX_1^2 + BX_1 + C = Y_1$$

$$AX_2^2 + BX_2 + C = Y_2$$

$$AX_3^2 + BX_3 + C = Y_3$$

where A , B and C are coefficients of the system of quadratic equations, and are variables while X_1 , X_2 , X_3 , Y_1 , Y_2 , and Y_3 are constants.

Step 1: The solution of the system in Step 0 is:

$$L_1 = \frac{X_1 + X_2}{X_1 X_2}, L_2 = \frac{X_1 + X_3}{X_1 X_3}, R_1 = \frac{Y_1 X_2^2 - Y_2 X_1^2}{X_1 X_2 (X_2 - X_1)},$$

$$R_2 = \frac{Y_1 X_3^2 - Y_3 X_1^2}{X_1 X_3 (X_3 - X_1)}, C = \frac{R_1 - R_2}{L_1 - L_2}, B = R_1 - CL_1, A = \frac{Y_1}{X_1^2} - \frac{B}{X_1} - \frac{C}{X_1^2}$$

where L_1 , L_2 , R_1 , and R_2 are intermediate variables which are used to determine the values of A , B , and C .

Step 2: Determine the gradient at point (X_2, Y_2) : $\frac{dY}{dX}(X_2, Y_2) = 2AX_2 + B$

Step 3: MCP toll at time t (associated with point (X_2, Y_2)) is $2AX_2 + B$ + existing flat toll.

(\$10 per hour)*(60 minutes/hour) = 1.98 \approx 2 minutes). This added time or “delay” obviously does not impact the actual time spent within the network, but it is used within the TDSP algorithm. The modified algorithm is called the time-dependent least cost path (TDLCP) algorithm, and it routes each vehicle such that it chooses a path with the least generalized cost (toll-based time penalty plus actual travel time). For the dynamic MCP application, two new modules are added to the original IADUE algorithm. The first module computes dynamic MCP tolls right after the traffic simulation step. The second module updates the link and path generalized costs using the computed dynamic MCP tolls. Further details are referred to Karoonsoontawong et al. (2008). Next, the computational experience on a real large-size network is shown.

COMPUTATIONAL EXPERIENCE

This work was originally developed for the application of credit-based congestion pricing (CBCP) in Texas, which is briefly described here. CBCP (Kockelman and Kalmanje 2005) is a novel strategy that seeks to overcome the negative equity impacts of congestion pricing CP by allocating monthly budgets to eligible travelers to spend on congestion tolls. The first step in predicting CP’s impact involves traveler behavior modeling. Kockelman et al. (2005) estimated joint destination-mode choice models for the Dallas-Fort Worth (DFW) metroplex from the region’s 1996 household and on-board transit survey datasets for different trip purposes. These models were applied for short-term (employment locations held fixed) and long-term (employment locations flexible) static cases with full feedback⁸ (using the method of successive averages⁹) to the DFW region. In addition to the status quo (which has some tolling), two MCP scenarios were simulated for the 1999 modeling year: MCP just on the region’s freeways and MCP applied on all roads (see Gulipalli 2005). Full model feedback of travel times and costs was implemented, and the method of successive averages (MSA) was used for route, destination, and mode choice equilibration for each of five daily time periods.

Since the MCP-on-all-roads scenario has very high associated initial and recurring costs, it is not likely to be practically feasible in the near future (Kockelman et al., 2005). Due to these facts and especially the excessive computational time of a DTA run for large-scale networks, the MCP-on-all-roads scenario is not considered here. Specifically, the proposed simulation-based approximation procedure to evaluate the MCP scenario when only freeways are priced is employed, and the simulation-based DTA to evaluate the status quo for the DFW region. Due to highly intensive computational requirements for large-scale DTA applications, the status quo and MCP scenarios are simulated without feedback (of travel times and costs, for destination and other choices). Only route choices are permitted to vary.

The DTA analysis focuses on the AM peak (6 to 9 AM), and an assignment interval is 10 minutes, resulting in 18 assignment intervals over three hours of simulation time. A simulation time step is six seconds, yielding 1800 time steps over three hours. A single VOTT of \$10.00 per hour (per vehicle) is assumed, so that the results can be comparable to Kockelman et al.’s (2005) static analysis. In order to build a set of competitive path choices for each time step and every OD pair, five IADUE iterations are run (approximate CPU time = one month). Then, the IADUE iterations are performed on the built path set (i.e., no new path is generated) until achieving convergence for both scenarios (status quo and MCP-on-freeways) (approximate CPU time = one week). The proposed simulation-based algorithms run on a Dell PowerEdge 6600 Server with dual 2.3 GHz Xeon processors and 4 GB of RAM, running under Redhat Fedora Core 3. The modified IADUE algorithm takes approximately five weeks to evaluate the results of dynamic MCP-on-freeways without feedback. While CPU times for the IADUE algorithm presently are quite high, these will fall dramatically over time, as computing capabilities rise.

The network and demand matrix assembly is described next, followed by the comparison of the status quo and MCP-on-freeways from static and dynamic traffic assignment. Possible reasons of considerable difference between STA and DTA results are discussed. Then, the density values on certain arbitrary freeway links from DTA analysis are shown. Although it is unclear if STA and

DTA models are comparable as they are based on different modeling assumptions, the comparison provides a systematic approach to compare the differences between these two approaches for CP. This comparison should facilitate future research to compare the obtained results with observed data.

