Strategies for Improving Travel Time Reliability

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16. Abstract

Deterministic network models, in which deterministic link travel time is a function of link volume, have been used by TxDOT in its transportation planning process. The use of stochastic network models, in which link travel time is subjected to variation even at a given volume could potentially provide a better precision and additional measures that relate to travel time reliability for transportation project selection. This research has developed and tested two traffic assignment approaches that include travel time variation in a network, and driver's route choice and departure time choice in response to such travel time uncertainty. Software tool to assist in the modeling of the proposed traffic assignment approaches in TransCAD have also been developed.

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ABSTRACT

Deterministic network models, in which deterministic link travel time is a function of link volume, have been used by TxDOT in its transportation planning process. The use of stochastic network models, in which link travel time is subjected to variation at a given volume, can potentially represent the network's traffic conditions more realistically and provide additional measures that relate to travel time reliability for transportation project selection. This research proposes and tests two traffic assignment approaches that include travel time variation in a network, and driver's route choice and departure time choice in response to such travel time uncertainty. A software tool to assist in the modeling of the proposed traffic assignment approaches in TransCAD has also been developed.

EXECUTIVE SUMMARY

A driver's route choice and departure time choice decisions for a trip do not depend on only the average travel time of the available routes, but also the travel time reliability of each of the routes. Transportation planners typically use deterministic network models in the traffic assignment process. Incorporating travel time reliability in the route choice and departure time choice modeling in traffic assignment could improve the precision of the evaluation of network performance. This research develops two traffic assignment approaches that include travel time uncertainty and driver's response to such uncertainty in route choice and departure time choice.

The traffic assignment approaches are based on a network in which the link travel time (at the same time of the day, at a given link volume) is subjected to day-to-day fluctuation. The variation could be due to incidents, weather, vehicle composition, driving behavior, and other random events. The average link travel time may be described by the standard Bureau of Public Roads function, but the variance of travel time is proportional to the link length and link volume. In this research, equivalent link disutility functions, corresponding to the different route choice behavior in such a network, have been derived. The function for risk averse drivers, who prefer a route with a longer average travel time but better travel time reliability (smaller travel time variance), is of particular interest in this research. A method to conduct driver survey so as to estimate the risk averse coefficients of the equivalent link disutility function has been developed.

The two traffic assignment approaches developed in this project are for modeling the morning commute to work, when drivers have to arrive at their destinations before their work-start time. With this constraint in arrival time, travel time reliability becomes an important consideration when a risk averse driver selects his/her route and/or departure time.

The first traffic assignment approach developed in this project is called *traffic assignment with a fixed origin-destination matrix*. It assumes that the average driver in the network is risk averse in route choice, but the departure time remains unchanged. The solution of this traffic assignment problem may be solved by any standard user-equilibrium algorithm, by simply replacing the standard link performance function in the deterministic network model with the equivalent link disutility function in our stochastic network model.

The second traffic assignment approach, called *traffic assignment with departure time choice*, considers both driver's route choice and departure time choice. The morning peak period is divided into smaller departure time intervals, each with its own origin-destination matrix. An iterative procedure has been developed to (1) adjust the origin-destination matrices to reflect the departure time choices of all the drivers; and (2) solve the user-equilibrium traffic assignment problem for each departure time interval, with the incorporation of the equivalent link disutility function that describes the risk averse behavior.

The two traffic assignment approaches have been tested with the El Paso network, with the corresponding origin-destination matrices. A procedure to measure the network capacity reliability has also been developed and its applications demonstrated with the El Paso network with existing and future scenarios.

The functions to assist in the implementation of the two traffic assignment approaches in Version 4.8 of TransCAD, including the pre-processing of the input data and post-processing of the results, have been coded into eight programs that are bundled in the Travel Time Reliability Program Suite. The Travel Time Reliability Program Suite, its User's Guide and sample data sets (which can be used for training workshops) have been compiled in the accompanying DVD.

IMPLEMENTATION STATEMENT

The software tool and modeling approaches developed in this project are ready for in-house evaluation by TxDOT's Transportation Planning and Policy (TP&P) staff.

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CHAPTER 1

INTRODUCTION

1.1 Background

Every TxDOT transportation project needs to be carefully evaluated, considering that many of them require significant capital investment and construction time. It is often difficult to estimate a project's eventual impacts on the state's stakeholders at the beginning of the project. One of the important aspects of driver's travel experience is travel time reliability. The objective of this project is to model travel time reliability in a transportation network, evaluate its impact on driver's travel pattern and eventually estimate the network's traffic performance. The modeling technique and tool developed in this research can be used to help prioritize future TxDOT projects. Consequently, implementable strategies to improve travel time and travel time reliability can be proposed.

A trip maker's frustration drastically escalates when the transportation system cannot deliver a reliable performance. In this case, from the user's perspective, reliable performance means consistency in travel time. It is comparatively easier for a driver to select a route and schedule his/her departure time when the transportation network has consistent and predictable travel time. On the other hand, the variability of travel time introduces complexity into the driver's perception on the transportation system performance and his/her decision criteria. A driver not only minimizes his/her travel time in choosing a route or departure time, but also minimizes the risk in arriving late at the destination when the travel time is unreliable.

Providing satisfactory transportation system performance to facilitate mobility and economy is the ultimate goal of every TxDOT project. Given limited funding, mixed public opinions, and heightened environmental concerns, selecting a project needs to rely on a holistic evaluation that emphasizes both immediate and long-term performance reliability. However, travel time reliability has not been explicitly included as a project selection criterion in the state of the practice. One reason is that the appropriate method to evaluating the performance reliability of a transportation system has not been well studied. No guideline exists to measure and gauge the measurement and improvement of travel time reliability.

1.2 Objectives

The objectives of this project are:

- To conduct a comprehensive review of the modeling of travel time reliability in a transportation network, including driver's response to travel time reliability in making travel decisions, with emphasis on transportation planning applications.
- To synthesize and propose practical transportation network modeling approaches that take travel time reliability and driver's response to travel time reliability into consideration.
- To demonstrate the applications of the proposed modeling approaches in selected networks.
- To develop a software tool to be used with TransCAD for the modeling of travel time reliability, and the accompanying user's guide.

