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What Matters Most in Transportation Demand Model Specifications: A Comparison of Outputs in a Mid-size Network

by T. Donna Chen, Kara M. Kockelman, and Yong Zhao

This paper examines the impact of travel demand modeling (TDM) disaggregation techniques in the context of medium-sized communities. Specific TDM improvement strategies are evaluated for predictive power and flexibility with case studies based on the Tyler, Texas, network. Results suggest that adding time-of-day disaggregation, particularly in conjunction with multi-class assignment, to a basic TDM framework has the most significant impacts on outputs. Other strategies shown to impact outputs include adding a logit mode choice model and incorporating a congestion feedback loop. For resource-constrained communities, these results show how model output and flexibility vary for different settings and scenarios.

BACKGROUND

Transportation directly provides for the mobility of people and goods, while influencing land use patterns and economic activity, which in turn affect air quality, social equity, and investment decisions. Driven by the need to forecast future transportation demand and system performance, Manheim (1979) and Florian et al. (1988) introduced a transportation analysis framework for traffic forecasting using aggregated data that provide the basis for what is known as the four-step model: a process involving trip generation, then trip distribution and mode choice, followed by route choice. Aggregating demographic data at the zone level, the four-step model generates trip productions based on socioeconomic data (e.g., household counts by income and size) and trip attractions primarily based on jobs counts. The model then proportionally distributes trips between each origin and destination (OD) zone pair based on competing travel attractions and impedances, under the assumption that OD pairings with higher travel costs draw fewer trips. Trips between each OD pair are split among a variety of transportation modes, allocating trips to private vehicle, transit, or other modes based on each mode's relative utility. Finally, the route choice step assigns trips between each OD pair for each mode onto the network links offering the lowest generalized route cost (typically based on travel times and, if applicable, tolls).

While the four-step model framework remains popular among most planning organizations today, transportation demand modeling (TDM) techniques have grown progressively more sophisticated. In particular, the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 linked air quality objectives to transportation plans and pushed transportation planners to improve their basic three-step and four-step transportation models to meet federal mandates. Driven by the need for air quality forecasts and evaluation of project alternatives, advanced TDMs in larger regions range from incorporating various levels of behavioral disaggregation within the traditional, trip-based, four-step model framework to microsimulation of individuals' itineraries and activity-based approaches to patterns of travel behavior. Such advanced TDMs recognize that travel decisions are made at the level of individuals and reflect choice behavior under specific circumstances, rather than statistical associations at an aggregate, zone, or group level. Under the United States' 2012s Moving Ahead for Progress in the 21st Century (MAP-21) legislation, TDMs have become an essential tool for tracking and analyzing current and future congestion levels, in efforts to achieve travel time goals. However, transportation planning practices in smaller (and typically less polluted and congested) communities are generally much less sophisticated, due to a lack of data and other resources and/or lack of urgency and regulatory requirements. In some states, like Texas (TTI 2011) and Illinois (Ullah et al. 2011), smaller MPOs rely on their state's department of transportation (DOT) for their local TDM framework, and those may lack behavioral disaggregation (e.g., no user class differentiation or time-of-day segmentation). In a 2004 survey of MPOs, 49% of regions with population under 200,000 rely on the state to develop travel demand models (Wachs et al. 2007).

Once considered a problem in major metropolitan areas, growing congestion is also plaguing smaller communities (populations under 250,000) across the U.S. and around the world. It is also a serious issue in developing countries, where there is substantial growth in private vehicle ownership. For example, between 1982 and 2005, total travel delay in 306 small- to medium-sized U.S. communities increased from 0.8 to 4.2 billion person-hours (Shrank and Lomax 2007). For these communities, with few (to no) modeling staff members on hand, there is a pressing need to identify which TDM modeling improvement strategies offer the most effective predictive capabilities in various scenarios. The data and specification sophistication requirements of any modeling improvements typically require added time and dollar expenditures, which are serious constraints on almost all communities. Furthermore, as transportation systems evolve to become more complex systems, possibly introducing various congestion pricing schemes (e.g., static and dynamic tolling scenarios) and alternative modes of transit and para-transit (e.g., bus rapid transit, car sharing, and bike sharing), these communities need to be aware of the most meaningful opportunities for behavioral disaggregation to reflect such transport system strategies.

This paper evaluates a suite of improvement strategies, as applied to a basic three-step TDM, based on their predictive power and behavioral flexibility. Examining the predictive performance of these strategies relative to top-model results can illuminate model sensitivity, feasibility, and versatility. Smaller communities can use the case study results presented here (for the Tyler, Texas, metropolitan statistical area, with 214,821 persons, according to 2012 American Community Survey results) to assess the value of adding the following strategies to their existing TDMs:

- Impacts of adding a mode choice sub-model, via logit and fixed-share specifications
- Impacts of a multi-period time-of-day analysis, versus a 24-hour (one-time-of-day) analysis
- Impacts of incorporating multiple classes of users across income levels and trip purposes in the route choice step, versus a single class, aggregate trip table
- Impacts of using an outer ("full") feedback loop (of travel time estimates back to trip distribution), for iteration of equilibrium flows and travel times

This study uses the Tyler network simply to demonstrate a set of traffic analysis zones with actual demographic characteristics and roadway links and nodes with realistic speed and capacity attributes. The simulations vary demand and network designs and travel costs significantly, so the results of this work are not intended to provide a future forecast of this particular region.

BASE CASE SPECIFICATION AND MODEL IMPROVEMENTS

The base-case scenario that serves as the starting point in this analysis is a simple 24-hour vehicle-trip-based model with trip generation, trip distribution, and traffic assignment (just three steps), for three trip purposes. The analysis considers various additions to this straightforward base model, including a mode-choice step, disaggregation of time-of-day periods and user classes, and implementation of an outer feedback loop that updates travel times and costs for every OD pair (back to the trip distribution step), as discussed in more detail below.

Time-of-Day Considerations

In congested networks, time-of-day (TOD) considerations are critical in TDMs because of driver responses to congestion (including alternative routes and alternative departure time choices). The relative utility of a tolled route depends largely on toll charges and perceived travel time savings, both of which can vary by TOD. While 75% of large MPOs assign at least two TOD periods in their models, many smaller MPO regions (with population between 50,000 and 200,000) assign average daily (24-hour) travel (Wachs et al. 2007). Typically, TOD segmentation is incorporated into TDMs after the mode choice step to reflect generalized travel costs that vary across different TODs (Parsons Brinckerhoff et al. 2012). Time-of-day segmentation into four periods (morning peak, mid-day, afternoon peak, and off peak) is common, but a simple peak-versus-off-peak distinction can also be quite effective when congestion is not excessive (Hall et al. 2013).

