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Distribution of Value of Time and Ways to Model Value of Time in Long-Range Planning Models

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Abstract

Distribution of Value of Time and Ways to Model Value of Time in Long-Range Planning Models

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As managed lanes (ML) become more integrated in regional urban networks with existing general purpose (GP) lanes, the distribution of travelers' value of time (VOT) is becoming more important for transportation planning agencies to quantify in order to accurately predict future travel patterns. Since travelers' VOT varies depending on a multitude of factors, this study investigates ways that we can determine the VOT distribution of a region from existing travel data as well as effective ways that we can model VOT using traffic assignment algorithms. In networks with available link volumes and toll data on segments where travelers have the option of choosing to stay on the GP lanes or entering a ML facility, a VOT distribution can be inferred assuming that travelers who enter the ML choose to do so based on a certain "threshold" VOT. When modeling these VOT distributions, errors are observed in the traffic assignment results when both the continuous nature of VOT distributions are discretized, and when varying toll values are assumed to be constant. Specifically in the context of TransCAD software, link travel time errors appear to be much less significant than flow errors when tested on a nine node network. Additional experimentation on larger regional networks is needed to verify the significance of these errors and their impact on predicted travel patterns.

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I. Introduction

Transportation planning is the process of forecasting future travel patterns in an urban area for the purpose of identifying necessary improvements to the transportation infrastructure in future years. As urban areas experience developing growth and require federal transportation funds to implement infrastructure changes, the reliance on accurate transportation modeling capabilities becomes more necessary [1]. For metropolitan planning organizations that are directly in charge of managing a region's transportation planning model, one important aspect of transportation planning is travel forecasting using the Four-Step Travel Demand Model which includes trip generation, trip distribution, mode choice, and traffic assignment.

One particular challenge in the area of traffic assignment is the process of quantifying and modeling travelers' value of time (VOT) in order to predict their route choice behavior. Studying VOT becomes particularly important in networks with an increasing number of toll facilities and managed lanes (ML) that offer travelers a more reliable route to their destination for a specified monetary cost. While some travelers will continue to consistently use general purpose (GP) lanes, there are inevitably many travelers who will choose to utilize tolled facilities if their perceived travel time savings is worth the added cost. As these facilities become more integrated in existing urban transportation networks, planning agencies will need to incorporate regionally representative VOT distributions into their long-range planning models to ensure that their assignment results account for future changes in travel behavior.

As Chapter 1 will discuss, a single average VOT value cannot accurately represent an entire region's value of time, and is often best characterized with a continuous distribution. The research discussed in Chapters 2, 3, and 4 will attempt to estimate a continuous VOT distribution from real time data as well as compare different ways to incorporate VOT in long-range planning models to improve agencies' existing models.

II. Chapter 1: Literature Review

Before quantifying a VOT distribution from a specific dataset, an extensive review of existing literature was conducted to determine (i) past methods of estimating VOT/recommended ranges of VOT values, (ii) the variance of VOT based on factors such as trip purpose, annual income, and other factors (iii) past traffic assignment methods for multiple user class assignment to capture varying VOT values.

i. Past Methods of Estimating VOT/Recommended Ranges of VOT values

In general, the two main methods of data collection for approximating VOT are revealed preference (RP) methods and stated preference (SP) methods. SP methods study the intended behaviors of travelers (how they think they will behave in a hypothetical situation) while RP methods study the actual decisions that travelers make. ***Table 1*** below provides a summary of recommended values of VOT from several studies over a variety of regions in the United States using either RP, SP, or a combination of both methods.

Table 1: *Summary of Past Recommended VOT Values and Methods Used to obtain VOT*

Reference	Type of Data Used	Recommended VOT Values
Small et al. (2005)	RP & SP data from SR 91, CA	$21.50/hour
Brent & Gross (2017)	RP data from SR167 lanes, WA	$38/hour
Burris et al. (2016)	RP data from Katy Freeway, TX	($1.96-$8.06)/hour
Lam & Small (2001)	RP & SP data from SR 91, CA	$22.87/hour
He et al. (2012)	RP data from MnPASS system	$11.63/hour

As the recommended values illustrate, VOT has been modeled with average discrete values, but across different regions and with different data collection methods, the range of VOT is large and there is no consistently agreed upon value.

In addition to the recommended VOT values discovered in this section of literature review, there were some other noteworthy findings that although did not directly inform the later analysis, served as important contextual background for the process of determining a VOT distribution. The National Cooperative Highway Research Program details a price metering method using SP data to determine the VOT of individuals by repeatedly changing the price point and time savings combination questions presented to each surveyed traveler until a "switching-point" (VOT) was discovered [14]. Additionally, in their analysis of the Katy Freeway ML network, Burris et al. observed that many I-10 travelers were willing to pay for ML usage even when little to no travel time was saved [3]. Assuming that travelers were aware of the travel time for both the GP lanes and ML, Devarasetty et al. conclude that predicting the use of ML should include variables other than VOT to model its usage accurately [5]. Finally, as a commentary on the differences observed between SP and RP methods, Small et al. conclude that the implied VOT values from SP data are much smaller on an average than the RP values possibly due to the tendency of travelers to overstate the travel time they experience during congestion periods (also termed as the stated preference bias) [18].