The modeling approaches and software tool developed in this research will provide TxDOT engineers and Metropolitan Planning Organization (MPO) planners models with better precision and additional measures that relate to travel time reliability in the evaluation of future transportation projects. These measures will also enable TxDOT engineers and MPO planners to experiment with various transportation improvement strategies (whether physical improvement or operational management strategies) in order to select the best one to improve network performance, including travel time reliability.

1.3 Outline of Report

This report summarizes the tasks conducted under TxDOT Research Project Agreement 0-5453, titled "Strategies for Improving Travel Time Reliability".

Chapter 2 of this report reviews the background materials and past research related to transportation modeling with travel time reliability consideration. It covers the concepts of travel time reliability, traffic assignment models, driver responses to travel time reliability, TransCAD and capacity reliability.

Chapter 3 describes the two proposed analysis approaches for evaluation of network performance: traffic assignment with a fixed origin-destination (O-D) matrix and traffic assignment with departure time choice.

Chapter 4 derives the equivalent link disutility functions that correspond to route choice behavior of drivers in a network with travel time reliability consideration. The functions are to be used as the link performance functions in traffic assignment.

Chapter 5 presents the applications of the traffic assignment with a fixed O-D matrix approach (proposed in Chapter 3, and incorporating the equivalent link disutility function derived in Chapter 4) in two networks: a test network with 25 nodes and the El Paso network.

The difference in the results of traffic assignments with and without travel time reliability considerations are analyzed in detail.

Chapter 6 presents the application of the traffic assignment with a departure time choice approach in the El Paso network.

Chapter 7 demonstrates the application of the traffic assignment with a fixed O-D matrix approach in the evaluation of a transportation improvement project. The examples used in this illustration are the El Paso network with and without the Southern Relief Route.

Chapter 8 concludes the findings in this project and recommends a few possible directions for continuing research.

1.4 Accompanying Products

This report itself is a product of TxDOT Research Project Agreement 0-5453.

A software suite, named Travel Time Reliability program suite, has been developed in this project and used in the applications and illustrations of the two traffic assignment approaches proposed in this project. This software suite is coded as a TransCAD Add-in. It consists of eight programs that are used to execute the procedures described in Chapters 3, 5, 6 and 7 of this report. An accompanying User's Guide for this program suite has been written.

This report, the Travel Time Reliability Program Suite, the User's Guide of Travel Time Reliability Program Suite, and sample data sets used in Chapters 5, 6 and 7 are provided in an accompanying DVD.

CHAPTER 2

REVIEW OF PREVIOUS WORK

This Chapter reviews the background materials and past research related to transportation modeling with travel time reliability consideration. It first reviews the various concepts of travel time reliability and clarifies the meaning of travel time reliability within the context of this project. Section 2.2 reviews the different types of traffic assignment models and selects a suitable model for this research. In Section 2.3, models to describe drivers' responses to travel time reliability, which manifest through route choice and departure time choice are presented. The models for route choice and departure time choice behaviors are integrated with the traffic assignment model selected in Section 2.2, in the TransCAD transportation planning and modeling software. A brief description of TranCAD is provided in Section 2.4. After running the integrated models in TransCAD, the performance of the transportation network is analyzed by the network's capacity reliability. The concept of capacity reliability is introduced in Section 2.5.

2.1 Concepts of Travel Time Reliability

Transportation networks are modeled by a set of nodes connected by a set of links. Travel times in a transportation network may be measured at the link or route level. A route is a series of connected links. Therefore, the travel time of a route is the sum of the travel time of the links along the route. If the travel time in a link is unreliable, it follows that the travel time along the route is also unreliable.

The term travel time reliability relates to the consistency and predictability of travel time. It arises because, in reality, travel time is uncertain to some degree. Van Lint and Van Zuylen (2005) state that travel time reliability relates to the day to day travel time distribution as a function of time of day, day of week, month of year and external factors such as weather, incidents and road works. That is, for the same link or route, the travel time at the same time on different days varies depending on many factors.

In the literature, in general, the term travel time reliability usually refers to the route travel time between an origin-destination (O-D) pair. There are two approaches in the definition and measurement of route travel time reliability. The first approach (probabilistic approach) focuses on the probability of a trip travel time smaller than a threshold value. The second approach (parametric approach) describes the variation or distribution of travel time, and measures the travel time reliability using the distribution parameters, for example, the variance of travel time.

The probabilistic approach is concerned with whether that a trip can be successfully finished within a specified time (or less than a specified cost). For example, Shao *et al*. (2006)

provide a definition of travel time reliability as "the probability that a traveler can arrive at the destination within a given travel time threshold." Chen *et al*. (2000) state that "it is concerned with the probability that a trip between a given O-D (origin-destination) pair is made successfully within a specified interval of time". More specifically, Lo *et al.* (1999) defines travel time reliability as "the probability that a trip between a given O-D pair can be made successfully within a specified interval of time for a given level of traffic demand in the network". The probabilistic approach in defining travel time reliability clearly relates to the travel time between an O-D pair in the network. In transportation modeling, trips between an O-D pair may be distributed between different routes. Chen *et al.* (2002a, 2003) further clarify the distinction between route travel time reliability and O-D travel time reliability. Route travel time reliability is "the probability that the travel time of a given path (between an O-D pair) is within an acceptable threshold". For an O-D pair that is connected by multiple paths, the O-D travel time reliability is "the probability that the weighted travel time of a given O-D pair is within an acceptable level of service". Here the route travel times are weighted by their respective path flow connecting the O-D pair to arrive at the weighted average travel time for the O-D pair. It has been mentioned that the probabilistic approach in quantifying travel time reliability is specific to an O-D pair. In a transportation network, there are many O-D pairs. Obviously, the process of estimating travel time reliability at the network level using the probabilistic approach is not a straight forward process.