Network and Demand Matrix Assembly

As provided by the North Central Texas Council of Governments (NCTCOG), the 1999 DFW roadway network has 26,748 lane miles and 22,187 links. For a static approach to network assignment (implemented in TransCAD), the DFW network has 13,694 nodes, 4,874 centroids, 22,187 links, and 9,805 centroid connectors. TransCAD's links and centroid connectors can be either unidirectional or bidirectional. Since VISTA has its own data format requirements, the TransCAD network data are converted into VISTA file formats. All links in the VISTA database must be unidirectional. Thus, the number of links used by VISTA is greater than that in TransCAD, but the number of nodes remains the same. A major concern in running DTA is the amount of memory consumed – especially when generating the competitive least-cost paths for every six-second time step and every OD pair. Since the number of zones (centroids) impacts these memory requirements directly, a relatively aggregate zonal system is used. In VISTA, the DFW roadway network still has 13,694 nodes, but just 919 centroids. It has 35,732 links, and 3,642 centroid connectors (or four connectors per centroid). The zonal structure is that previously used by NCTCOG.

Note that the networks differ only slightly on the centroid structure, whereas the structures of nodes and links are the same. Comparison of STA and DTA methods is a complex subject in many senses (see, e.g., Boyles et al. 2006). DTA makes use of detailed, time-dependent inputs (e.g., OD trip tables for every five minutes), whereas STA relies on aggregate OD demand values for long periods (e.g., 3 to 24 hours). STA link capacities are simply employed as parameters in the continuous link performance functions, rather than serving as true capacity values and resulting in backups when demand exceeds capacity.

Next, the time-dependent OD demands are derived as follows. Gulipalli's (2005) short-term static travel demand model application for the status quo yielded trip origin-destination (OD) information for the region's five traffic assignment periods and four modes. The static ODs for the three modes (drive alone, shared ride and truck trips) in the five times of day were then combined by first converting each truck trip to two passenger car equivalents (HCM 2000) and summing up the drive-alone trips, shared-ride trips and converted truck trips for each OD and time of day. With these 24-hour static OD trips, the demand profiling method¹⁰ by Karoonsoontawong et al. (2008) is used to generate the smoothed time-dependent OD trips every six seconds. Only the demands during the three-hour AM peak (6:00 AM – 9:00 AM) are used for this analysis.

Comparison of Traffic Impacts for the Status Quo and MCP-on-Freeways from Static and Dynamic Traffic Assignment

The DTA results are compared both to one another (status quo vs. MCP-on-freeways scenarios) and to the static analysis with its full behavior feedbacks. It is noted that the value of MCP toll for static analysis is based on the standard Bureau of Public Roads (BPR) formulation:

$$(2) \quad t_i = t_{i,f} \left[1 + \alpha \left(\frac{v_i}{C_i} \right)^\beta \right]$$

where t_i = travel time of link i ; $t_{i,f}$ = free-flow travel time of link i ; v_i = volume of link i ; C_i = capacity of link i ; and α and β = calibration parameters. The static MCP toll is determined from differentiating

t_i with respect to v_i ; thus, the value of link toll for static MCP scenario is (Gulipalli 2005):

$$(3) \quad Toll_i = k_i + VOTT \cdot t_{i,f} \cdot \alpha \cdot \beta \left(\frac{v_i}{C_i} \right)^\beta$$

where k_i = any existing toll on link i .

Traffic impacts for the status quo and MCP-on-freeways scenarios are compared in terms of vehicle-miles traveled (VMT), vehicle-hours traveled (VHT) and average speed during the AM peak period. For the comparison with the static models, the long-term STA traffic impacts come from all five time periods, so they are not perfectly comparable to the three-hour AM peak period results found using DTA. However, the differences are so striking that this distinction is not of major consequence. All STA results are taken from Kockelman et al. (2005).¹¹

System Level Comparison. The predicted changes in system-level (i.e., total) VMT, VHT and average speed during the AM peak when freeways are priced, versus status quo, are shown in Table 1. The DTA results appear insignificant, both in isolation and when compared to the behavioral changes evident under the STA approach. Part of this insensitivity is due to the smaller share of VMT on freeways in the DTA model (see Figure 2) when compared with STA model. The directions of changes for STA and DTA results are not in agreement for system VHT and average speed. The STA results seem to be consistent with expectations. The DTA results seem less so. Of course, the DTA model runs do not permit the behavioral feedbacks that the STA approach allows, so the travelers are far more constrained and changes are fully expected to be much less dramatic. Although it is well accepted by researchers (e.g. Peeta and Ziliaskopoulos 2001; Mahmassani 2001) that DTA captures traffic realities better, it should be noted that a more valid comparison should involve the observed traffic data to conclusively test the validity of the proposed approaches. Our research in this work is a step in that direction.