For this analysis, two types of time-of-day segmentation are considered. The first is a simple (two-period) peak (6 to 9 a.m. and 3 to 6 p.m.) versus off-peak (9 a.m. to 3 p.m. and 6 p.m. to 6 a.m.) structure. This setup may be sufficient in network settings where congestion is not excessive or highly variable. The second time-of-day segmentation setup considered here consists of four periods: AM peak (6 to 9 a.m.), midday (9 a.m. to 3 p.m.), PM peak (3 to 6 p.m.), and off-peak (6 p.m. to 6 a.m.). Hourly distributions for personal and commercial trip making in the modeling scenarios used here are based on TransCAD 6.0's default rates for home-based work (HBW), home-based non-work (HBNW), home-based other (HBO), and non-home based (NHB) trip purposes, which are based on Sosslau et al.'s (1978) NCHRP Report 187. Average auto occupancy rate assumptions are based on the U.S. 2009 National Household Travel Survey (NHTS) values (Santos et al. 2011), with auto occupancy rates of 1.1, 1.75, and 1.66 (persons per passenger vehicle) for HBW, HBO, and NHB trip purposes, respectively.

Mode Choice

While more than 90% of large MPOs include a mode choice step in their models, only 25% of small to medium MPOs incorporate mode choice (Wachs et al. 2007). Perez et al. (2012a) recommends that mode choice be incorporated in all TDMs, preferably via a logit or nested logit specification. However, modelers seem to agree that, for small- and medium-sized communities, a simpler approach (such as a fixed-shares model based on travel distance) can also be effective (Hall et al. 2013). For these reasons, two mode-choice models were tested in this evaluation. The first is the fixed-share model, where preference for non-motorized (e.g., walking and cycling) modes and transit fall with trip distance, as shown in Table 1.

Table 1: Fixed-Share Mode Splits

Trip Distance	Auto Share	Transit Share	Non-motorized Share
< 1 mile	75%	5%	20%
1–5 miles	94%	5%	1%
> 5 miles	98%	2%	0%

According to the 2012 American Community Survey (U.S. Census Bureau 2012), the auto share estimates assumed here are close to Tyler's work-trip mode splits, where respondents reported relying on personal motorized vehicles for approximately 92% of their commute trips. The transit share assumptions used here, however, are more reflective of a region with a more extensive and better-used transit system. In Tyler, there are only four bus-service routes, and the actual transit share for work trips is less than 1%.

The second mode-choice model used here is a multinomial logit (MNL) model to split trips across auto, transit, and non-motorized (bike/walk) travel modes. The systematic utility functions for each of the modes used in this simplified MNL model are based only on the three modes' competing travel times. The parameters used are shown in the following equations, and they yield mode splits similar to those in the fixed-share (Table 1) setting.

(1) $V_{auto} = -0.2 \times AutoTT$

(2) $V_{transit} = -2.5 - 0.2 \times TransitTT$

(3) $V_{nm} = -1.0 - 0.2 \times NmTT$

where V_{auto}, $V_{transit}$, and V_{nm} represent the competing modes' (systematic) utility values and *AutoTT*, *TransitTT*, *NmTT* represent the travel times associated with each mode (i.e., auto, transit, and non-motorized modes). Both mode-choice model specifications shown above reflect a network with fairly low shares of transit and non-motorized modes, typical of many U.S. settings. To appreciate whether auto shares may significantly affect model performance, another MNL mode choice model was tested (with higher alternative-specific constants for the non-auto modes), to deliver a "High Transit" scenario, with parameters shown in the following equations. In this scenario, approximately 25% of trips under five miles were made by transit or non-motorized modes.

(4) $V_{auto} = -0.2 \times AutoTT$

(5) $V_{transit} = -1.0 - 0.2 \times TransitTT$

(6) $V_{nm} = -0.5 - 0.2 \times NmTT$

Table 2 directly contrasts the mode splits for all trips between the first MNL model with higher auto mode shares (Scenario Mode Choice 2) and the second MNL model with lower auto mode shares (Scenario High Transit).

Table 2: MNL Mode Choice Splits

Scenario	Auto Share	Transit Share	Non-motorized Share
Mode Choice 2	98.0%	1.4%	0.6%
High Transit	86.4%	12.5%	1.1%

User Class and Values of Time

The utility of a tolled route varies by time of day (due to changing congestion levels and potentially changing toll rates) and its competitive appeal should reflect some heterogeneity in travelers and trips. Those who value time highly are more likely to pay tolls to save travel time than those who value time relatively less. The model's response to tolls becomes more accurate with more stratification in value of travel time (VOTT) (Perez et al. 2012b), as demand estimates smooth to reflect more realistic travel patterns. Current best practices in user class segmentation vary widely. The Ohio DOT segments traveler classes based on household income and trip purpose (commute versus other), while the Oregon DOT segments only work trips by (three) income levels (Hall et al. 2013). In their managed lanes guide (for the FHWA), Perez et al. (2012a) recommended class segmentation across a *minimum* of four travel purposes, three income groups, and three to four vehicle types (e.g. auto, truck, commercial vehicle). For toll revenue estimation, URS (2010) distinguishes three trip purposes (home-based work, home-based non-work, and non-home-based trips) for person trips and three vehicle classes (light-, medium-, and heavy-duty trucks) for commercial trips. Within the truck fleet, Slavin et al. (2012) recommend that owner-operator and fleet-driven trucks be distinguished, due to notable differences in average VOTTs. On a per-mile basis, heavy-duty vehicles add more to pavement deterioration and congestion than a light-duty vehicle, and are thus tolled at significantly higher rates (Balducci and Stowers 2008).