The conclusion regarding this section of literature review is simply that although there are recommended values of VOT, no unique VOT value can be taken from existing studies and directly applied to a specific region.

ii. Variation of VOT based on Trip Purpose, Annual Income, and other factors

Across an entire population, VOT varies and can be approximated with a probability distribution. Gardner et al. approximate VOT as an income distribution that is based on the assumption that travelers with higher incomes will have higher VOT values [8]. In addition to modeling VOT variation as a distribution, other studies have investigated the factors impacting this variation. In their study for determining VOT for the UK, Hess et al. demonstrate the variability and heterogeneity of the value with several factors: time and cost gains/losses, person characteristics (e.g. "age, gender, employment status, household composition and income"), trip mode, trip purpose, trip distance, and trip geography [10]. Using SP surveys and discrete choice models as well as three "games": SP1, SP2, SP3, they consider the trade-offs between time vs. money, time vs. money vs. reliability, and time vs. money vs. crowding/congestion respectively to estimate VOT. Brent and Gross use RP data on SR167 managed lanes in Seattle, WA, to show that VOT values on a corridor also depend on direction of travel, which can be explained by dependence of VOT on commuters' trip purpose [2].

Rezaeestakhruie et al. investigated VOT values for different passenger classes, trip purposes, trip time periods and different transportation modes with combined data from a SP and RP survey in Iran. They found that the values of VOT varied significantly between different passenger classes and transportation modes. For example, students who took the bus for trips unrelated to education had a VOT of $0.40/hr while highly educated workers who took the bus for trips related to work had a VOT of $6.04/hr [17]. With their results, they concluded that one unique VOT and/or VOR value cannot be used to represent all user classes.

Patil et al. argue that VOT varies substantially based on the urgency of the trip (10%-300% higher than the VOT of an ordinary trip) [17]. Acknowledging that VOT has been shown to depend heavily on users' socio-economic characteristics and trip purposes, Paleti et al. also investigated the relationship between VOT and daily activity patterns and confirmed the intuitive hypothesis that a user's VOT for two trips of the same purpose can vary depending on the mandatory or non-mandatory nature of the trip [15]. The authors classify trip time periods into three mandatory patterns: before primary mandatory (BPM), during primary mandatory (DPM), and after primary mandatory (APM). According to their results, VOT for users during the BPM and DPM periods is higher than during the APM period.

The most common methods to deal with this VOT variation in planning models is to create sections of population based on income and trip purpose and use different VOT values for each group. However, Lemp and Rossi argue that "using average VOTs may not be sufficient, even when travelers are segmented by income or other measures" since the variation cannot be modeled accurately by an average number [12]. They propose creating VOT segments for different trip purposes and income classes and using household travel survey and income data to determine the percent of travelers in each income class and trip purpose belonging to each VOT segment. They propose using these percentages to generate modified origin-destination matrices for each VOT segment. The authors mention that they are currently validating the usefulness of the proposed method on the Metropolitan Washington Council of Government's (MWCOG) planning model. **Chapter 4** will discuss some anlaysis based on Lemp and Rossi's idea of generating modified OD matrices for each VOT class.

On the application front, Mouter and Chorus investigated the reliability of using behavioral VOT values for transportation policy purposes through a stated choice experiment and found no substantial proof to support a prior claim that users' VOT as a consumer varied significantly from their VOT as a citizen (Mouter and Chorus, 2016). Thus, they assumed that users' VOT measured with consumer framed surveys is a good estimate of citizens' VOT for modeling and policy purposes.

iii. Traffic Assignment for Multiple User Class Assignment to Capture Varying VOT

Improved traffic assignment models that capture varying VOT values include Robert B. Dial's proposed bicriterion traffic assignment algorithm that accounts for multiple vehicle classes by making small changes to the user equilibrium principle [6]. This algorithm predicts likely traveler paths when VOT values fall within a certain range. Dial also later proposed a simplicial decomposition algorithm that uses multiclass assignment to produce user-optimal equilibrium [7]. Using variational inequality methods, Nagurney also approached the same multiclass assignment problem assuming convexity and "strict monotonicity…[for] both the travel time and travel cost functions" and found that although multiclass equilibrium's total link flow output was unique, this did not always necessarily mean the individual vehicle class flows were also unique [13]. **Chapter 4** will involve a comparison of multi-class traffic assignment results produced from Dial's 1996 algorithm to those from Caliper Corporation's travel demand modeling software, TransCAD.

III. Chapter 2: NPMRDS Data

Based off data from National Performance Management Research Data Set (NPMRDS), this chapter will discuss the (i) objective of this analysis and the context behind the dataset, (ii) the methodology used to obtain a range of VOT values from real time travel data, present the (iii) resulting tables and figures that were generated from analyzing the dataset, and the (iv) final conclusions.

i. Context and Objective

The data obtained from NPMRDS was from a small section of the Lyndon B. Johnson (LBJ) Freeway TEXpress Lanes, which is a managed lane facility in Dallas, Texas. Along this roadway segment are four Traffic Message Channels (TMCs), two of which are directed in the eastbound (EB) direction, while the other two are directed in the westbound (WB) direction, both with speed limits of 70 mph. ***Figure 1*** on the following page depicts the location of these TMCs in relation to the Dallas network.