On the other hand, several studies have measured travel time reliability based on the parametric approach. FHWA (2006) defines travel time reliability as a measure of consistency or dependability in travel time in day to day variation, or across different times of the day. Among the measures suggested are 90^{th} or 95^{th} percentile value of travel time. In the report by Hellinga and Fu (1999) the route selection is based on the criterion of the 95th percentile of travel time. The Travel Rate Index (TRI), used by many urban planners, measures the amount of additional time needed to make a trip in the peak period rather than at the other time of the day (Lomax *et al*., 2001; Cambridge, 2002). The Texas Congestion Index (TCI) is based on this concept. Most of these indices are derived from travel time variation of peak hour. In the same approach, Noland *et al*. (1998) use the term "travel time uncertainty" to denote the variation in travel time in day to day commuting. They use standard deviation of travel time, and a coefficient of variation of travel between an O-D pair as the measures of travel time uncertainty in their route choice models. Several other researchers have used this approach to model route choice behavior when travel time in a network is uncertain (Chen and Recker 2000; Chen *et al*. 2000, 2002a, 2002b, 2003; Mirchandani and Soroush, 1987; Tatineni, et al., 1997). Based on this parametric approach, they are able to perform traffic assignment in a network with uncertain travel time and quantify the network performance.

After reviewing the various definitions of travel time reliability, the notions of travel time reliability provided by Van Lint and Van Zuylen (2005) and Noland *et al*. (1998) are modified and adopted in this research. We consider travel time reliability as the variation of travel time in day to day commuting during the morning peak period. The variation could be caused by fluctuations in traffic volume, vehicle composition, driving behavior, day of week, month of year and external factors such as weather, incidents and road works. This project is concerned with modeling the network performance in view of drivers' route choice caused by the variation of travel time. The parametric method of describing travel time uncertainty can be easily adapted to model the route choice behavior and is therefore adopted in this research.

2.2 Traffic Assignment Models

At present, a large number of transportation network models are based on the assumption that travel time in a link is a deterministic function of the link's characteristics (such as free-flow travel time and link capacity) and link volume. A network with such a deterministic link travel time function is called a Deterministic Network (DN). In reality, link travel time, even for the same traffic flow in a link, is subjected to variations. These variations are due to the difference in vehicle mix, difference in driver reactions, weather, incident conditions, etc. These variations are small when the traffic flow is light but they become much larger as the link becomes more congested. A network with such probabilistic link travel times is called a Stochastic Network (SN). According to the parametric method, a natural way to model link travel time variation is to consider it as a probability distribution, with mean and variance expressed as functions of the link characteristics and link volume.

Most transportation network models assume that the drivers have perfect knowledge of the link travel times (in the deterministic case) or of the probabilities of different values of link travel times (in the stochastic case). The resulting state of the transportation network, after traffic assignment, is called Deterministic User Equilibrium (DUE). In reality, a driver's knowledge is usually somewhat imperfect. The driver's perception of a (deterministic or stochastic) link travel time may be slightly different from the actual travel time. Some transportation network models take this perception error into account by modeling it as a normal distribution with zero mean. Due to these perception errors the selected routes of the drivers vary stochastically. The resulting state of the transportation network is called Stochastic User Equilibrium (SUE).

Based on the assumptions in link travel times and drivers' perception on the link travel times, traffic assignment models may therefore be classified into four types: Deterministic Network-Deterministic User Equilibrium (DN-DUE), Deterministic Network-Stochastic User Equilibrium (DN-SUE), Stochastic Network-Deterministic User Equilibrium (SN-DUE), Stochastic Network-Stochastic User Equilibrium (SN-SUE) (Chen and Recker 2000).

Table 2.1: Classification of traffic assignment models
(from Chen and Recker 2000 and Chen *et al*. 2002a)

		Perception Error?	
		No	Yes
Travel Time Uncertainty?	No	DN-DUE	DN-SUE
	Yes	SN-DUE	SN-SUE

Where DN = Deterministic Network
SN = Stochastic Network
DUE = Deterministic User Equilibrium
SUE = Stochastic User Equilibrium

The DN-DUE is the simplest, the easiest to understand, and the most widely accepted traffic assignment model. It assumes that drivers have perfect knowledge of the deterministic link travel times (with a given flow distribution) in the network, and they always select the paths that have the shortest travel times between their origins and destinations. This model was originally formulated by Beckman *et al*. (1956) and can be solved by DUE algorithms (for examples, the Frank-Wolfe algorithm (LeBlanc *et al*., 1975), Algorithm B (Dial, 2006), and others). In DN-SUE, the network's link travel times are deterministic (with a given flow distribution), but they may be perceived differently by different drivers. Due to the error in travel time perception, drivers will always select what they perceive as the shortest paths but these may not be the actual shortest paths. The DN-SUE model was originally formulated by Daganzo and Sheffi (1977). A popular solution algorithm for the DN-SUE model is the Method of Successive Averages proposed by Sheffi and Powell (1982).

In DN, the travel time is uniquely determined by the path; a driver selects the path connecting an origin and a destination with the shortest travel time. In SN, the travel time is not uniquely determined by the path; each driver selects the path with the lowest expected value of the disutility. Such SN models were first studied by Mirchandani and Soroush (1987). In particular, the SN-DUE assumes that drivers have perfect knowledge of the degree of variation in link travel times, and they factor this variation in their route choice decisions. While DN-DUE and DN-SUE models are used by many transportation modelers, only a few papers (Mirchandani and Soroush, 1987; Tatineni, et al., 1997; Chen and Recker, 2000; Chen et al. 2000) used SN models because these models are much more computationally complex than the DN models. It is known that, under certain conditions, the SN-DUE model can be solved by the DUE algorithm (e.g., Frank-Wolf algorithm) simply by replacing the link travel time function with a suitable Equivalent Link Disutility (ELD) function (see for examples Mirchandani and Soroush, 1987; and Tatineni, 1996). More details of the ELD will be covered in the next section.

In principle, it is possible to consider an even more realistic SN-SUE model which adds drivers' perception errors into the link travel time variations. However, according to Chen and Recker (2000), the SN-DUE model is quite suitable for modeling of peak hour traffic because regular commuters have a good knowledge of the mean and variance of peak hour travel times.