This analysis compared the following four types of user class segmentation, using distinct VOTTs:

- 2-Class Setup: Light-duty vehicles (LDVs) and heavy-duty vehicles (HDVs)
- 4-Class Setup: LDVs segmented by three income categories and HDVs
- 7-Class Setup: LDVs segmented by three income categories and two (personal) trip purposes and HDVs
- 8-Class Setup: LDVs segmented by three income categories and two (personal) trip purposes and HDVs segmented by for-hire versus privately owned carrier status

The base scenario here with a 2-class setup is typical of less sophisticated modeling frameworks, such as that in Texas (TTI 2011) and Georgia (FHWA 2013). The single-class LDV VOTT is assumed to be $12 per hour, based on the Austin, Texas, (five-county metro population of 1.8 million) Capitol Area Metropolitan Planning Organization value (CAMPO 2010). In reality, Tyler's median household income is 18% lower than that of Austin ($42,279 versus $51,596, according to the 2007-2011 American Community Survey's five-year estimates). So a $12/hour LDV VOTT value may be biased high for a (smaller-region) setting, but the purpose of this work is not to mimic Tyler's traffic patterns; it is to evaluate different model specifications, for a range of settings (with more and less transit use, more and less congestion, and different user classes, for example).

For the 4-class VOTT segmentation, the three LDV classes are segmented by household income, as shown in Table 3 "VOTT for All Trip Purposes" column. For the 7-class and 8-class VOTT setups, VOTT assumptions vary by income class and trip purpose, as shown in Table 3. These values are roughly derived from USDOT-suggested values (USDOT 2011).

Table 3: VOTTs per Vehicle by Traveler Income and Trip Purpose Segmentation

Household Income (per year)	**VOTT for All Trip Purposes**	**VOTT for Work Trips**	**VOTT for Non-work Trips**
< $30,000	$8/hour	$10/hour	$6/hour
$30,000–$75,000	$12/hour	$14/hour	$10/hour
> $75,000	$16/hour	$18/hour	$14/hour

Using data from the 2010 American Community Survey for the Tyler region, 37% of households fall into the low-income group, 36% fall in the medium-income group, and 27% fall into the high-income group, as defined by the income thresholds shown in Table 3.

For heavy trucks, the single-class HDV VOTT is assumed to be $40 per (truck) hour, based on values from four larger Texas MPOS: Austin, Dallas-Fort Worth, Houston, and San Antonio (Hall et al. 2014). Though there are many classifications among heavy-duty trucks that can affect VOTT, this study disaggregates by fleet ownership, as recommended by Slavin et al. (2012). Past studies (e.g., Smalkoski and Levinson [2005] and Kawamura [2000]) have estimated significantly higher VOTTs of for-hire carriers than for private carriers. FHWA (2000) found that private carriers handled 55% of the total tons carried by the trucking industry, with for-hire carriers handling the remaining 45%. Based on Smalkoski and Levison (2005) and Kawamura (2000), in the 8-user-classes scenario examined here, for-hire carriers (assumed to be 45% of the HDVs) were assigned a $60/hr VOTT and private carriers (assumed to be 55% of the HDVs) were assigned a $20/hr VOTT.

Congestion Feedback Loop for Behavioral Convergence

The most sophisticated TDMs in use today apply outer feedback loops in order to equilibrate model outputs, ultimately achieving convergence and a unique, stable transport-system solution (of travel times and flows, for example). While Perez et al. (2012a) emphasize the importance of incorporating *full*-model feedback in achieving a stable equilibrium solution in regions with congestion, actual modeling practices vary. Like in the case of time-of-day disaggregation, congestion feedback is a common practice among large MPOs (more than 80% include feedback) but less common in small MPOs (Wachs et al. 2007). Such feedback helps ensure consistency between model inputs (in the form of travel time and cost assumptions) and model outputs (in terms of updated times and costs, and associated flows).

This work evaluates the convergence improvement of introducing an outer feedback loop, for link-level travel times, using average travel times between successive model iterations. This loop recycles the congested network's lowest-impedance (lowest generalized cost) routes, travel times, and costs (for all OD pairs and all traveler types) resulting from the network assignment step back to the trip distribution step. This feedback ensures consistency, allowing the travel patterns to reach a behavioral equilibrium (in theory) and the system of model equations to achieve convergence. Convergence of the iterative model system is determined by calculation of the percent root-mean squared-error (%RMSE) term for differences in upstream generalized travel costs (as used in the trip distribution phase: GC'_j) and the assignment-based (outputted) generalized travel costs: GC°_j), as shown in the following equation:

$$(7)\quad \%\mathrm{RMSE} = \frac{\sqrt{\sum_j \left(GC^{t}_j - GC_j^{t-1}\right)^2 / (\#OD\ Pairs)}}{\sum_j (GC^{t-1})/(\#OD\ Pairs)} 100$$

where j indexes the 204,304 OD pairs in the Tyler zone system, and generalized travel costs (GC) are typically for a single mode (the auto mode here) at a single time of day (such as AM peak period).

Convergence is established here when the %RMSE summed over all OD pairs is 1% or less as recommended by Slavin et al. (2012). In this study, as in general practice, the %RMSE for convergence is calculated for a single time of day (when multiple periods exist) for a specific mode (e.g., the AM peak period for auto mode, as used here).

MODELING SCENARIOS

Tyler Network and Trip Generation

Tyler, Texas, was chosen as the demonstration setting and network for these modeling scenarios, due to the city's medium size (approximately 215,000 persons). The region's 2002 network includes 452 zones, 1,475 nodes, and 2,291 bi-directional links. For non-commercial personal travel, vehicle-trip generation was performed using standard NCHRP Report 365 rates (Martin and McGuckin 1998) for each of three personal-trip purposes (HBW, HBO, and NHB trips), as is standard in TransCAD 6.0. The person-trip attraction rates are calculated as functions of the number of households (HH), whether a zone is in the central business district (CBD), and the numbers of retail, service, and basic (non-retail and non-service) jobs in the zone, as shown in the following equations, from Martin and McGuckin (1998):

(8) HBW Attractions in all zones = 1.45 × Jobs (in zone)

(9) HBO Attraction in CBD zones = (2.0 × CBD Retail Jobs) + (1.7 × Service Jobs) + (0.5 × Basic Jobs) + (0.9 × HHs)

(10) HBO Attraction in non-CBD zones = (9.0 × non-CBD Retail Jobs) + (1.7 × Service Jobs) + (0.5 × Basic Jobs) + (0.9 × HHs)

(11) NHB Attraction in CBD zones = $(1.4 \times \text{CBD Retail Jobs}) + (1.2 \times \text{Service Jobs}) + (0.5 \times \text{Basic Jobs}) + (0.5 \times \text{HHs})$