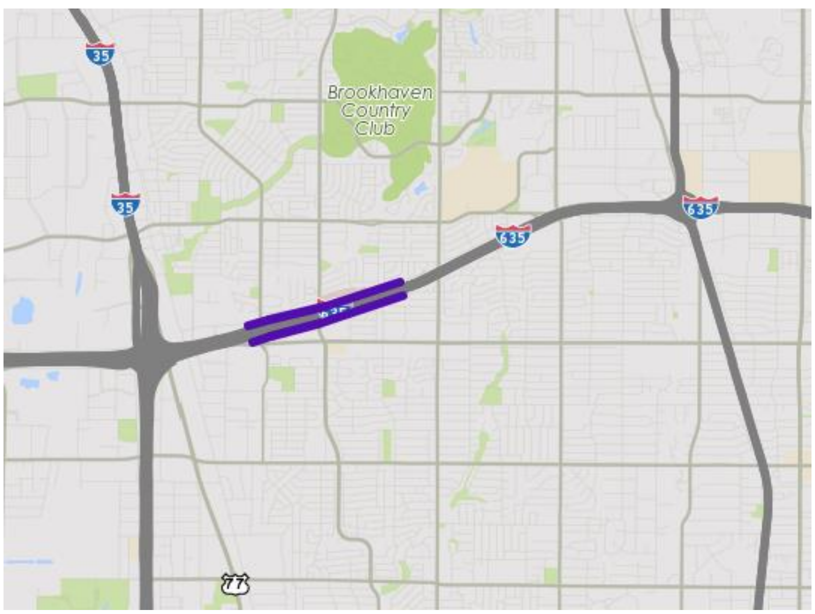


Figure 1: *Location of 4 TMCs along LBJ TEXpress lanes in Dallas, TX*

The corresponding data at these locations was provided in the form of NPMRDS trucks and passenger vehicle data between August 1, 2017 to September 30, 2017 averaged to every 15th minute. The objective of this analysis was to compare the travel times and volumes on the ML and GP lanes, quantify the difference, and obtain an idea of the range of VOT values for travelers in this location. In the case of this dataset, the eastbound direction was randomly selected as the direction of interest. ***Figure 2*** below gives a simplified illustration of the layout of the two TMCs between at Exit 26 and 25 along EB Interstate 635.

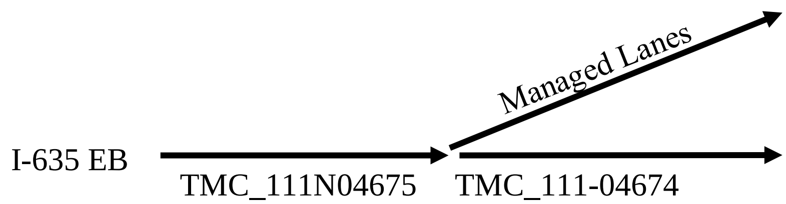


Figure 2: *Simplified network illustration of sample TMC segments*

TMC_111N04675 is approximately 0.16 miles long while TMC_111-04674 is approximately 1.15 miles long. As section (ii) will discuss in further detail, the decrease in volume from TMC_111N04675 to TMC_111-04674 is assumed to represent the volume along the ML facility at this location.

ii. Methodology and Assumptions

The provided NPMRDS dataset included speeds, and travel times for each TMC, however, volumes on the lanes were not provided, nor were toll values throughout the day. Thus, several assumptions were made in order to generate sufficient information to obtain VOT values. These assumptions included:

1. Volume is measured at the end of each TMC section.
2. Greenshield's macroscopic fundamental diagram is applicable.

a. ***Equation 1:*** $Q = k_j * v * \left(1 - \frac{v}{v_f}\right)$

b. $Q =$ flow or volume in veh/hr/lane

c. $k_j =$ jam density (maximum density per km) = assumed value of 165 veh/km (266 veh/mi)

d. $V =$ speed (km/hr) or (mi/hr)

e. $V_f =$ free-flow speed (speed limit) (km/hr) or (mi/hr)

3. An average toll price of $0.1/mile applies during all times of day (TOD).
4. The captured platoon of vehicles in TMC_111-04674 is the same as that captured in the data set for TMC_111N04675 despite the fact that NPMRDS collects data in 5-minute time increments.

After making these assumptions, the following methodology was applied for all times in a certain day to obtain a range of VOT values:

1. Extract the date, speeds, and travel times from the NPMRDS readings.
2. Calculate the travel time along TMC_111-04674 if one is traveling at the speed limit using the speed limit of 70 mph and the given distance of the TMC. This will be assumed to represent the travel time on the ML.
3. Subtract the ML travel time from the travel time given in the NPMRDS data set for TMC_111-04674 (which represents the travel time along the GP lane). This will be (t_1-t_{bar}.)
4. Convert travel time on TMC_111-04674 to a volume based off Assumption 2 using Greenshield's fundamental diagram relationship.
    a. Calculate a value of Q using ***Equation 1*** in Assumption 2 a.

b. Multiply this value by the total number of GP lanes on TMC_111-04674 to obtain a veh/hr volume on the GP lane. This will be Volume $_2$.