Table 1: Traffic Impacts of MCP-on-Freeways, as Compared to the Status Quo*

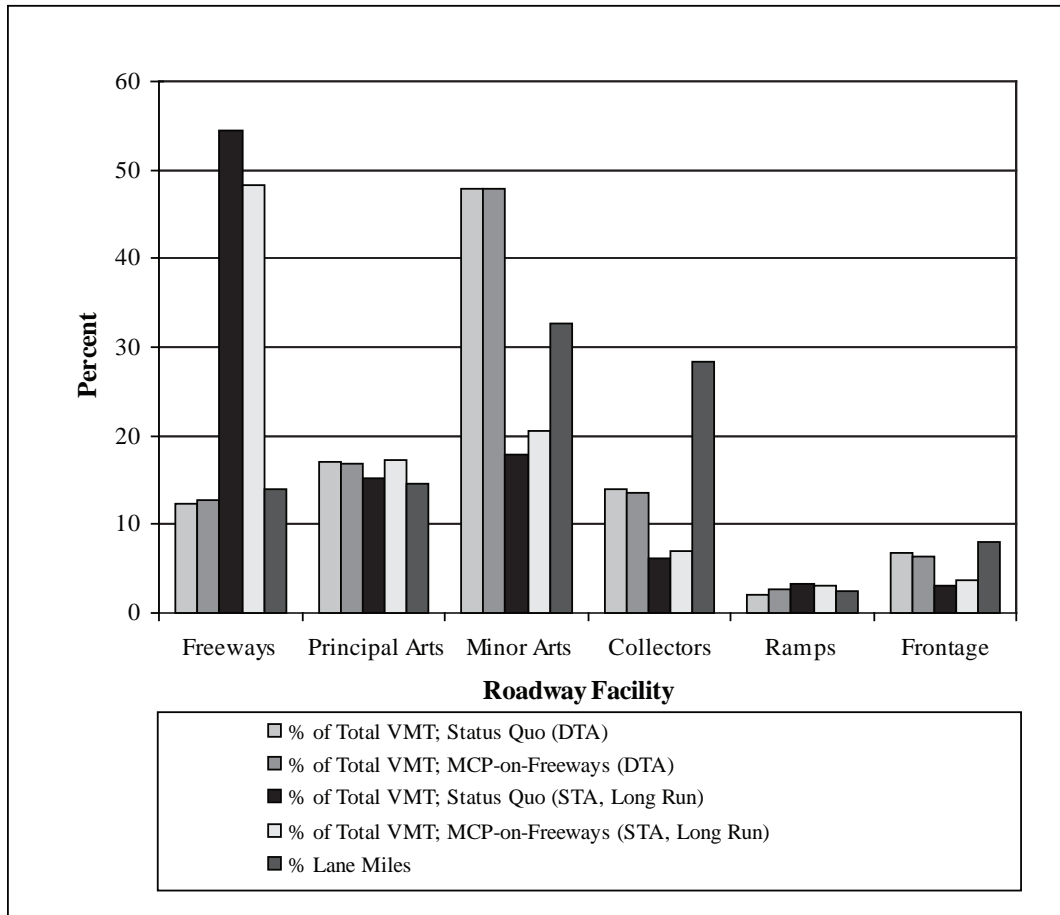
	DTA-based on MCP-on-Freeways (AM Peak)	STA-based MCP-on-Freeways (Long-Term; All Times of Day)
System VMT	Fall by <1%	Fall by 9.4%
System VHT	Rise by <1%	Fall by 16.7%
System Average Speed	Fall by <1%	Rise by 8.7%

*The status quo is the existing condition and without MCP.

Comparison from DTA Analysis. Estimates of %VMT, %VHT and average speed categorized by different roadway facility types for DTA analysis are shown in Figures 2-4. From Figure 2, freeway and ramp VMTs for the MCP-on-freeways scenario are predicted to rise very slightly (less than 1%, i.e., from 12.25% to 12.84% for freeways and from 2.15% to 2.60% for ramps). From Figure 3, freeway and ramp VHTs for the MCP-on-freeways scenario are predicted to fall slightly (less than 1%, i.e., from 7.92% to 7.03% for freeways and from 3.60% to 3.20% for ramps). From Figure 4, freeway and ramp average speeds for the MCP-on-freeways are predicted to rise by 1.89% (from 32.81 mph to 33.44 mph for freeways) and less than 1% (from 13.58 mph to 14.01 mph for ramps), respectively. This may imply that more short-trip travelers using freeways in the status quo tend to choose non-freeway routes to avoid MCP tolls, while more long-trip travelers use freeways, thanks to the travel time savings offsetting MCP tolls.

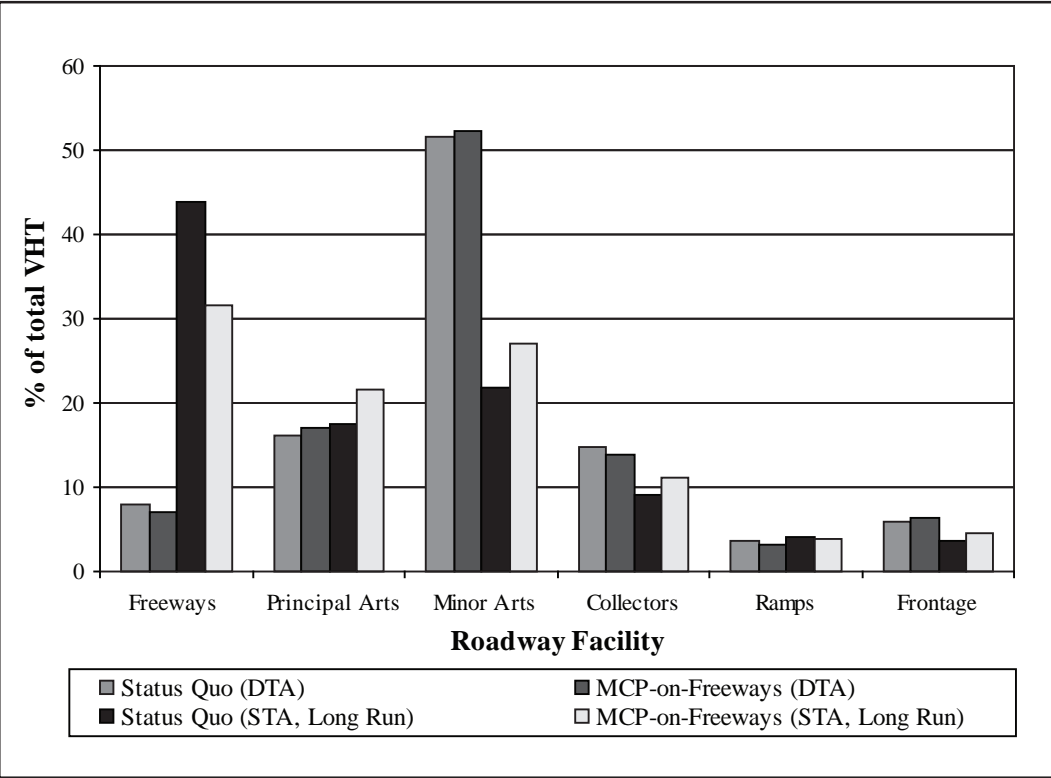
Figure 3 shows that principal-arterial, minor-arterial and frontage-road VHTs for the MCP-on-freeways scenario are predicted to rise very slightly (by less than 1%, i.e., from 16.14% to 17.16%, from 51.63% to 52.31%, and from 5.95% to 6.40%, respectively). Figure 4 shows that their speeds are predicted to fall by less than 1%, less than 1% and 3.32% (i.e., from 20.13 mph to 20.00 mph, from 18.25 mph to 18.11 mph, and from 21.28 mph to 20.58 mph, respectively). This