(12) NHB Attraction in non-CBD zones = $(4.1 \times \text{non-CBD Retail Jobs}) + (1.2 \times \text{Service Jobs}) + (0.5 \times \text{Basic Jobs}) + (0.5 \times \text{HHs})$

For commercial-truck trips, an average of trip rates provided by the Northwest Research Group for Southern California and for Seattle's MPO (the Puget Sound Regional Council) was used here, based on NCHRP Report 716 (Cambridge Systematics 2012). Productions and attractions were calculated as functions of the total number of households and total number of jobs, as shown in the following equations:

(13) Truck trip Productions = $(0.014 \times \text{HHs}) + (0.062 \times \text{Jobs})$

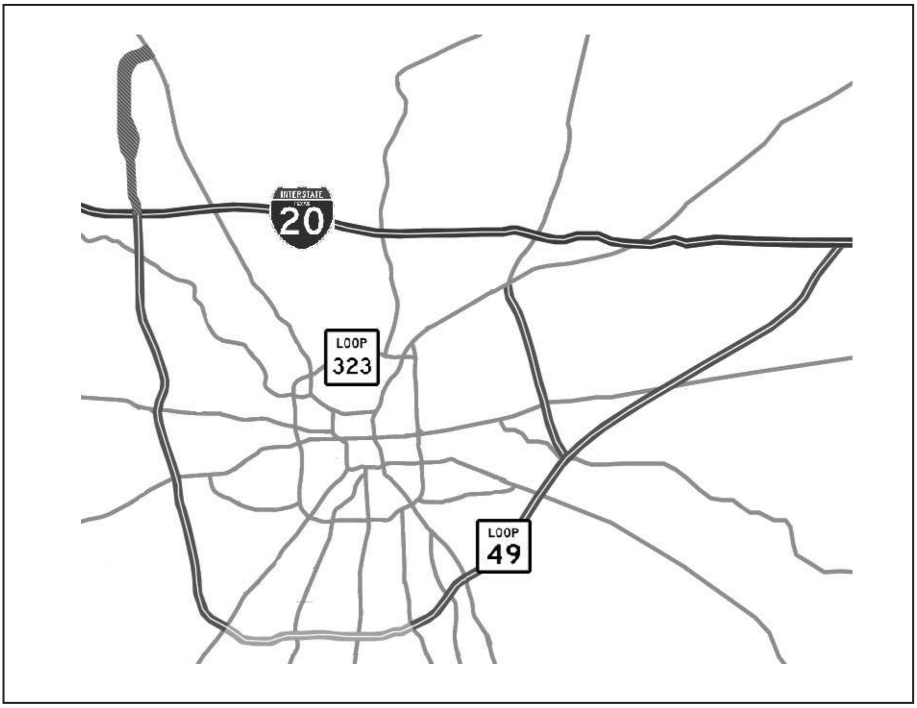
(14) Truck trip Attractions = $(0.020 \times \text{HHs}) + (0.065 \times \text{Jobs})$

Trip distribution for three trip purposes (HBW, HBO, and NHB) was done via a gravity model using friction factors generated from Martin and McGuckin's (1998) gamma impedance function, the default parameters in TransCAD 6.0. The impedance term provides a structure for measuring relative spatial separation (such as travel distance, time, and cost) of trips between origins and destinations. Here, the gravity model is doubly constrained by productions and attractions in each zone, for each of the three trip purposes.

While Loop 49 is Tyler's current toll corridor, its distance from the region's downtown and current traffic volumes (below 2000 AADT on at least two segments) make the route an unsuitable candidate for testing the sensitivities of the previously described criteria. For example, any percentage change in Loop 49's low flows may easily overstate the sensitivity of such results to the alternative modeling approaches being tested here. For this reason, Loop 323, which is a 19.7-mile four- to six-lane major arterial about three miles from the region's primary downtown, was used as a (hypothetical) tolled corridor to test the alternative model specifications. Loop 323 is one of the most congested corridors in the region, due to its relative abundance of retail destinations and proximity to existing urban development.

Texas' current distance-based toll rates *average* between \$0.12 to \$0.23 per mile for passenger vehicles with toll tags (transponders or RFID chips). But minimum toll charges of \$0.25 and \$0.19 apply at each mainlane gantry and ramp gantry, respectively. This minimum-charge situation means that some tolls are as high as \$0.40 per mile for very short intra-city trip segments on the tolled facility (Hall 2014). Therefore, for purposes of this paper's test scenarios, distance-based tolls of \$0.20 per mile for autos and \$0.55 per mile for trucks are assumed to apply.

Figure 1: Loop 49 and Loop 323 Locations in the Tyler, Texas, Highway Network



SCENARIO RESULTS

The various model improvements discussed previously were incorporated into test runs on the Tyler network using TransCAD 6.0. Martin and McGuckin's (1998) daily trip generation and attraction values were increased 50% (by applying a 1.5 multiplier on all trip attraction rates) to better characterize a moderately congested network. Those volumes were then increased another 50% (or 125% versus Tyler's 2002 trip-making levels) to help reflect a severely congested network, with all results shown in Table 4. As a reference, the trip counts on Loop 323 on the moderately congested network are about 80% of the actual 2012 daily traffic volumes (Hall 2014), whereas traffic counts on Loop 323 in the severely congested network case are about 120% of the 2012 trip counts.

As described earlier, the base model is a non-tolled 24-hour assignment setup with a single user class, no mode-choice step (private vehicle-trips only), a 0.001 network assignment convergence (gap) criterion[1] (as currently used in the Texas DOT's model framework) and no outer feedback loop. Experts (e.g., Boyce and Xie [2012], Slavin et al. [2012], and Morgan and Mayberry [2010]) recommend convergence as defined by gaps of 10^{-4} or less, which is the network assignment gap defined in all scenarios other than the base model. Building on this base model, two alternative base models (Base Alt 1 and Base Alt 2) that recognize two user classes (commercial trucks and LDVs) were also considered, the first without tolls and the second tolled. From these alternative base-case models, the model improvements were first tested individually and then in various combinations (of two or more enhancements/extensions), with full-network and Loop-323-only VMT, vehicle-hours traveled (VHT) values, and toll revenues compared with the base model's values (as shown in Tables 4 and 5). Results of 36 scenarios are shown in Tables 4 and 5 (18 for each of the two trip generation or general congestion levels). Additional scenarios with more congestion and overall lower and higher VOTTs were also run, and are discussed briefly below. Since Loop 323 is the only true ring road in Tyler with no true substitute route, to test the different models' performances