5. Repeat Step 4 with the travel time on TMC_111N04675. The resulting volume will be Volume $_1$.

6. Calculate the proportion of travelers choosing to enter the ML facility out of all total travelers by computing:

   a. ***Equation 2:*** $ML\ proportion = \frac{(Volume\ 1 - Volume\ 2)}{Volume\ 2}$

7. Calculate the threshold VOT ($/hr) by computing:

   a. *Equation 3:* $Threshold\ VOT = \frac{Toll\ Price}{(t_1 - t_{bar}) * 3600}$

iii. Analysis and Results

The above methodology in ii. was applied to travel data from Tuesday, August 1 2017. Unfortunately, the resulting VOT distribution plot (where f (x) = $(1 - \frac{Volume_1 - Volume_2}{Volume_1}$) and x = VOT) from this analysis yielded no meaningful pattern between VOT and the proportion of travelers choosing the ML facility. This is most likely due to errors in the initial assumptions that were made regarding this dataset. Some of the signs of these errors were evident when the reported volumes on TMC_111-04674 exceeded those of TMC_111N04675 at certain times of day and thus yielded negative proportions. In addition, certain data points produced unreasonably large VOT values.

After removing the outlying incidents where the volume on TMC_111-04674 exceeded that of TMC_111N04675 and VOT was exceedingly large, the remaining differences in travel time between the GP lanes and the ML yielded a range of threshold VOT values between approximately $2-$86/hour. Contextually, these VOT values represent the range of points above which travelers will choose to remain on the GP lanes and below which travelers will choose to take the ML. ***Figure 3*** below illustrates the frequency distribution of the threshold VOT values.

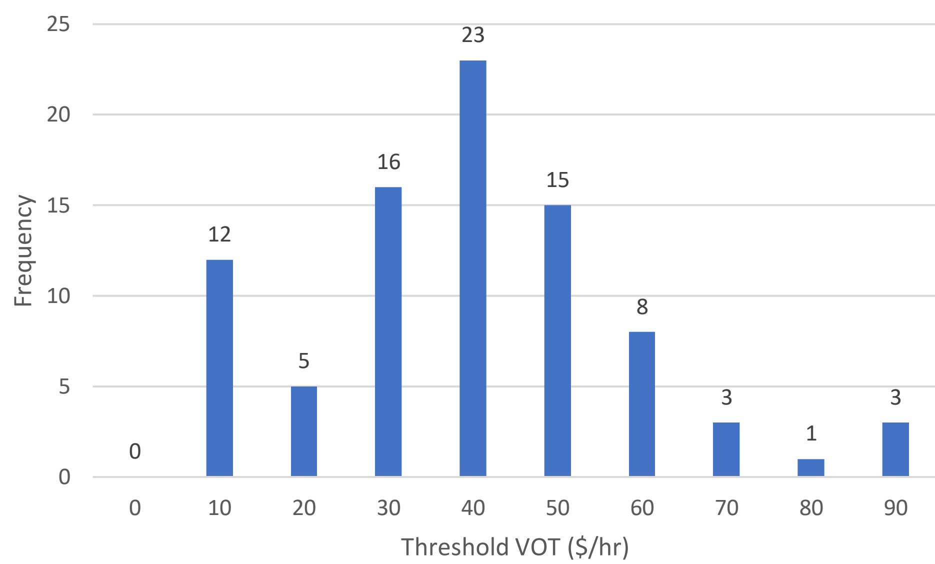


Figure 3: *Histogram of Threshold VOT for 08/01/17*

As ***Figure 3*** shows, the threshold VOTs with the highest frequency fall between $30-$50/hr, with some falling in the lower and higher ranges.

iv. Conclusions

The 5-minute time gap in NPRMDS's data combined with the assumptions that were made in order to conduct the analysis ultimately rendered the resulting VOT distribution unusable. Although the NPMRDS analysis did not yield a reliable VOT distribution for travelers along I-635, it provided a reasonable preliminary idea of VOT threshold values along I-635. The methodology laid a good framework for future analysis when reported volume and tolls at different TOD data becomes available. When recorded volume data as well as toll prices throughout the day becomes available within a dataset with more reliability than the one used in this analysis, the same methodology could theoretically be applied to obtain a more informative VOT distribution in the future.

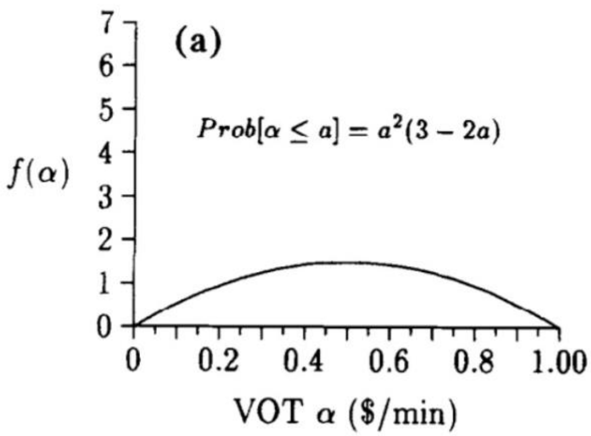
IV. Chapter 3: TransCAD vs. Dial's Multiclass Traffic Assignment

Besides obtaining region-specific VOT distributions, another important objective for transportation planners is to determine ways to model VOT accurately in their long-range traffic assignment models. Currently, most Metropolitan Planning Organizations (MPOs) utilize TransCAD, a Geographic Information System (GIS) that fully integrates GIS with travel demand modeling capabilities. TransCAD has the ability to "run a multi-modal, multi-class equilibrium or stochastic equilibrium assignment model…that uses class specific values of time" [4]. However, TransCAD is unable to receive a continuous VOT distribution as an input in its traffic assignment component, and only provides for discrete VOT value inputs, as well as assumes a constant toll when a link is assigned a toll value. As a result, TransCAD is suspected to inherently produce assignment errors in link flows and/or travel times on a network.