In this research, we adopt the SN-DUE approach to model the traffic flow distribution in a network during the peak hour commute when the network has uncertain travel time. We assume that during this peak hour, all the drivers in the network are regular commuters who have good knowledge of their alternative routes and the respective average route travel time and travel time variation.

2.3 Driver Responses to Travel Time Reliability

When the travel time on a route (connecting an origin and a destination) has high variation, a driver may respond by selecting another route (connecting the same O-D pair) that has a more certain travel time, or use the original route but depart earlier to avoid the risk of arriving late at the destination. The models that describe route choice and departure time choice behavior in a network with uncertain travel time are reviewed next.

2.3.1 Route Choice Behavior

A driver's route selection depends on how the driver reacts to travel time uncertainty. This is particularly important if the drivers has constraints in the time of arrival (e.g., scheduled events, work starting times) with heavy penalties for late arrivals. Mirchandani and Soroush (1987), Tatineni et al. (1997) and Chen and Recker (2000) describe three types of such behavior: risk averse, risk prone and risk neutral. The term risk here refers to the risk of a late arrival at the destination. A risk averse driver prefers a route with longer expected travel time but smaller variation to a route with faster expected travel time but higher variation. That is, he/she would rather use the route with longer travel time (and depart early) to lower the risk of arriving late. On the contrary, a risk prone driver would select the route with a faster travel time but higher variation. A driver with risk neutral behavior does not consider travel time variation in his/her route choice decision.

In a SN, travel time in a link is deterministic. Drivers select a route *r* with the smallest value of the route travel time $t_r = \sum_{i \in r} t_i$. To describe the deterministic link travel time t_i, the most popular function used by transportation modelers is the Bureau of Public Roads (BPR) function:

$$t_i = t_i^f \left[1 + \alpha \left(\frac{v_i}{c_i} \right)^{\beta} \right] \qquad (2.1)$$

where t_i is the travel time in link *i*, t_i^f is the free-flow travel time in link *i*, v_i is the volume in link *i*, c_i is the capacity of link *i*, and α and β are constants. The t_i^f is computed by dividing l_i, the length of link *i*, by u_i^f, the free-flow speed of link *i*. Typical values of α and β are 0.15 and 4 respectively.

According to decision theory (see for example Watson and Buede, 1994), in a SN, a rational decision maker maximizes the expected value of his/her utility function, or equivalently minimizes the expected value of the disutility function. In particular, for the stochastic traffic assignment problem, given a choice of routes $r \in R$ connecting an origin-destination pair, a driver will select the route r' which has the smallest expected disutility $E[DU_r]$

$$E[DU_{r'}] = \min_{r \in R}\{E[DU_r]\} \tag{2.2}$$

For the drivers with risk neutral behavior, the route disutility function DU_r is equal to the route travel time t_r. Therefore the expected route disutility $E[DU_r]$ is equal to the average route travel time $\bar{t}_r$. The route travel time t_r, for a route *r* which is made up of *L* links, is equal to the sum of the link travel times: $t_r = t_1 + ... + t_L$. So, the average route travel time is equal to the sum of the average link travel times: $\bar{t}_r = \bar{t}_1 + ... + \bar{t}_L$. Thus selecting a route with the smallest $E[DU_r]$ is equivalent to selecting a route with the smallest value of the sum of $\bar{t}_i$. Hence, a risk neutral driver can be described by an ELD function $DU_i = \bar{t}_i$.

For describing risk averse and risk prone behavior, the most commonly used disutility functions are the exponential functions (Watson and Buede, 1994). Such functions have been used by Tatineni et al. (1997) and Chen and Recker (2000) to represent the risk averse and risk prone behaviors in a SN:

$$DU_r = \begin{cases} b_1[exp(\omega t_r) - 1] & \text{for risk averse drivers} \\ b_2[1 - exp(-\varphi t_r)] & \text{for risk prone drivers} \end{cases} \tag{2.3}$$

where t_r is the route travel time, and $b_1, b_2, \omega, \varphi$ are positive constants. Given a choice of routes $r \in R$ connecting an origin-destination pair, a driver will select the route r' which has the smallest expected disutility $E[DU_r]$.

Under these assumptions, it was shown that selecting a route with the smallest value of $E[DU_r]$ is equivalent to selecting a route with the smallest value of the sum $du_r = \sum_{i \in r} DU_i$ for some values DU_i. This minimized expression is similar to the minimized expression $t_r = \sum_{i \in r} t_i$ in the deterministic case.

In particular, in the SN-DUE case, when there is no perception error, for risk averse drivers the equivalent link disutility function takes the following form (Tatineni, 1996; Tatineni, et al., 1997)

$$DU_i = \bar{t}_i + c\sigma_{t_i}^2 \left(\frac{1}{2} + \frac{1}{3} c \frac{\sigma_{t_i}^2}{\bar{t}_i - t_i^f} \right) \tag{2.4}$$

where $\sigma_{t_i}^2$ is the variance of the link travel time and c is a constant determined by the parameters of the exponential disutility function. In the derivation of this formula, the authors assume that the difference between the actual link travel time t_i and that average travel time $\bar{t}_i$ is reasonably small, so we can ignore higher order terms in $(t_i - \bar{t}_i)$.

The fact that the user's preferences can be expressed in the form of minimizing the expression $du_r = \sum_{i \in r} DU_i$ allows us to use Frank-Wolf algorithm to solve the traffic assignment problem in the stochastic case as well (Tatineni et al., 1997; Chen and Recker, 2000). However, to use (2.4), one has to know the variance of travel time $\sigma_{t_i}^2$ of every link. For an urban transportation which has several hundred to several thousand links, the estimation of all the $\sigma_{t_i}^2$ is not an easy task. This research has derived a simpler form of DU_i to describe the route choice preference of risk averse drivers, which will be explained in Chapter 4.

2.3.2 Departure Time Choice Behavior

The paper by Noland *et al.* (1998) has reported several departure time choice models incorporating travel time reliability measures. The models have been calibrated with an extensive set of real data, and are deemed suitable for use in this research. This section reviews the departure time choice models in detail.