Figure 2: VMT by Roadway Facility Type for Status Quo and MCP-on-Freeways from DTA (AM Peak) and STA (Long Run, All Times of Days)



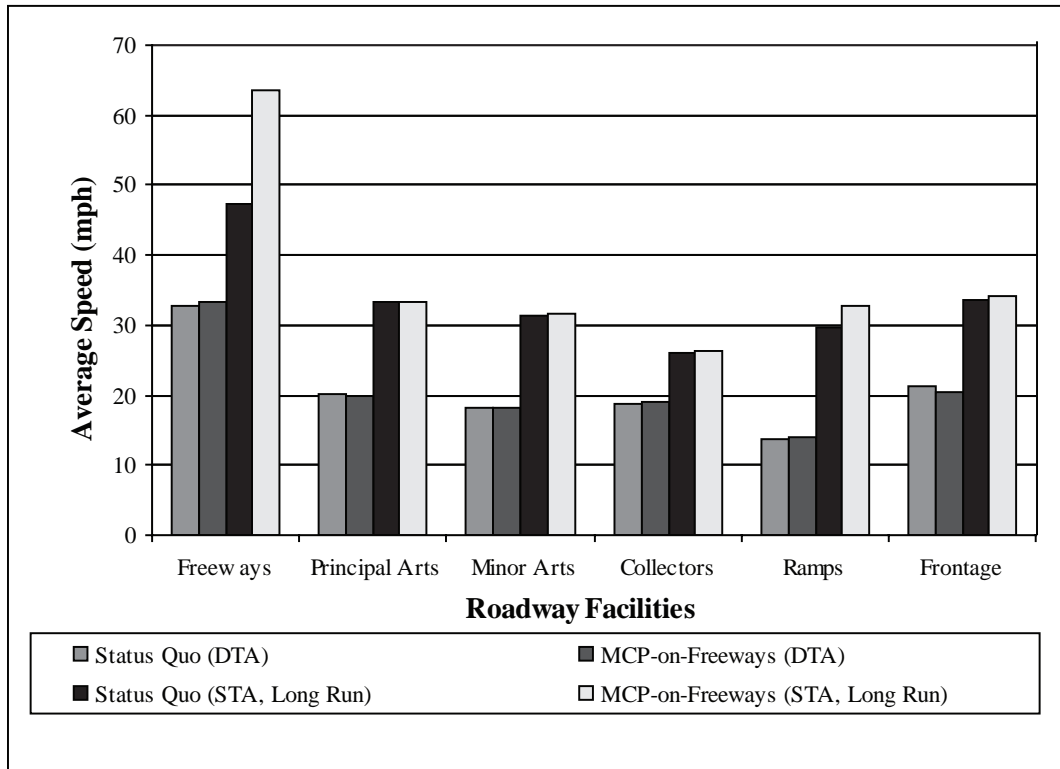
Facility Type	% of Total VMT				% Lane Miles
	Status Quo (DTA)	MCP-on-Freeways (DTA)	Status Quo (STA, Long Run)	MCP-on-Freeways (STA, Long Run)	
Freeways	12.25	12.84	54.39	48.23	14.0
Principal Arts	17.06	16.77	15.17	17.28	14.6
Minor Arts	47.87	47.86	17.89	20.63	32.6
Collectors	13.91	13.60	6.13	6.99	28.4
Ramps	2.15	2.60	3.23	3.11	2.4
Frontage	6.75	6.34	3.18	3.77	8.0

Figure 3: VHT by Roadway Facility Type for Status Quo and MCP-on-Freeways from DTA (AM Peak) and STA (Long Run, All Times of Days)



Facility Type	% of Total VMT			
	Status Quo (DTA)	MCP-on-Freeways (DTA)	Status Quo (STA, Long Run)	MCP-on-Freeways (STA, Long Run)
Freeways	7.92	7.03	43.95	31.58
Principal Arts	16.14	17.16	17.40	21.63
Minor Arts	51.63	52.31	21.80	27.15
Collectors	14.75	13.90	9.04	11.10
Ramps	3.60	3.20	4.17	3.94
Frontage	5.95	6.40	3.63	4.60