Table 4: Network and Tolled Route Metrics with Moderate Congestion Across All Scenarios

							Network Results				Loop 323 Results				
SCENARIO	**Toll**	**# Times of Day**	**# of User Classes**	**Mode Choice**	**NA Conv.**	**Fdbk. Loop**	**VHT (hrs)**	**% Change**	**VMT (10^6 miles)**	**% Change**	**VHT (hrs)**	**% Change**	**VMT (miles)**	**% Change**	**Toll Revenue**
Base	N	1	1	-	0.001	N	159,266	-	4.662	-	10,793	-	436,920	-	$91,753
Base Alt 1	N	1	2	-	0.0001	N	162,953	2.32%	4.736	1.57%	11,028	2.18%	445,900	2.06%	$93,639
Base Alt 2	Y	1	2	-	0.0001	N	161,065	1.13%	4.683	0.46%	10,785	-0.07%	436,501	-0.10%	$91,665
Time-of-day 1	Y	2	2	-	0.0001	N	164,000	2.97%	4.736	1.57%	11,059	2.47%	446,193	2.12%	$93,700
Time-of-day 2	Y	4	2	-	0.0001	N	179,308	12.58%	4.742	1.71%	11,040	2.29%	444,739	1.79%	$93,395
User Class 1	Y	1	4	-	0.0001	N	159,918	0.41%	4.689	0.58%	10,917	1.15%	441,683	1.09%	$92,753
User Class 2	Y	1	7	-	0.0001	N	159,443	0.11%	4.757	2.02%	10,818	0.23%	437,917	0.23%	$91,963
User Class 3	Y	1	8	-	0.0001	N	151,341	-4.98%	4.496	-3.56%	10,376	-3.86%	420,498	-3.76%	$88,305
Mode Choice 1	Y	1	2	Fixed-share	0.0001	N	153,261	-3.77%	4.606	-1.22%	10,730	-0.58%	434,653	-0.52%	$91,277
Mode Choice 2	Y	1	2	MNL	0.0001	N	159,966	0.44%	4.464	-4.24%	10,473	-2.96%	421,688	-3.49%	$93,216
High Transit	Y	1	2	MNL	0.0001	N	139,623	-12.33%	4.434	-4.89%	10,251	-5.02%	416,094	-4.77%	$87,380
Feedback Loop	Y	1	2	-	0.0001	Y	151,445	-4.91%	4.464	-4.24%	10,473	-2.96%	421,688	-3.49%	$88,554
Comb. 1	Y	4	2	-	0.0001	N	179,308	12.58%	4.742	1.71%	11,040	2.29%	444,739	1.79%	$93,395
Comb. 2	Y	4	4	-	0.0001	N	178,057	11.80%	4.596	-1.43%	10,516	-2.57%	438,946	0.46%	$92,179
Comb. 3	Y	4	7	-	0.0001	N	169,104	6.18%	4.550	-2.41%	10,437	-3.30%	414,405	-5.15%	$87,025
Comb. 4	Y	4	7	Fixed-share	0.0001	N	168,186	5.60%	4.322	-7.30%	10,412	-3.53%	410,872	-5.96%	$86,283
Comb. 5	Y	4	7	MNL	0.0001	N	166,120	4.30%	4.512	-3.22%	10,503	-2.69%	399,549	-8.55%	$83,905
Comb. 6	Y	4	7	MNL	0.0001	Y	158,515	-0.47%	4.406	-5.50%	9,779	-9.39%	380,283	-12.96%	$79,859

Table 5: Network and Tolled Route Metrics with Severe Congestion Across All Scenarios

							Network Results				Loop 323 Results				
SCENARIO	Toll	# Times of Day	# User Classes	Mode Choice	NA Conv.	Fdbk. Loop	VHT (hours)	% Change	VMT (10^6 miles)	% Change	VHT (hours)	% Change	VMT (miles)	% Change	Toll Revenue
Base	N	1	1	-	0.001	N	458,246	-	7.068	-	16,497	-	636,701	-	$133,707
Base Alt 1	N	1	2	-	0.0001	N	473,362	3.30%	7.178	1.55%	16,871	2.27%	648,374	1.83%	$136,159
Base Alt 2	Y	1	2	-	0.0001	N	471,066	2.80%	7.170	1.43%	16,768	1.64%	643,386	1.05%	$135,111
Time-of-day 1	Y	2	2	-	0.0001	N	479,311	4.60%	7.187	1.68%	17,122	3.79%	652,769	2.52%	$137,081
Time-of-day 2	Y	4	2	-	0.0001	N	589,349	28.61%	6.467	-8.51%	17,212	4.33%	651,264	2.29%	$136,765
User Class 1	Y	1	4	-	0.0001	N	458,012	-0.05%	7.105	0.52%	16,695	1.20%	642,965	0.98%	$135,023
User Class 2	Y	1	7	-	0.0001	N	457,218	-0.22%	7.081	0.18%	16,539	0.26%	638,037	0.21%	$133,988
User Class 3	Y	1	8	-	0.0001	N	428,706	-6.44%	6.832	-3.34%	15,895	-3.65%	615,310	-3.36%	$129,215
Mode Choice 1	Y	1	2	Fixed-share	0.0001	N	408,950	-10.76%	6.866	-2.86%	15,978	-3.14%	620,322	-2.57%	$130,268
Mode Choice 2	Y	1	2	MNL	0.0001	N	456,687	-0.34%	7.137	0.97%	16,667	1.03%	645,199	1.33%	$135,492
High Transit	Y	1	2	MNL	0.0001	N	351,149	-23.37%	6.710	-5.07%	15,499	-6.05%	603,100	-5.28%	$126,651
Feedback Loop	Y	1	2	-	0.0001	Y	446,640	-2.53%	6.905	-2.31%	16,284	-1.29%	634,394	-0.36%	$133,223
Comb. 1	Y	4	2	-	0.0001	N	589,349	28.61%	6.467	-8.51%	17,212	4.33%	651,264	2.29%	$136,765
Comb. 2	Y	4	4	-	0.0001	N	548,934	19.79%	6.088	-13.87%	16,485	-0.07%	622,974	-2.16%	$130,825
Comb. 3	Y	4	7	-	0.0001	N	575,722	25.64%	6.192	-12.40%	16,838	2.07%	638,324	0.25%	$134,048
Comb. 4	Y	4	7	Fixed-share	0.0001	N	558,760	21.93%	6.195	-12.36%	15,749	-4.53%	604,288	-5.09%	$126,900
Comb. 5	Y	4	7	MNL	0.0001	N	568,192	23.99%	6.090	-13.84%	16,710	1.29%	644,111	1.16%	$135,263
Comb. 6	Y	4	7	MNL	0.0001	Y	541,834	18.24%	5.789	-18.10%	15,978	-3.15%	600,330	-5.71%	$126,069