Noland *et al*. (1998) actually presents a simulation model to illustrate the effect of travel time reliability on drivers' departure time choice. The simulation model uses a simple network of an O-D pair connected by one link. The BPR function is used as the link performance function. Travel time uncertainty was generated by random incidents that reduced the link capacity in the BPR function. The model assumes a constant travel demand of a 5000 vehicles in a peak hour. A multinomial logit model is used to represent the departure time choice to allocate the 5000 trips into 11 departure time intervals. The idea of time varying demand is to replicate drivers' decision to depart earlier to compensate for the travel time uncertainty.

The utility function in the logit model for departure time choice assumes the general form of:

$$C_S = \alpha T + \beta(SDE) + \gamma(SDL) + \theta D_L \tag{2.5}$$

Where C_S is the scheduling cost (if the trip departs earlier or later than desired), T is the travel time, *SDE* and *SDL* are binary variables of schedule delay early and late respectively,

D_L is the delay penalty, and α, β, γ are coefficients (Small, 1982). From here, Noland *et al*. (1998) derived the total expected cost of scheduling choice as

$$EC = \alpha E(T) + \beta E(SDE) + \gamma E(SDL) + \theta P_L + \sigma f(S) \tag{2.6}$$

where P_L is the probability of arriving late, S is the variance of travel time and σ is a coefficient.

Stated preference survey data was obtained from Noland and Small (1995) to calibrate five models of similar forms. The survey was conducted from 700 morning commuters in the Los Angeles region, of which 543 users completed data with information about employers, work start times, travel times. Among the models, they have recommended the following utility function:

$$EC = -0.1051E(T) - 0.0931E(SDE) - 0.1299E(SDL) - 1.3466P_L - 0.3463\frac{S}{E(T)} \tag{2.7}$$

The above utility function takes into account the expected travel time T, travel time variance S, and expected penalty of early or late arrival. Obviously, the above equation (EC, T and S) depends on the trip origin, destination and departure time interval. Furthermore, SDE, SDL and P_L depend on the trip maker's work start time.

Noland *et al*. (1998) applied this utility function to calculate the probability of each of the 5000 commuter-drivers in choosing the 11 10-minute departure time intervals. In applying each model, they assumed that each commuter had a work start time (randomly assigned based on a normal distribution). To obtain S, the variance of travel time, the model first assumed a probability of a driver (departing at a specific time interval) encountering an incident during a trip. If an incident had occurred, there were associated conditional probabilities of having incidents of three different severities, resulting in three different levels of capacity reduction. Furthermore, incidents of different severity had different length of occurrence. With a number of trips departing at a time interval, the distribution of travel times for all the trips (with and without encountering an incident) can be obtained, from which $E(T)$ and S can be derived. Hence, assuming that each of the 11 departure time intervals has an associated $E(T)$ and S, the individual driver's E(SDE), $E(SDL)$ and P_L was then computed.

Obviously, $E(T)$, S, and the associated E(SDE), $E(SDL)$ and P_L affects an individual's departure time choice. The individual departure time choice is then aggregated into different traffic volume in the link at a particular time interval, which will then affect $E(T)$, S of all the trips depart in an interval, and the associated E(SDE), $E(SDL)$ and P_L of an individual trip maker. The simulation model is solved iteratively until a certain predefined convergence criteria is met.

2.4 TransCAD

TransCAD is a Geographical Information System (GIS) developed for transportation applications (Caliper 2005a). It links a transportation application oriented database with a graphical representation of a network, and assists engineers in planning, managing and analyzing the characteristics of transportation systems and facilities. The GIS engine provides a powerful tool for visualization of the input and output data. Embedded in TransCAD are many travel demand modeling tools including those that can be applied to the four-step travel demand forecasting process (Caliper 2005b). It also offers an extensive set of traffic assignment models, including the SN-DUE model which is used in this research. In TransCAD, the SN-DUE model is solved by means of the Frank-Wolfe algorithm (LeBlanc *et al*., 1975).

Since 1997, TransCAD has been used in many transportation applications. Some of them are listed below:

- Travel time analysis in the siting of Michigan DOT's service centers (Robinson *et al*., 1997)
- Estimation of travel time from origin-destination survey data (Thériault *et al*., 1999)
- Four-step transportation modeling process for small cities in Kansas (Russell *et al*., 2000)
- Computation and display of congestion indices and hot spots in Lubbock, TX (Zhang and Lomax 2006)

The GIS Development Kit (GISDK) that comes with TransCAD is a collection of software tools for users to automate repetitive TransCAD functions or tasks, create user-defined add-ins, build customized applications and integration with other programs. The GISDK is provided with a programming language called Caliper Script. Users can write C or FORTRAN programs to interact with TransCAD through the Caliper Script (Caliper 2005c). In other words, the GISDK with the Caliper Script language is the gateway for users to write customized routines to work with the internal functions of TransCAD, or interface external programs with TransCAD. This powerful and yet flexible feature of TransCAD provides the researchers an avenue to implement the departure time choice model not found in TransCAD and other software.

2.5 Capacity Reliability

Capacity reliability is a measure introduced to address the issue of planning for adequate capacity in a road network to accommodate the demand for travel. Capacity reliability is defined by Chen *et al*. (2000, 2002b) as "the probability that the network can accommodate a certain traffic demand at a required service level, while accounting for drivers' route choice behavior". In other words, the travel time uncertainty at the link or route level affects the drivers' route choice and/or departure time choice. Capacity reliability is a measure to quantify the effect of travel time uncertainty at the network level. Chen and his co-authors (Chen and Recker 2000; Chen *et al*. 2000, 2002a, 2002b, 2003) are the most active in transportation network reliability research. They have applied various traffic assignment methods incorporating travel time uncertainty to evaluate the network capacity.

Clearly, the capacity reliability of a transportation network, given a fixed O-D demand, is related to the number of links that have reached their capacities. The estimation of the capacity reliability is based on the concept of network reserve capacity.