Figure 4: Average Speed by Roadway Facility Type for Status Quo and MCP-on-Freeways from DTA (AM Peak) and STA (Long Run, All Times of Days)



Facility Type	% of Total VMT			
	Status Quo (DTA)	MCP-on-Freeways (DTA)	Status Quo (STA, Long Run)	MCP-on-Freeways (STA, Long Run)
Freeways	32.81	33.44	47.39	63.55
Principal Arterials	20.13	20.00	33.38	33.24
Minor Arterials	18.25	18.11	31.42	31.61
Collectors	18.79	19.11	25.97	26.19
Ramps	13.58	14.01	29.68	32.83
Frontage	21.28	20.58	33.54	34.11

means the principal arterial, minor arterial and frontage roads are predicted to become somewhat more congested when MCP tolls are applied on freeways, because more short-trip travelers that use freeways in the status quo leave the freeways to use these facility types when tolls are applied.

Figure 2 shows that principal-arterial, minor-arterial and frontage-road VMTs for the MCP-on-freeways are predicted to fall by less than 1% (i.e., from 17.06% to 16.77%, from 47.87% to 47.86%, and from 6.75% to 6.34%, respectively). This may imply more longer-trip travelers that use arterials in the status quo are attracted to freeways in the MCP-on-freeways. All these results are expected to be amplified considerably when behavioral feedbacks for destination and mode choice shifts are permitted.

Comparison Between DTA and STA Results. The %VMT, %VHT and average speed by roadway types for STA analysis are also shown in Figures 2-4. From Figure 2, in the DTA model, minor-arterial VMT is predicted to be highest, followed by principal-arterial VMT and freeway VMT (approximately 12% of total VMT). In dramatic contrast, under the STA model, freeway VMT is predicted to be highest (around 48-54% of total VMT), followed by minor-arterial VMT and principal-arterial VMT. A similar trend is witnessed for VHT's distribution across the network, as can be seen in Figure 3. Of course, the STA model is a 24-hour model, so freeways may attract more travel during the off-peak hours, but the contrast is still striking if one considers just the three-hour peak period for the STA analysis. The STA results match our expectations better than the DTA results, since one expects a greater share of VMT on freeways than on other facility types (due to higher speeds on freeways). However, the percentage of freeway VMT under the STA model may well be too high, simply because many local network links are not coded. Thus, true freeway %VMT should lie somewhere between STA and DTA results.

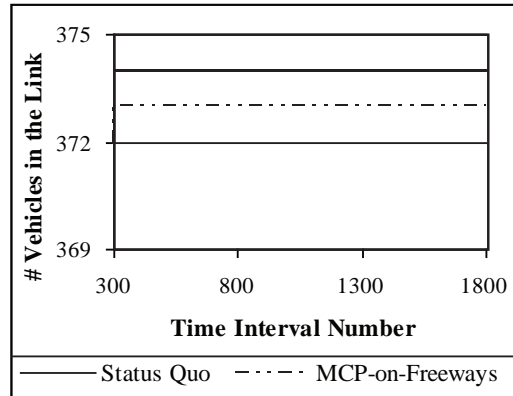
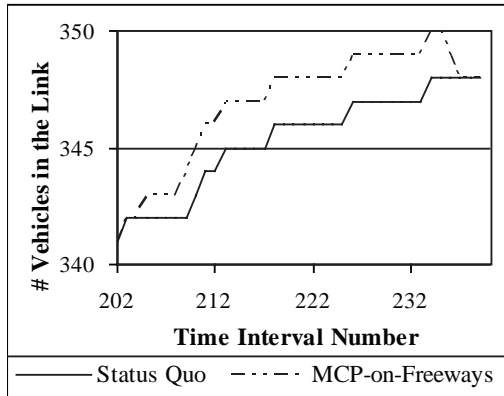
Figure 4 shows that predicted freeway speeds average between 45 and 65 mph under the 24-hour STA analysis, while under a DTA approach for the morning peak period just 30-35 mph is predicted. The range of estimated average speeds for all facility types under the STA approach is 25-63 mph, while that for DTA in the three-hour peak is just 13-34 mph. These indicate a drastic difference between STA and DTA results, and suggest very different behavioral assumptions regarding traffic performance.

Possible Reasons of Considerable Differences Between STA and DTA Results

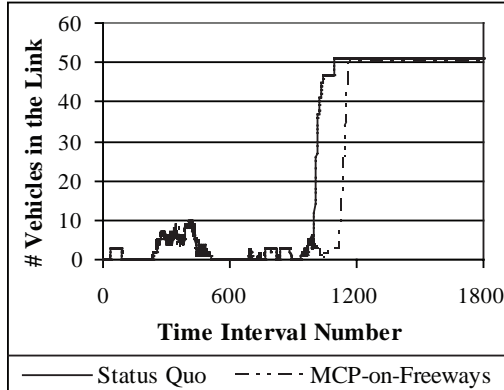
As also discussed in the limitations section, the dramatic differences between DTA and STA results may stem from the following modeling distinctions. First and foremost, the static analysis allows feedback of travel time and cost information to destination and mode choices. The dynamic model is without feedback: travelers are only allowed to change route. Thus, travelers in the dynamic model are substantially more restricted, resulting in negligible estimates of VMT, VHT and speed changes when MCP is applied. Secondly, the centroid structure employed in the DTA model is much more limited than in the STA case. It consists of 919 zones (or centroids) and 3,642 centroid connectors, while the STA model uses 4,874 zones and 9,805 centroid connectors. Thus, the DTA's centroid structure cannot load and unload the network as uniformly or rapidly as the STA's structure. This may result in more congestion around entry nodes in the DTA network. Third, there is a difficulty in DTA peak period analysis: a small number of travelers' departures cannot complete their trips by the end of the three-hour AM peak period analysis. The ideal analysis is a 24-hour period; however, this is effectively impossible at present, due to computer memory limitations. The three-hour study period (AM peak) may not be sufficient for "warming up" and "cooling down" the network; substantial traffic shoulders¹² may exist, making congestion more severe at the start and end of the peak period. Note that in the beginning of DTA, the network is empty, so the warming-up period is employed to populate the network; then, the true analysis period starts. In the same way, the cooling down period is employed after the analysis period to clear all vehicles from the network. All DTA results are determined only from the analysis period.