In order to quantify these errors and determine their significance for planning purposes, TransCAD was compared against Dial's 1996 bicriterion traffic assignment model. Dial's algorithm makes provisions for multiple vehicle classes with continuous VOT distribution, and thus its link flow and travel time outputs will be used as an accuracy benchmark against which TransCAD's results will be compared [6].

i. Introduction to Nine Node Network Problem Statement

The traffic assignment capabilities of TransCAD will be tested on a nine node network that Dial presents as a numerical example with 1,000 OD trips to which he applies a parabolic VOT distribution. ***Figure 4a*** below gives thesymmetric parabolic probability density function (PDF) applied with the VOT PDF being $f(\propto) = 6(\propto - \propto^2)$, while ***Figure 4b*** below gives the network model and its final equilibrium link flows, and speeds (values above and to the right of each link represent the flows, values below and to the left of each link represent the speeds). Note that arcs (4,5) and (5,6) possess a $1 toll value.



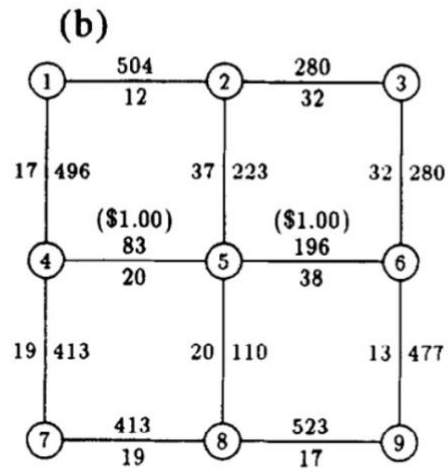


Figure 4: *Nine Node Network /1000 OD Trips:* ***(a)*** *Symmetric Parabolic PDF.* ***(b)*** *Volume, Speed, and Toll values on Illustrated Nine Node Network [6].*

This network contains OD demand moving from Node 1 to Node 9 and was assumed as the network with which to compare traffic assignment results between TransCAD and Dial's method.

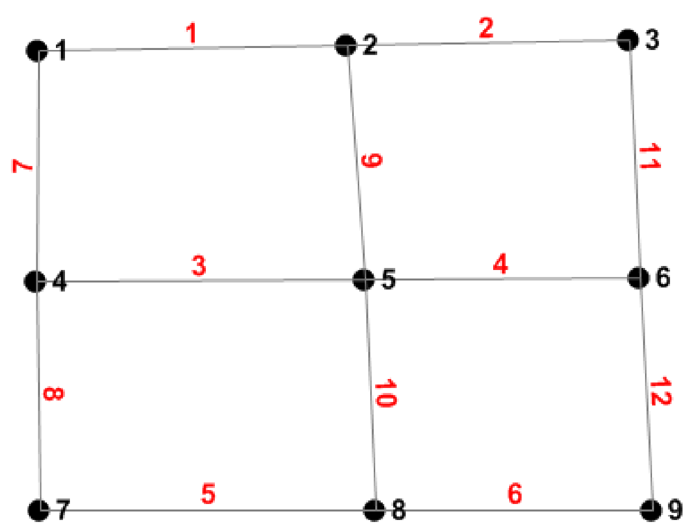


Figure 5: *TransCAD Nine Node Network with node IDs (black) and link IDs (red)*

ID	Dir	Length	Capacity	fftt	Toll
2	0	0.08	250	4.50	0
1	0	0.08	250	4.50	0
8	0	0.06	500	9.00	0
11	0	0.06	250	4.50	0
6	0	0.07	500	9.00	0
10	0	0.06	500	9.00	0
3	0	0.09	500	9.00	1
9	0	0.06	250	4.50	0
4	0	0.07	250	4.50	1
7	0	0.06	500	9.00	0
5	0	0.09	500	9.00	0
12	0	0.06	250	4.50	0

Figure 6: *Dataview Table from TransCAD containing link information*

Figure 5 above shows the network drawn in TransCAD with correspondingly labeled node and link IDs. ***Figure 6*** above shows the capacity, free-flow travel time, and toll value inputs for each link in the TransCAD network. These values were obtained from Dial's specified input values in his numerical example corresponding to this network.

ii. Methodology

In order to test the impact of TransCAD's discrete VOT inputs on its traffic assignment results, Dial's continuous parabolic VOT distribution was discretized in three ways:

(1) 3 discrete, symmetric VOT classes (***Figure 7*** below)

(2) 10 discrete, symmetric VOT classes (***Figure 8*** below)

(3) 3 discrete, asymmetric VOT classes (***Figure 9*** below)

In doing so, the effect of VOT discretization itself can be investigated as well as the question of whether different types of VOT discretization can improve the approximation of a continuous VOT distribution and consequently reduce the output error. In other words, if MPOs plan to continue using TransCAD in the future, what is the best method of providing discrete VOT input values in order to accommodate TransCAD's inability to accept a continuous VOT distribution input?