Network reserve capacity is defined as the largest multiplier applied to an existing O-D matrix that can be allocated to a transportation network without violating the link capacities (Chen *et al*. 1999, 2000, 2002b). Mathematically stated, it is to find the maximum O-D matrix multiplier μ such that no link in the network, as a result of user equilibrium traffic assignment, has volume that exceeds the capacity:

$$\text{Max} \ \mu$$

$$\text{subject to:} \ v_i(\mu \mathbf{q}) \le c_i \qquad \forall i \in A \tag{2.8}$$

where $v_i(\mu\mathbf{q})$ is the user equilibrium volume on link *i*, in the network with all the links *A*, with the demands of all the O-D pairs **q** being uniformly scaled by μ, and c_i is the capacity of link *i*.

Route choice behavior (with travel time uncertainty) is explicitly considered by solving the user equilibrium traffic assignment problem in the processing of determining $v_i(\mu\mathbf{q})$. More specifically, $v_i(\mu\mathbf{q})$ is obtained by solving

$$\text{Min} \ Z = \sum_{i \in A} \int_0^{v_i} t_i(x, c_i)\,dx \tag{2.9}$$

Subject to:

$$\sum_{r \in R_w} f_r = \mu q_w \qquad \forall w \in W \tag{2.10}$$

$$v_i = \sum_{r \in R} f_r \delta_{ir} \qquad \forall i \in A \tag{2.11}$$

$$f_r \ge 0 \qquad \forall r \in R \tag{2.12}$$

where

W = set of O-D pairs in the network

R = set of routes in the network

R_w = set of routes between O-D pair *w*

t_i = travel time on link i

c_i = capacity of link i

q_w = existing demand between O-D pair w

f_r = flow on route r

δ_{ir} = 1 if route r uses link i, and 0 otherwise

Note that, when μ =1, the problem expressed in Equations (2.9) to (2.12) are reduced to the standard user equilibrium traffic assignment problem which is formulated by Beckman *et al*. (1956).

The problem of determining μ is a bi-level programming problem. At the upper level, a set of possible values of μ, say, at a constant increment, is specified. For each μ value, the solution of the user equilibrium traffic assignment problem is obtained at the lower level. The highest μ value, with the all the link flows $v_i \leq C_i, \forall i \in A$ is taken as the network's reserve capacity.

The network reserve capacity $\mu_{\max}$ may be interpreted as follows. It indicates whether the current network has reserve capacity or is overcrowded. If $\mu_{\max} > 1$, the network has capacity to accommodate more traffic demand before some of the links become too congested. If $\mu_{\max}$ <1, some of the links in the network are already overcrowded.

Instead of computing the network reserve capacity which gives only a $\mu_{\max}$ value, we propose to use the results of all the user equilibrium traffic assignments at the different μ values to plot the capacity reliability curve. The curve indicates the change in the level of service in the transportation network when the overall traffic demand (O-D matrix) grows ($\mu > 1$) or declines ($\mu < 1$). Essentially, the computation of capacity reliability curve is also a bi-level programming problem. At the upper level, a set of possible values of μ is specified. For each μ value, the solution of user equilibrium traffic assignment problem (taking into account route choice behavior due to uncertain travel time) is obtained at the lower level. The level of service measures are then computed based on the solution of the traffic assignment problem. Examples of the measures are the percentage of links that have volume that exceeds the capacity ($v_i > c_i$) and the percentage of lane-miles that have volume that exceeds the capacity. The latter is more representative as it takes into account the number of lanes and length of affected links. It is expected that, as μ increases, there will be more links and lane-miles that have $v_i > c_i$. Therefore, it is expected that the capacity reliability curve should follow an "S" shape as in Figure 2.1. For two transportation networks subjected to the same set of demand variations, the network with the curve on the right is more reliable than the network with the curve on the left, as it has fewer links or lane-miles that reach capacity when the demand increases.

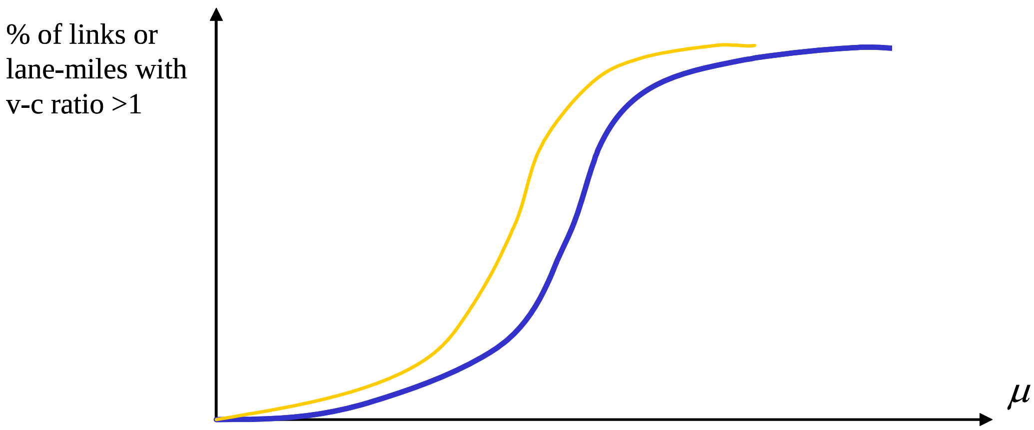


Figure 2.1: Typical capacity reliability curves

CHAPTER 3

DEVELOPMENT OF ANALYSIS APPROACHES

In Chapter 2 of this report, important concepts in traffic assignment with travel time reliability consideration were reviewed. This chapter presents the syntheses of these concepts that form the two analysis approaches proposed in this research: traffic assignment with a fixed O-D matrix, and traffic assignment with departure time choice.

3.1 Traffic Assignment with a Fixed O-D Matrix

3.1.1 General Idea

This section relates to performing traffic assignment with a fixed O-D matrix to estimate the traffic conditions in a network when travel time reliability is taken into consideration. It only models route choice behavior of the drivers and does not consider departure time choice as a possible outcome. The model that also considers departure time choice (in addition to route choice) will be discussed in Section 3.2 in this chapter.