Figure 5: Time-Varying Traffic Density on Freeway Links

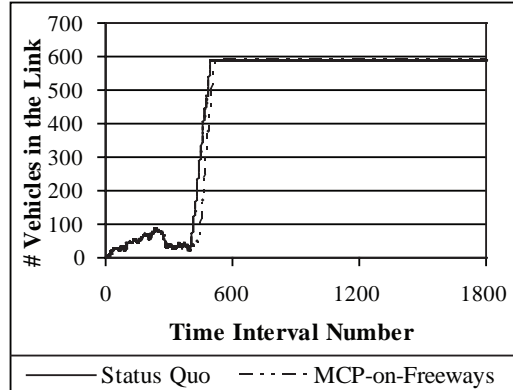
- a) SH114 NB, Between Macarthur and W SH114 (Length = 1267.2 ft, MCP toll Rate Max = \$0.27/mile) (Total Vehicles = 626,114 for Status Quo; 624,675 for MCP-on-freeways; Capacity = 6450 vph*)



- b) US287 SB, Near Wise CO LIN (Length = 3273.6 ft, MCP Toll Rate Max = \$0.39/mile) (Total Vehicles = 41,861 for Status Quo, 35,109 for MCP-on-freeways, Capacity = 4600 vph)



- c) IH30 WB, Near GALLOWAY (Length = 2112 ft, MCP Toll Rate Max = \$0.04/mile) (Total Vehicles = 815,561 for Status Quo, 798,301 for MCP-on-freeways; Capacity = 4300 vph)



* vph = vehicles per hour

** Time Interval Number on the horizontal axis refers to a time interval of six seconds for the dynamic traffic assignment application. The horizontal axis starts at 0 and ends at 1800 (i.e., 0 seconds and $1800 \times 6 = 10800$ seconds = 3 hours). To illustrate, Figure 5a shows that between the time interval numbers 300 (i.e. $300 \times 6 = 1800$ seconds = 30 minutes) and 800 (i.e., $1800 \times 6 = 10,800$ seconds = 180 minutes), there are 374 vehicles in the link for the Status Quo and 373 vehicles in the link for the MCP-on-Freeways.

Exploration of Density on Freeway Links and Toll Rates

Next, the numbers of vehicles or the values of traffic density along four arbitrary links over the analysis period are explored using DTA methods. Figures 5a-5c show the density of freeway links that presently operate without tolls. It can be seen that time shifts in traffic demands take place on these freeways, as a result of MCP tolls. The MCP toll estimates under the DTA-based approximation method range from \$0.10 to \$29.2 per mile on the region's freeway links during the AM peak (6 to 9 am). Obviously, anything over \$10 or \$20 per mile is probably unrealistic, at any time of day, even for very short sections (such as narrow bridge crossings). The DTA model seems to be overestimating MCP tolls. In the STA approach, the toll rates went only as high as \$0.79 per mile.

LIMITATIONS

This DTA analysis assumes inelastic demand in both destination and mode choice, substantially limiting behavioral changes. Due to computational limitations in VISTA, the number of vehicle trips for the status quo and MCP-on-freeway scenarios between all OD pairs come from the static analysis (as found in Gulipalli [2005]), and these are considered fixed. Departure times are also considered fixed. Although VISTA's path-based simulation model can assume different VOTTs across OD pairs (as explained in Ziliaskopoulos et al. 2004), a single VOTT of \$10.00 per vehicle-hour is used here since it is more comparable to the STA approach and no obvious means of ascertaining VOTT variations by OD pair is available. The centroid structure is aggregated to enable DTA analysis. The static demand is smoothed across times of day by the selected model. Lastly, the dynamic MCP toll calculation is an approximation method, unlike the analytical method in the STA.

CONCLUSIONS

An approximation algorithm for computing dynamic marginal cost pricing (MCP) tolls was developed, employing the link marginal costs to calculate the time-dependent toll. This approximation was incorporated into the inner approximation dynamic user equilibrium (IADUE) algorithm in VISTA to evaluate the dynamic MCP. This represents a whole new application environment for VISTA and a major step forward for this kind of DTA model. The proposed approximation of dynamic MCP tolls can be applied in other simulation-based DTA models, such as those by Lu et al. (2006) and Lu and Mahmassani (2007).

The 1999 DFW roadway network was converted from TransCAD format into VISTA format. Due to computer memory limitations, DFW's past, more aggregated zonal system was used, composed of 919 zones/centroids and 3,642 centroid connectors. The network structure used in the dynamic analysis was the same as the static analysis, but the analysis focused on the AM peak (6:00 AM – 9:00 AM). The time-dependent OD demands for the status quo and MCP-on-freeways scenarios were the same, as derived from the status quo of the static analysis. The DTA parameters are as follows: the assignment interval of 10 minutes, the simulation time step of six seconds and the single value of travel time (VOTT) of \$10 per hour. For both scenarios, the DTA module was run for five iterations to construct a path set, followed by running the DTA on the built path set until convergence.