in a network with substitute routes, additional scenarios were also examined where Loop 323 was changed to a tolled four-lane freeway facility with the existing arterial links converted to parallel frontage roads. It is important to note that currently the land use along arterial Loop 323 is heavily commercial with abundant driveway access, and such land use may not be realistic if Loop 323 is converted to an access-controlled freeway (such as the case in the substitute route scenarios). The results of these runs are included in Appendix A, and the relevant results are also discussed below.

Impact of Incorporating Time-of-Day Disaggregation

When looking only at single-strategy improvements (and thus ignoring combination strategies), allowance for different travel times and network loads across distinct times of day resulted in the largest VMT and VHT changes (network-wide and on Loop 323), versus the base model, as compared with the other model enhancements' impacts. In the severely congested case, the base model underestimates network VHT by 28.6% and overestimates network VMT by 8.5%, as compared with the scenario utilizing four time periods per day, which corresponds to a 2.3% underestimate in toll revenues on Loop 323. This result highlights the importance of disaggregating travel behavior across time periods, since a single 24-hour period model ignores the severe peak-hour congestion levels that reduce travel speeds and cause a corresponding increase in vehicle-hours traveled. Moreover, differences in other model outputs between the two- and four-time-of-day segmentations were noticeable, with the added periods resulting in greater changes in network and Loop 323 metrics (i.e., flows and Loop 323 toll revenues), particularly under the most congested scenario (Table 5's Time of Day 2 Scenario). For example, under severe congestion, the four-times-of-day scenario underestimates network VMT by 11.7%, whereas the two-times-of-day scenario underestimates network VMT by 24.1%, compared with the most sophisticated scenario modeled here (Combination 6). In addition to more accurate model outputs, incorporating such temporal disaggregation in the TDM also allows modelers, planners, and policymakers to directly model the impacts of variable tolling policies - like those whose rates and high-occupancy-vehicle (HOV) policies vary by time of day and/or with congestion, as is the case with most managed lanes (Perez et al. 2012b).

Impact of Incorporating a Mode-Choice Step

The addition of a mode-choice step was next in line, in terms of magnitude of impact on model results, versus the base specification. Under severe congestion, the base model overestimates network VHT by 10.8%, as compared with the scenario with a fixed-shares mode choice step. With auto travel dominating mode choices (capturing approximately 95% of person-trips in the test network), the MNL mode-choice model did not provide significantly better estimates than the fixed-mode-shares (as a function of trip distance) model. For example, under moderate congestion (Table 4), Loop 323 VHT and VMT outputs from the fixed-share model are actually closer to the estimates from the most sophisticated Scenario Combination 6, while the reverse is true under severe congestion (Table 5). However, in a network with greater shares of transit and non-motorized travel (as evident in Table 4's and Table 5's High Transit scenario, which predicted 25% transit and non-motorized trips), the differences are quite significant: the base model underestimates network VHT by 23.4%, as compared with the scenario with an MNL mode choice step (Table 5). The more behaviorally defensible MNL mode-choice model is also generally preferred in current TDM practice (URS 2011).

Impact of Incorporating Multi-class Assignment

When road tolls distinguish vehicle types, as they almost always do (e.g., LDVs pay much less than HDVs), simply distinguishing between these vehicle types (using at least two user classes) is quite important for tolling traffic and revenue (T&R) estimation. When comparing the Base and Base Alt 1 scenarios, Loop 323's estimated toll revenues rise by 2.1% and 1.8%, under moderate and severe congestion, as a direct result of adding two user classes. However, differences in model results were not estimated to be significant when the specifications incorporated multiple (user) classes within the LDV category when analyzed in a single 24-hour period. Differences in VMT and VHT were less than 2% when the LDV trips were classified by household income versus by household income and trip purpose (work versus non-work), relative to the base specification, even when the network was congested. However, combined with incorporation of time-of-day disaggregation (Scenarios Combination 2 and Combination 3) in the severely congested case, the models' metrics are comparable to those in the most sophisticated scenario modeled here (Combination 6), with all network and Loop 323 metrics within 7% of those of Combination 6. Scenario Combination 2 (which uses four times of day with four user classes) suggests that the base model underestimates network VHT by 19.8% and overestimates network VMT by 13.9% under severe congestion. While these differences may be exaggerated by the lack of a substitute route for Loop 323 in Tyler, scenarios with good substitute routes (on a network with tolled Loop 323 freeway lanes and non-tolled frontage lanes, as seen in Appendix A) still reflect that the Base model underestimates network VHT by 18.5% and overestimates network VMT by 9.1%, as compared with scenario Combination 2 under severe congestion.

Interestingly, the introduction of two HDT user classes in Scenario User Class 3 (segmented as for-hire versus private carriers) produced more significant model-output differences. The high income LDV user class had double the VOTT of the low income LDV user class, whereas the high VOTT HDV user class had triple the VOTT of the low VOTT HDV user class. These results suggest that multi-class assignment in a model recognizing user classes with relatively high VOTTs (as is the case of for-hire carriers, modeled here at \$60/hour – versus \$20/hour for the privately held HDVs and \$18/hour and under for all LDV trips), output differences are more significant, up to 6% in the severely congested condition. However, additional scenarios in which all LDV and HDV VOTTs were assumed to be extremely high (double the VOTTs originally assumed) or extremely low (half the VOTT originally assumed) did not yield significant differences in model outputs. Thus, these results appear to highlight the importance of *relative* differences in competing user classes' VOTTs for TDM outputs: absolute VOTT increases or decreases across user classes are less important than big relative differences within a single model run, at least in this situation with no true competing route. In addition, and as expected, a more congested setting meant that incorporation of such multi-class assignment (and reliance on more user classes) had a greater effect on the tolled corridor's VHT and VMT values and revenues. Incorporating eight user classes brought toll revenue estimates to within 11% of the estimate from the most sophisticated scenario (Combination 6) under moderately congested conditions, and within 3% under severely congested conditions.