In Chapter 2, it has been discussed that:

- When modeling a network with travel time reliability consideration, the analyst is actually modeling the network with travel time uncertainty (a SN), and driver's departure time and/or route choice under such uncertainty.
- When route travel time is uncertain, drivers will exhibit different behaviors when they are facing constraints in the arrival times. Therefore, modeling a network's performance with travel time reliability is more appropriate for the rush hours. Typically this refers to the morning peak period when the traffic in the network is congested (hence the travel time is more uncertain) and regular commuters have to arrive on time to work.
- When faced with route travel time uncertainty, drivers will exhibit risk averse, risk neutral and risk prone behavior. They will make their route choice decision based on route disutility (which is an exponential function of route travel time) rather than the route travel time itself. In the morning commute, an average driver can be described as risk averse.
- Under certain assumptions, the exponential route disutility function corresponds to a certain ELD function. For the morning commute to work, an analyst can apply the SN-DUE model to solve the traffic assignment problem for risk averse drivers in a network with travel time uncertainty.

This section therefore focuses on how to apply the SN-DUE model in TransCAD. As reviewed in Chapter 2, the SN-DUE model can be implemented as a DN-DUE model by replacing the link performance function in the DN-DUE model (e.g., the BPR function) with the ELD function. The easily implementable ELD will be derived in Chapter 4 of this report.

In TransCAD, the modeling and implementation of the DN-DUE model is under Planning $\rightarrow$ Traffic Assignment in the main menu (Caliper, 2005b). The default link performance function provided by TransCAD is the BPR function. It turns out that the derived ELD function (to be presented in Chapter 4) is very similar to the BPR function. The analyst can manipulate the default TransCAD input value in Planning $\rightarrow$ Traffic Assignment to make the program perform traffic assignment using the ELD function. In another words, the analyst can play a trick by changing the input value of α in the BPR function from the standard value of 0.15 to a higher value to depict the risk averse route choice behavior.

3.1.2 Use of Hourly O-D Matrix

In transportation planning, the traffic demand in the current year or future years is normally expressed in the form of a daily 24-hour O-D matrix. That is, the planners have a good idea on how many trips will be made between an O-D pair in a day. However, they do not have a very precise idea of the distribution of these trips over all 24 hours.

The SN-DUE model proposed in this research is to model the traffic distribution during the morning peak hour, with risk averse behavior. Therefore, the analyst should use a O-D matrix that consists of trips made during the morning peak hour. In addition, the model should reflect driver response to traffic congestion and travel time uncertainty. The response is more drastic during the highest peak hour, when the traffic is most congested and travel time is most uncertain. This single-hour typically happens immediately before the average work-start time in the network. Therefore, the analyst should first determine the peak hour within the morning peak of the day, and construct the hourly O-D matrix from the 24-hour matrix. The unit measure of all the elements in the hourly O-D matrix is “vehicles per hour”.

To determine the highest peak hour within the morning peak in the current year, the analyst should collect traffic count data at representative locations in the network continuously for 24 hours. These representative locations may be the major freeways, critical intersections, etc. Count data are typically aggregated at 15-minute intervals. At each counting location, the average traffic count data for all the 15-minute intervals over the 24 hours are then plotted. The highest four consecutive 15-minute intervals are then designated as the peak hour. The analyst may repeat the plot for different locations. It is natural that data collected at different locations will indicate different peak hours. The analyst should then exercise his/her engineering judgment to decide the peak hour of interest. Instead of using a data aggregation interval of 15 minutes, some agencies use the data aggregation interval of one hour (e.g., 7:00 a.m. to 8:00 a.m., 8:00 a.m. to 9:00 a.m.).

Having decided the peak hour, the next step is to construct the so-called K-factor. It is assumed that, the peak hour O-D matrix can be obtained by multiplying the 24-hour O-D matrix by a factor known as the K-factor. This K-factor factor is the proportion of the peak hour traffic volume over the 24-hour volume. The K-factor is obtained by dividing the existing year's traffic volume counted at the representative locations during the identified peak hour, by the 24-hour total volume counted at the same locations.

The above procedure applies to the traffic counts and 24-hour O-D matrix in the existing year. The hourly O-D matrix for a future year may be obtained as follows:

- Estimate the future year's daily O-D matrix from the trip generation model.
- Apply the same K-factor obtained for the existing year. That is, assume that (1) the peak hour in the future year is the same as the peak hour as the existing year; and (2) the proportion of traffic during the peak hour over the 24-hour day remains unchanged over the years.
- Multiply the future year's 24-hour O-D matrix by the K-factor to obtain the future year's peak hour O-D matrix.

3.1.3 Use of Hourly Capacity

The O-D matrix used in traffic assignment is the hourly O-D matrix. Since the elements in the O-D matrix are "vehicles per hour". The link capacity must also be in units of vehicles per hour.

If the link capacities of the network are provided in vehicles per day, they must be changed to vehicles per hour. Unlike the O-D matrix, the capacity of a link remains constant throughout the day. However, converting a link capacity from daily capacity to hourly capacity is not as straight forward as dividing the former by a factor of 24. In fact, the daily link capacity may have been adjusted during the calibration process (of traffic assignment with 24-hour matrix to produce reasonable link volume).

Therefore, hourly link capacity is better estimated from the guidelines provided by the Highway Capacity Manual 2000 (TRB, 2000). The values may be adjusted based on the analyst's experience.

3.1.4 Link Performance Function

Having obtained the hourly O-D matrix, and hourly link capacity, traffic assignment for SN-DUE model can then be carried out.

The default Planning $\rightarrow$ Traffic Assignment function in TransCAD is used to execute the DUE algorithm, which in TransCAD is the Frank-Wolfe algorithm. The only important modification to the Planning $\rightarrow$ Traffic Assignment function is the input of a numerical value in the α field that describes the risk averse drivers. This will force the Frank-Wolfe algorithm to use the ELD function as a BPR function.

3.2 Traffic Assignment with Departure Time Choice

3.2.1 O-D Matrices for Different Time Intervals

The analysis described in the previous section was based on the simplified assumption that the analyst knows the O-D matrices for all time intervals. This assumption is reasonable when one is dealing with the existing traffic networks. Indeed, for these traffic networks, the analyst can experimentally determine, for every two zones and for every time interval, how many drivers from the first zone need to get to the second zone.