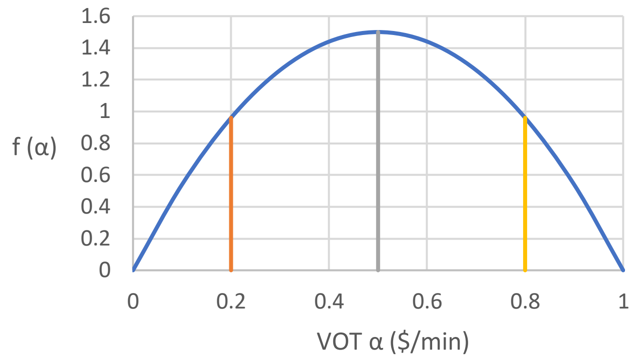


Figure 7: *Continuous VOT Distribution discretized into 3 symmetric VOT classes (V_{3S})*

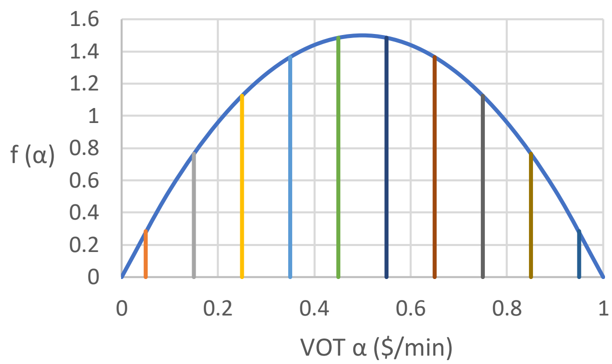


Figure 8: *Continuous VOT Distribution discretized into 10 symmetric VOT classes (V_{10S})*

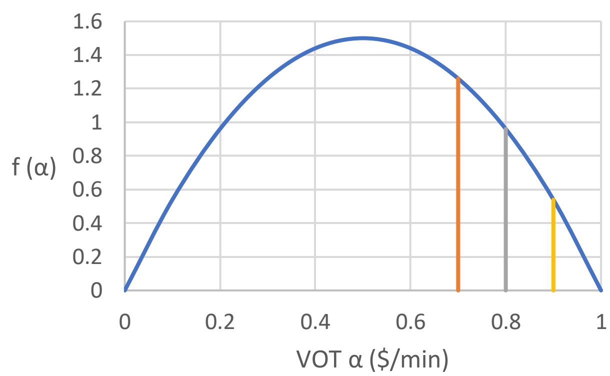


Figure 9*: Continuous VOT Distribution discretized into 3 asymmetric VOT classes (V_{3A})*

To account for the VOT discretization in TransCAD's accompanying OD matrix input, the proportion of each VOT class (as shown in ***Figure 10*** below) was multiplied by the total OD demand (1,000 trips). For example, in the V_{3S} case, an OD matrix file was created with three nine-by-nine matrices nested within. The first matrix represented VOT Class 1 ($0.2/min), and contained a value of $(0.281 * 1000) = 281$ trips in the element representing travel from Node 1 to Node 9 ($a_{1,9}$). The second matrix represented VOT Class 2 ($0.5/min), and contained a value of $(0.439 * 1000) = 439$ trips in element $a_{1,9}$. The third matrix represented VOT Class 3 ($0.8/min) and contained a value of $(0.281 * 1000) = 281$ trips in element $a_{1,9}$.

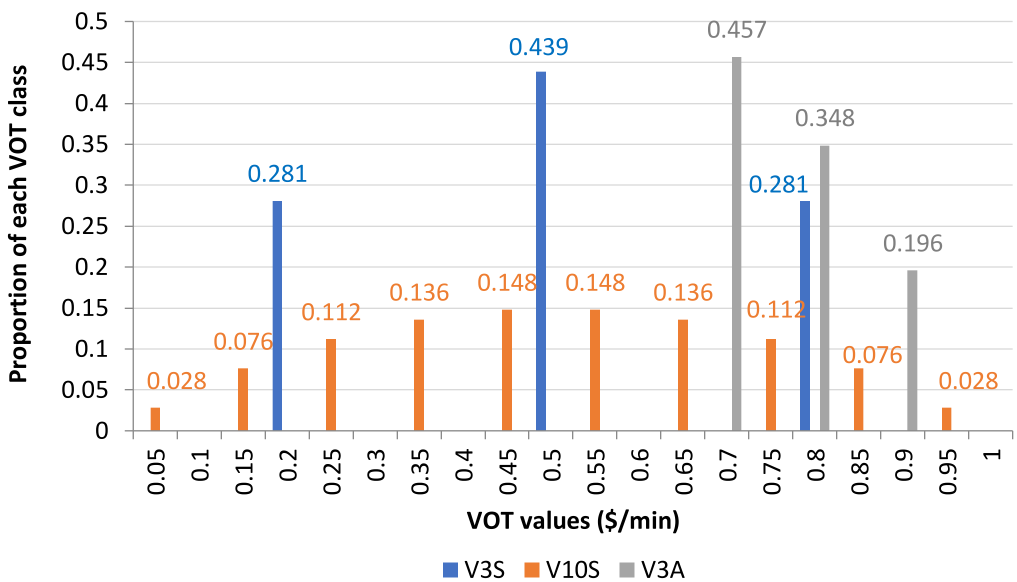


Figure 10: *Proportion of each VOT class with each discretization group*

For each of these three VOT cases, 4 cases of different toll and demand settings were also tested to verify whether any differences in output error were made more or less significant by increased values on the toll links and/or increased total OD demand. A total summary of all 12 cases of traffic assignment runs tested on TransCAD against Dial's algorithm is illustrated below in ***Table 2***.