The results of static and dynamic traffic assignments were remarkably inconsistent. The reasons for this are felt to be as follows: (1) The STA approach allowed behavioral feedbacks, whereas the DTA did not. (2) The time periods and traffic demand profiles were distinct (all times of day constant-demand STA results were compared to AM-only DTA results for a smoothed demand profile). (3) The STA employs link performance functions; in contrast, the DTA model employs the cell transmission model, a traffic flow theoretical model developed by Daganzo (1994), to propagate

traffic. (4) The DTA's MCP method is an approximation, whereas that of STA is analytical. (5) The DTA zone and centroid connection structure was relatively coarse, so the DTA network could not load (and unload) traffic as smoothly as the STA network.

Although the findings of this single empirical study may not be able to be highly generalized, they provide interesting and insightful information, as described below. Minor changes in DTA-predicted freeway use following implementation of MCP-on-freeways suggest that short-trip travelers may avoid the priced freeways while longer-trip travelers are more willing to pay the congestion tolls. Using the DTA-based approximation method, MCP tolls on freeways during the AM peak period were predicted to range between \$0.1 and \$29.2 per mile. Predicted freeway link density values and associated MCP tolls indicated observable shifts in traffic flows due to pricing. Some minor system benefits were observed, including a delay in the onset of congestion. Of course, traffic impact predictions would have been much more dramatic had behavioral feedbacks been incorporated. Future implementations should allow such feedback, to incorporate destination, departure-time, and mode-choice decisions as well as heterogeneous users. This paper is essentially the first step toward the more realistic, deployable model for dynamic MCP. In essence, this paper identifies the possibilities and the challenges that should be addressed while implementing DTA for large networks. The insights from computational implementation obtained from this work should allow other researchers and practitioners to draw lessons while solving large scale DTA problems.

Endnotes

1. Amesoscopic traffic simulation is an intermediate solution between microscopic and macroscopic models. The microscopic model simulates single vehicle-driver units, capturing microscopic properties such as position and velocity of a single vehicle. The macroscopic model simulates a traffic stream, describing the relationships of three static variables: average speed, traffic flow and traffic density. The mesoscopic model can model the network and vehicle movements at the same level of detail as microscopic simulations, but with simplified driver behaviors.
2. The cell transmission model is a simple representation of traffic on a highway with a single entrance and exit. It can be used to predict traffic's evolution over time and space, including transient phenomena such as the growth, spillback, reduction and disappearance of vehicle queues.
3. A queue spillback is when a link's queue of vehicles extends to (and impacts) upstream links.
4. A shockwave is the jump (upwards or downwards) in traffic density, as seen at the start and end points of queues.
5. A link performance function is the formula for link travel time, as a function of flow on or demand for the link.
6. Upstream links come before the link in question (in the direction of travel), while downstream links come after the link in question.
7. The equilibrium gap function is simply a metric of how much current traffic loads differ from those under equilibrium conditions. Once traffic patterns and link flow estimates have stabilized, the gap falls below a pre-specified tolerance and the assignment routine is assumed to have converged to equilibrium conditions.

8. Full feedback refers to the process of feeding back traffic assignment results to the trip distribution (and mode choice) components of the model, to ensure equilibrium across all choices and network conditions (rather than just network equilibrium).
9. The method of successive averages is an iterative equilibration method simply averaging current assignment flows with earlier flows, providing for simple, yet well behaved convergence of network conditions.
10. The demand profiling method takes a 24-hour OD trip matrix as input and produces the time-dependent OD trip matrices, offering a smooth profile over time.
11. The BPR parameters used in Kockelman et al. (2005) ($\alpha = 0.15$ and $\beta = 4$) are based on effective capacity (maximum service flow under level of service C, rather than true capacity, under level of service E) and thus were biased low. In this paper, the static results are employed; and these are based on more appropriate BPR parameters ($\alpha = 0.85$ and $\beta = 5.5$), which imply higher static tolls and somewhat higher VMT reductions and speed increases.
12. Here, “traffic shoulders” refers to vehicles still in the network at the beginning and end of the three-hour simulation period.

References

- Arnott, R. and K. Small. “The Economics of Traffic Congestion.” *American Scientist* 82, (1994): 446-455.
- Boyles, S., S. Ukkusuri, S. T. Waller and K. Kockelman. “A Comparison of Static and Dynamic Traffic Assignment Under Tolls: A Study of the Dallas-Fort Worth Network.” *Proceedings of the 85th Annual Meeting of the Transportation Research Board*, 2006.
- Cascetta, E. *Transportation Systems Engineering: Theory and Methods*. Kluwer Academic Publishers, MA, 2001.
- Chang, E. J. “Time-Varying Intermodal Person Trip Assignment.” Dissertation (Ph.D.), Department of Civil and Environmental Engineering, Northwestern University, 2004.
- Daganzo, C.F. “The Cell Transmission Model: A Simple Dynamic Representation of Highway Traffic Consistent with the Hydrodynamic Theory.” *Transportation Research* 28B (4), (1994): 269-287.
- Dial, R.B. “Network-Optimized Road Pricing: Part I: A Parable and A Model.” *Operations Research* 47 (1), (1999): 54-64.
- Friesz, T.L., D. Bernstein and N. Kydes. “Dynamic Congestion Pricing in Disequilibrium.” *Networks and Spatial Economics* 4, (2004): 181-202.
- Friesz, T.L., C. Kwon, A. Chow, and B. Heydecker. “A Computable Theory of Dynamic Congestion Pricing.” *Sixth Triennial Symposium on Transportation Analysis (TRISTAN VI)*, Phuket Island, Thailand, 10-15 June, 2007.
- Gulipalli, P. K. “Credit-Based Congestion Pricing: Impact Assessment for the Dallas-Fort Worth Region and Policy Recommendations.” Master’s Thesis, The University of Texas at Austin, 2005.
- HCM. *Highway Capacity Manual*. Transportation Research Board, Washington, D.C., 2000.