Impact of Incorporating Outer Feedback Loop

In both the moderately and severely congested network cases, incorporating an outer feedback loop provided moderate model improvements, as suggested by changes of less than 5% in network and Loop 323 VHT and VMT values. Under congested conditions, an outer feedback loop helps ensure that models do not prematurely stop at an intermediate solution before reaching true convergence (as measured by the %RMSE differences across generalized travel costs for all OD pairs for a select time period: peak auto travel time for two time-of-day specifications and AM peak auto travel time for four time-of-day specifications). Other benefits of this outer feedback loop are behavioral defensibility and no added model assumptions (Slavin et al. 2012).

CONCLUSIONS, CAVEATS, AND RECOMMENDATIONS

As demonstrated on the Tyler network, a wide variety of behaviorally disaggregate model improvements can enhance the basic TDM specifications that are common in many smaller cities and regions, and some larger regions, in the U.S. and/or abroad. Under the scenarios tested here, model improvements that resulted in the greatest VHT and VMT changes on the tolled corridor and entire network are as follows (in order of impact, with the most important enhancements shown first):

- Recognizing multiple time periods in a day (to reflect variable travel times and to add flexibility for modeling time-variable tolls)
- Adding a mode-choice step (particularly in regions with higher transit and non-motorized trip shares)
- Disaggregating traveler classes by values of time (particularly when there are significant differences in VOTTs across user classes)
- Incorporating an outer feedback loop to reflect congestion levels and ensure consistency in travel cost assumptions

Combination 6 represents the most sophisticated and disaggregate model pursued in this study, by recognizing tolling, four times of day, seven user classes, an MNL mode-choice specification, a 0.0001 network convergence criterion, and an outer feedback loop (designed to meet a 1% RMSE target). Compared with Combination 6, the base model overestimates toll revenues along Loop 323 by 13% in the moderately congested scenario and 5.7% in the severely congested scenario. Such differences suggest important mis-prediction errors that can harm decision-making and budget allocations. With respect to the different combination scenarios (which rely on a set of model enhancements), adding both multi-class assignment and time-of-day disaggregation to a standard TDM (as done in the Combination 2 and 3 scenarios) seems to be very effective in mimicking results of the most sophisticated, behaviorally disaggregate model tested here, Combination 6 (particularly in Combination 2), which utilizes four times of day and four user classes and estimates severe-congestion toll revenues within 4%, as shown in Table 5. Given that most if not all commercially available TDM packages can readily accommodate such model specifications, it seems wise for most if not all regions to enable such modeling improvements in their TDM setups. When transit mode shares are significant in a community, the incorporation of a mode choice step, along with multi-class assignment and time-of-day-disaggregation (as modeled in Combinations 4 and 5), brings the toll revenue estimates to within 8% under moderate congestion and 7% under severe congestion, when compared with the most sophisticated model (Combination 6). The results presented here highlight the importance of having a behaviorally defensive TDM that will better forecast travel demands (and other outputs of interest, like toll revenues), particularly in communities with new transportation policies (such as tolls that vary by vehicle occupancy or time of day) and important alternative modes (such as transit, walking, cycling, carsharing, bike sharing, and carpooling).

While model outputs in this paper appear specific to the Tyler, Texas, context, the use of Tyler data sets simply allows one to demonstrate model specification effects across a set of realistic traffic analysis zones and network conditions. Model inputs are based primarily on national averages, and demand levels, network attributes, mode shares, and other behaviors were varied; so predicted outputs are not a future forecast for this particular region. However, the general magnitude of the effectiveness of specific TDM improvement strategies should be transferrable to other transportation networks, since contextual modifications (like higher transit shares, extremely low and high VOTTs, and addition of substitute network routes) did not impact the relative effectiveness of model improvement strategies.

Of course, each region has its own pressing transportation challenges and unique transportation culture. As discussed in the results, a region's specific transportation characteristics (e.g., existence of dynamically or occupancy-based tolled facilities, and high transit and/or non-motorized mode shares) also impact the rankings of these strategies, and model flexibility may override absolute output differences.

Moreover, it would be worthwhile testing different model specifications. For example, the trip distribution step used here follows a traditional gravity model calibrated to highly aggregated metrics (in this case, trip-length-based frequency distributions). In practice, singly constrained destination choice models based on MNL specifications are generally considered more behaviorally defensible for almost all trip purposes and can be applied in a disaggregate manner, relative to gravity models (Cambridge Systematics 2010). There are also limitations to modeling toll demand within a traditional trip-based model. Microsimulation via a journey-based modeling approach (associating multiple, connected trips to a unique decision maker) may be key for capturing individuals' valuations of time and trip-making heterogeneity (Parsons Brinkerhoff et al. 2013), and tour-based and activity-based models can better account for the dependence of related trip-making. Lastly, current TDMs are built upon household travel survey data, describing past trip patterns and travel alternatives so they can miss the rise of carsharing, bike-sharing, and other emerging options (Lawton 2014).

The relative performance of these competing model improvements also depends on the TDM's specific, intended application(s). For example, in applications focused on emissions estimation, rather than toll demand estimation, time-of-day disaggregation becomes more important, along with the presence of multiple user classes (for trucks versus auto travel), since emissions rates and route preferences can vary quite a lot with speeds – unless there truly is no real congestion (or speed variation) expected in these networks 20 years forward. Finally, increased complexity of a region's transportation system, via introduction of various congestion pricing schemes (e.g., static and dynamic tolling scenarios) and alternative modes of transit and para-transit (e.g., bus rapid transit, car and bike sharing), highlight a need for transportation planners in all regions to appreciate the type of flexibility and result variations that each of these TDM enhancements (to better reflect human behavior and heterogeneity) enables when evaluating various system changes, over time and space. In a 2004 survey of MPOs, 70% mentioned needed improvements to their modeling processes to better model road pricing, time-specific transportation policies, and non-motorized travel (Wachs et al. 2007). This work illuminates many of the options and their effects on a mid-size network.