Table 2: *Summary table of all traffic assignment cases tested on TransCAD*

	Low Toll ($1)	High Toll ($4)
Low Demand (1,000 OD Trips)	-V_{3S} -V_{10S} -V_{3A}	-V_{3S} -V_{10S} -V_{3A}
High Demand (10,000 OD Trips)	-V_{3S} -V_{10S} -V_{3A}	-V_{3S} -V_{10S} -V_{3A}

iii. Analysis and Results

After comparing TransCAD's outputs to those of Dial's algorithm, discrepancies in link volumes and travel times were observed. ***Figure 11*** below shows a comparison of all 3 VOT classes link flow outputs against those of Dial for the low demand, low toll case.

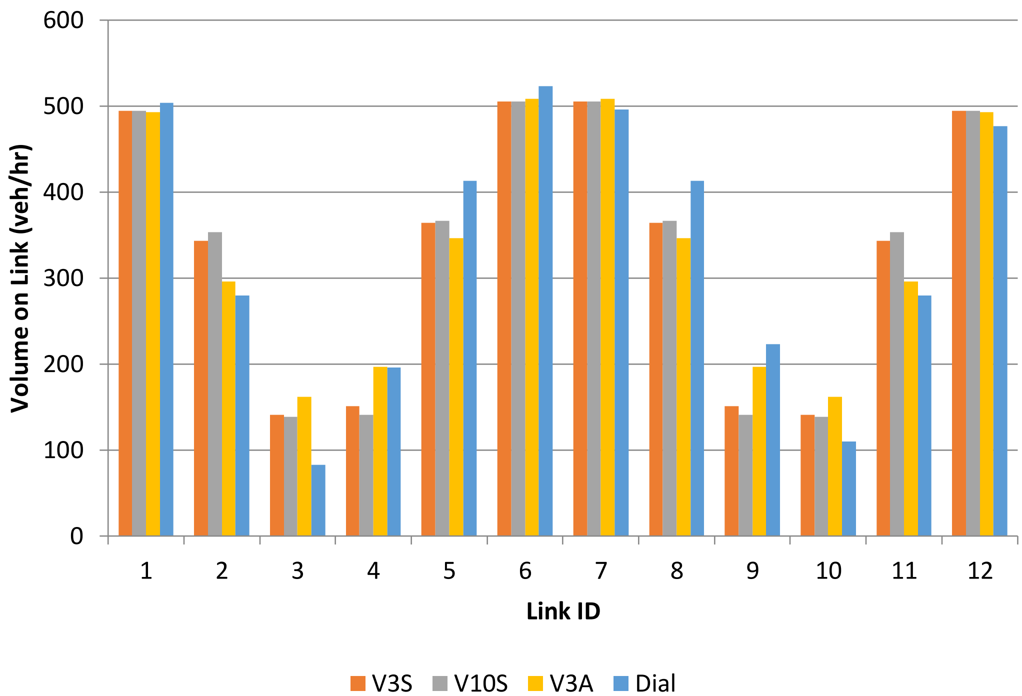


Figure 11: *Comparison of VOT Classes against Dial for link flow outputs (Low Demand, Low Toll)*

While TransCAD produces generally similar results to those of Dial, it is clear that certain links in the network experience greater volume differences in than others. In addition, V_{3S} is observed to give approximately the same link flows as V_{10S} for all links in the network. From this, it can be inferred that increasing VOT discretization does not necessarily improve the accuracy of TransCAD's traffic assignment results. However, on certain network links, the resulting volumes of the asymmetric discretization vary substantially from those of both symmetric discretizations. In fact, when comparing Root Mean Square Errors (RMSE) between all three discretization classes, V_{3A} proves to yield the lowest value of error when compared to Dial's volumes.

In regards to travel time differences, similar conclusions to volume differences apply. ***Figure 12*** below shows a comparison of travel time differences between the three VOT discretizations in the low demand, low toll case.

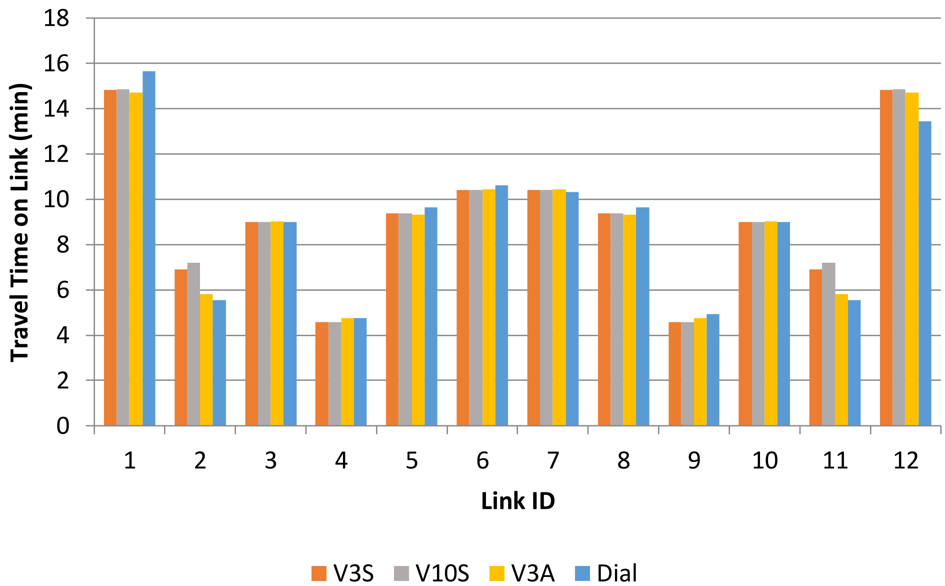


Figure 12: *Comparison of VOT Classes against Dial for link travel time outputs (Low Demand, Low Toll)*

Increasing discretization does not appear to improve the accuracy of the results and the asymmetric distribution seems to produce the least error when compared to Dial's method (approximately 41% less RMSE than that of V_{10S}). Overall however, travel time differences on the network are much smaller (approximately 80% less) than volume differences.