- Joksimovic, D., M.C.J. Bliemer and P.H.L. Bovy. "Optimal Toll Design Problem in Dynamic Traffic Networks with Joint Route and Departure Time Choice." *Journal of the Transportation Research Board* 1923, (2005): 61-72.
- Karoonsoontawong, A., S. Ukkusuri, S. T. Waller, and K. M. Kockelman. "Simulation-Based Heuristic Approach for Dynamic Marginal Cost Pricing." Presented at the 87th Annual Meeting of Transportation Research Board, Washington D.C., 2008.
- Knight, F. "Some Fallacies in the Interpretation of Social Costs." *Quarterly Journal of Economics* 38 (4), (1924): 582-606.
- Kockelman, Kara and Sukumar Kalmanje. "Credit-Based Congestion Pricing: A Policy Proposal and the Public's Response." *Transportation Research A* 39, (2005): 671-690.
- Kockelman, K.M. "Traffic Congestion." Chapter 22 in *Handbook of Transportation Engineering*, McGraw-Hill, New York, 2004.
- Kockelman, K.M., S.T. Waller, P. Gullipalli, S. Kalmanje, A. Karoonsoontawong and S. Ukkusuri. "Application of Credit-Based Congestion Pricing in Texas: Operational Considerations and Impacts." Technical Report 0-4634-1, Center for Transportation Research, University of Texas at Austin, 2005. (Available at http://www.utexas.edu/research/ctr/pdf_reports/0_4634_1.pdf)
- Liu, L. N. and J. F. McDonald. "Economic Efficiency of Second-Best Congestion Pricing Schemes in Urban Highway Systems." *Transportation Research Part B* 33, (1999): 157-188.
- Lu, C.C. and H.S. Mahmassani. "Heterogeneous Users and Variable Road Pricing: Model and Algorithm for the Bi-Criterion Dynamic User Equilibrium Problem on Large Networks." *Sixth Triennial Symposium on Transportation Analysis (TRISTAN VI)*, Phuket Island, Thailand, 10-15 June, 2007.
- Lu, C.C., X. Zhou and H.S. Mahmassani. "Variable Toll Pricing and Heterogeneous Users: Model and Solution Algorithm for Bicriterion Dynamic Traffic Assignment Problem." *Journal of the Transportation Research Board* 1964, (2006): 19-26.
- Mahmassani, H.S. "Dynamic Network Traffic Assignment and Simulation Methodology for Advanced System Management Applications." *Networks and Spatial Economics* 1 (3-4), (2001): 267-292.
- Peeta, S. and H.S. Mahmassani. "System Optimal and User Equilibrium Time-Dependent Traffic Assignment in Congested Networks." *Annals of Operations Research* 60, (1995): 81-113.
- Peeta, S. and A.K. Ziliaskopoulos. "Foundations of Dynamic Traffic Assignment: The Past, the Present and the Future." *Networks and Spatial Economics* 1 (3-4), (2001): 233-265.
- Pigou, A. C. *Wealth and Welfare*. Macmillan, London, 1920.
- Vickrey, W. S. "Pricing in Urban and Suburban Transport." *American Economic Review Papers and Proceedings* 53, (1963): 452- 465.
- Wie, B.W. and R.L. Tobin. "Dynamic Congestion Pricing Models for General Traffic Networks." *Transportation Research Part B* 32 (5), (1998): 313-327.
- Yang, F., Y. Ying, and J. Lu. "A Steepest-Descent Day-to-Day Dynamic Toll." Presented at the 86th Annual Meeting of Transportation Research Board, Washington, D.C., 2007.

Zhao, Y. and K.M. Kockelman. "On-Line Marginal Cost Pricing Across Networks: Incorporating Heterogeneous Users and Stochastic Equilibrium." *Transportation Research* 40B (5), (2006): 424-435.

Ziliaskopoulos, A.K. and H.S. Mahmassani. "Time-Dependent, Shortest-Path Algorithm for Real-Time Intelligent Vehicle Highway System Applications." *Journal of the Transportation Research Board* 1408, (1994): 94-100.

Ziliaskopoulos, A.K. and S. Lee. "A Cell Transmission Based Assignment-Simulation Model for Integrated Freeway/Surface Street Systems." *Journal of the Transportation Research Board* 1701, (1996): 12-23.

Ziliaskopoulos, A.K. and S.T. Waller. "An Internet-Based Geographic Information System that Integrates Data, Models and Users for Transportation Applications." *Transportation Research Part C* 8, (2000): 427-444.

Ziliaskopoulos, A.K. S.T. Waller, Y. Li, and M. Byram. "Large-scale Dynamic Traffic Assignment: Implementation Issues and Computational Analysis." *Journal of Transportation Engineering* 130 (5), (2004): 585-593.

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