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Endnotes

1. Convergence gap is defined as $Gap = \frac{\sum_{i \in I} \sum_{k \in K} f_k t_k - \sum_{i \in I} d_i t_{min,i}}{\sum_{i \in I} d_i t_{min,i}}$, where I is the set of all OD pairs, K_i is the set of all paths used by trips traveling between OD pair I, f_k is the number of trips taking path k, t_k is the travel time on path k, d_i is the current flow on link i, and $t_{min,i}$ is the travel time on the shortest (or minimum-cost) path between OD pair I (Morgan and Mayberry 2010).

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APPENDIX A

Table 6: Network and Tolled Route (with Substitute Route for Loop 323) Metrics with Moderate Congestion Across Select Scenarios

							Network Results				Loop 323 Results			
SCENARIO	**Toll**	**# Times of Day**	**# User Classes**	**Mode Choice**	**NA Conv.**	**Fdbk. Loop**	**VHT (hours)**	**% Change**	**VMT (10^6 miles)**	**% Change**	**VHT (hours)**	**% Change**	**VMT (miles)**	**% Change**
Base	N	1	1	-	0.001	N	158,346	-	4.732	-	8,569	-	468,283	-
Base Alt 1	N	1	2	-	0.0001	N	158,348	0.00%	4.732	0.00%	8,570	0.01%	468,352	0.01%
Base Alt 2	Y	1	2	-	0.0001	N	159,758	0.89%	4.732	0.01%	8,581	0.14%	468,053	-0.05%
Time of Day 1	Y	2	2	-	0.0001	N	161,214	1.81%	4.732	0.01%	8,578	0.11%	466,229	-0.44%
Time of Day 2	Y	4	2	-	0.0001	N	159,936	1.00%	4.731	-0.03%	8,540	-0.34%	466,363	-0.41%
User Class 1	Y	1	4	-	0.0001	N	156,683	-1.05%	4.686	-0.97%	8,486	-0.97%	463,281	-1.07%
User Class 2	Y	1	7	-	0.0001	N	159,757	0.89%	4.741	0.19%	8,598	0.34%	468,900	0.13%
Mode Choice 1	Y	1	2	Fixed Share	0.0001	N	150,071	-5.23%	4.601	-2.78%	8,360	-2.44%	457,120	-2.38%
Mode Choice 2	Y	1	2	MNL	0.0001	N	156,893	-0.92%	4.706	-0.54%	8,551	-0.21%	466,618	-0.36%
Feedback Loop	Y	1	2	-	0.0001	Y	160,454	1.33%	4.664	-1.43%	8,558	-0.13%	466,681	-0.34%
Comb. 1	Y	4	2	-	0.0001	N	159,936	1.00%	4.731	-0.03%	8,540	-0.34%	466,363	-0.41%
Comb. 2	Y	4	4	-	0.0001	N	138,223	-12.71%	4.296	-9.21%	7,834	-8.58%	429,510	-8.28%
Comb. 3	Y	4	7	-	0.0001	N	148,282	-6.36%	4.560	-3.64%	8,200	-4.30%	449,544	-4.00%
Comb. 4	Y	4	7	Fixed Share	0.0001	N	139,861	-11.67%	4.418	-6.64%	7,964	-7.06%	442,247	-5.56%
Comb. 5	Y	4	7	MNL	0.0001	N	136,433	-13.84%	4.350	-8.07%	7,950	-7.22%	437,614	-6.55%
Comb 6.	Y	4	7	MNL	0.00001	Y	136,816	-13.60%	4.259	-10.00%	7,970	-6.99%	436,316	-6.83%

Table 7: Network and Tolled Route (with Substitute Route for Loop 323) Metrics with Severe Congestion Across Select Scenarios

							Network Results				Loop 323 Results			
SCENARIO	Toll	# Times of Day	# User Classes	Mode Choice	NA Conv.	Fdbk. Loop	VHT (hours)	% Change	VMT (10^6 miles)	% Change	VHT (hours)	% Change	VMT (miles)	% Change
Base	N	1	1	-	0.001	N	456,335	-	7.160	-	13,209	-	675,490	-
Base Alt 1	N	1	2	-	0.0001	N	456,350	0.00%	7.159	0.00%	13,204	-0.04%	675,305	-0.03%
Base Alt 2	Y	1	2	-	0.0001	N	466,142	2.15%	7.162	0.03%	13,240	0.23%	673,122	-0.35%
Time of Day 1	Y	2	2	-	0.0001	N	474,918	4.07%	7.169	0.13%	13,346	1.04%	671,723	-0.56%
Time of Day 2	Y	4	2	-	0.0001	N	465,279	1.96%	7.170	0.15%	13,258	0.37%	679,604	0.61%
User Class 1	Y	1	4	-	0.0001	N	450,941	-1.18%	7.089	-0.98%	13,084	-0.95%	667,211	-1.23%
User Class 2	Y	1	7	-	0.0001	N	465,081	1.92%	7.174	0.20%	13,270	0.46%	674,427	-0.16%
Mode Choice 1	Y	1	2	Fixed Share	0.0001	N	415,702	-8.90%	6.958	-2.82%	12,851	-2.71%	658,948	-2.45%
Mode Choice 2	Y	1	2	MNL	0.0001	N	449,575	-1.48%	7.121	-0.54%	13,177	-0.24%	670,948	-0.67%
Feedback Loop	Y	1	2	-	0.0001	Y	464,640	1.82%	7.172	0.17%	13,330	0.92%	673,221	-0.34%
Comb. 1	Y	4	2	-	0.0001	N	465,279	1.96%	7.170	0.15%	13,258	0.37%	679,604	0.61%
Comb. 2	Y	4	4	-	0.0001	N	372,005	-18.48%	6.507	-9.11%	12,078	-8.56%	627,214	-7.15%
Comb. 3	Y	4	7	-	0.0001	N	405,812	-11.07%	6.906	-3.55%	12,657	-4.18%	656,390	-2.83%
Comb. 4	Y	4	7	Fixed Share	0.0001	N	359,383	-21.25%	6.743	-5.82%	12,264	-7.15%	639,935	-5.26%
Comb. 5	Y	4	7	MNL	0.0001	N	346,724	-24.02%	6.730	-6.00%	12,179	-7.80%	638,441	-5.48%
Comb. 6	Y	4	7	MNL	0.00001	Y	344,934	-24.41%	6.760	-5.58%	12,249	-7.27%	643,367	-4.76%