To compare the impact of toll values, ***Figure 13a*** and ***Figure 13b*** below show the travel time difference for a V_{10S} low demand case with low toll and high toll respectively.

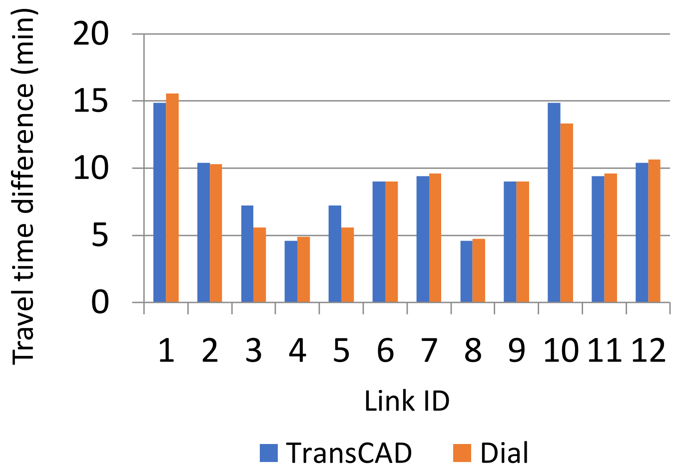


Figure 13: ***(a)*** *Travel time difference comparison for V_{10S}, low demand, low toll*

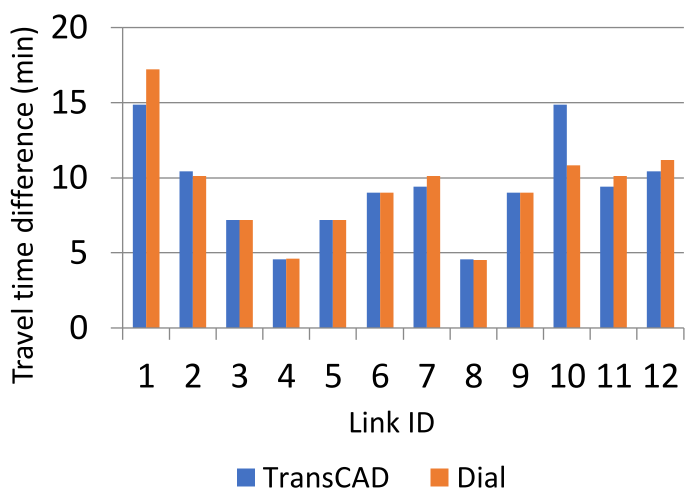


Figure 13: ***(b)*** *Travel time difference comparison for V_{10S}, low demand, high toll*

Comparing with Dial's method, TransCAD produces greater travel time difference error in the high toll case than in the low toll case.

In general, the relative toll values on each link in the network compared to the travel time on each link in the network makes a difference.

iv. Conclusions

Overall, TransCAD does produce some errors in its traffic assignment outputs when compared to Dial's method. The differences observed in link volumes seem to be more significant than those observed in link travel times. This is most likely due to the fundamental theory of traffic flow – After the volume on a link reaches a certain value, the travel time difference on the link does not vary much with further changes in volume. If transportation planning agencies plan on continuing to utilize TransCAD's multi-modal, multi-class traffic assignment capabilities, they should consider using an appropriately skewed VOT discretization as opposed to increasing the number of symmetric discretizations to achieve the greatest approximation to the results of a known continuous VOT distribution. The magnitude of the errors observed on the nine node network was small but in the future if the same tests were conducted on a larger network that is more representative of an urban region's scale, the effect of TransCAD's discrete VOT value inputs and constant toll assumption might be more significant.

V. Conclusion & Future Work

Travelers' VOT can vary depending on income class, trip purpose, and many other factors, making it clear that real-time data can and should be used to generate a region specific VOT distribution when possible. In this study of the distribution of VOT, using the idea of "threshold VOT" to reveal travelers' VOT in the context of ML and GP lanes presents a promising methodology with which MPO's can determine an approximation of the VOT distribution from travel volume and toll data on their network.

When moving onto applying known VOT distributions in the context of multi-modal and multi-class traffic assignment in long-range planning models, TransCAD does produce inherent errors in its assigned volume and travel time outputs due to a combination of its simplified VOT capabilities and assumption of constant toll. To offset these errors, this study has revealed that increasing discretization of a continuous VOT distribution does not greatly impact the accuracy of traffic assignment. However, TransCAD does appear to be sensitive to changes in toll values on links. Future work will focus on investigating the effect of varying toll values in combination with a VOT input. In addition, similar tests as those conducted in **Chapter 3** will be performed on a network of a larger scale to ascertain the magnitude of errors that MPOs face when using TransCAD.

VI. References

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