The main intent of the tools described in this report is to help in road planning, so that the agency is able to predict the traffic conditions under different scenarios. In each of these scenarios, it is assumed that

- that the new roads have been built;
- that the capacity of some of the existing roads has been increased, and at the same time;
- that the population has increased and therefore, the traffic demand has increased.

There exist tools and techniques for predicting population growth in different zones, and for describing how this population growth will affect the overall traffic demand. TxDOT have been using the resulting predictions of daily O-D matrices corresponding to different future times (such as the year 2030). To get a better understanding of the future traffic patterns, the analyst must be able to describe how this daily traffic is distributed over different time intervals, in particular, how much of this traffic occurs during the critical time intervals in the morning rush hour. In other words, it is necessary to "decompose" the daily O-D matrix into O-D matrices corresponding to different time intervals, e.g., 15 minute intervals.

3.2.2 Setting Up O-D Matrices

It is reasonable to assume that the future distribution of departure times will be approximately the same as at present. Under this assumption, the analyst can estimate the O-D matrix corresponding to a certain time interval by simply multiplying the (future) daily O-D matrix by the corresponding present day's K-factor – portion of traffic which occurs during this time interval. These K-factors can be determined by an empirical analysis of the current traffic: a K-factor corresponding to a certain time interval can be estimated as a ratio between

- the number of trips within this time interval, and

- the overall number of trips.

At present, the empirical values of the K-factor are only available for hourly intervals. If the analyst wants to find the K-factors corresponding to 15 minute intervals, it is reasonable to use linear interpolation. Let us illustrate linear interpolation on a simple example. Let us assume that we know K-factors corresponding to the hourly traffic, in particular, we know that:

- at 7:00 a.m., the K-factor is 0.06, meaning that at this moment of time, the traffic volume (in terms of vehicles per hour) is equal to 6.0% of the daily traffic volume (in terms of vehicles per day); and
- at 8:00 a.m., the K-factor is 0.08, meaning that at this moment of time, the traffic volume (in terms of vehicles per hour) is equal to 8.0% of the daily traffic volume (in terms of vehicles per day).

If for an O-D pair, the daily traffic volume is 1,000 vehicles per day, then:

- at 7:00 a.m., the traffic volume will be 0.06x1000 = 60 vehicles per hour, and
- at 8:00 a.m., the traffic volume will be 0.08x1000 = 80 vehicles per hour.

If we are interested in half-hour intervals, then we need to also estimate the traffic volume at 7:30 a.m. Linear interpolation means that as such an estimate, we use the value (0.06+0.08)/2 = 0.07. So, K-factors for the half-hour time intervals are:

- at 7:00 a.m., the K-factor is 0.06;
- at 7:30 a.m., the K-factor is 0.07;
- at 8:00 a.m., the K-factor is 0.08.

Similarly, to extrapolate into 15 minute intervals, we use (0.06 + 0.07)/2 = 0.065 for 7:15 a.m. and (0.07 + 0.08)/2 = 0.075 for 7:45 a.m. So, the K-factors for the 15 minute time intervals are:

- at 7:00 a.m., the K-factor is 0.06;
- at 7:15 a.m., the K-factor is 0.065;
- at 7:30 a.m., the K-factor is 0.07;
- at 7:45 a.m., the K-factor is 0.075;
- at 8:00 a.m., the K-factor is 0.08.

Once the K-factors for the time intervals have been estimated, they can be used as the multiplication factors into the daily O-D matrix to obtain the O-D matrix for the corresponding time intervals. Note that, after multiplying by the interpolated K-factors, the elements of new O-D matrices have a unit of vehicles per hour.

3.2.3 Justification for Considering Departure Time Choice

The previous section describes how to use the interpolated K-factors to divide the daily O-D matrices into O-D matrices for different time intervals. The resulting O-D matrices are, however, only a first approximation to the actual O-D matrices. A driver selects his or her departure time based on the time that the driver needs to reach the destination (e.g., the work-start time), and the expected travel time. For example, if the driver needs to be at work at 8:00 a.m., and the expected travel time to his or her destination is 30 minutes, then the driver leaves at 7:30 a.m.

Population changes and new roads will change the expected travel time. For example, if due to the increased population and the resulting increase road congestion the expected travel time increases to 45 minutes, then the same driver leaves at 7:15 a.m. instead of the previous departure time of 7:30 a.m. So, the trips in the corresponding entry in O-D matrix corresponding to 7:30 a.m. will decrease while a similar entry in the O-D matrix corresponding to 7:15 a.m. will increase.

Similarly, if a new freeway decreases the expected travel time to 15 minutes, then the driver will leave at 7:45 a.m. instead of the original 7:30 a.m. In this case, the corresponding entry in O-D matrix corresponding to 7:30 a.m. will decrease while a similar entry in the O-D matrix corresponding to 7:45 a.m. will increase.

In general, the change in a transport network and/or the change in travel time will change the departure time choice and thus, change the resulting O-D matrices. The following sub-section describes how one can take this departure time choice into consideration.

3.2.4 Logit Model for Departure Time Choice

As mentioned in Chapter 2, the most widely used model for describing the general choice (especially the choice in transportation-related situations) is the logit model. It is therefore reasonable to use this model to describe the driver's choice of departure time. In the logit model, the probability of departure in different time intervals is determined by the utility of different departure times to the driver. According to this model, the probability P_i that a driver will choose the *i*th time interval is proportional to $exp(u_i)$, where u_i is the expected utility of selecting this time interval. The coefficient at $exp(u_i)$ must be chosen from the requirement that the sum of these probabilities be equal to 1. So, the desired probability has the form

$$P_i = \frac{exp(u_i)}{\sum_{j=1}^{n} exp(u_j)} \tag{3.1}$$

To apply the logit model, we must be able to estimate the utilities of different departure time choices. As we have mentioned in Chapter 2, the utility u_i of choosing the *i*th time interval is determined by the following formula:

$$u_i = -0.1051E(T) - 0.0931E(SDE) - 0.1299E(SDL) - 1.3466P_L - 0.3463\frac{S}{E(T)} \qquad (3.2)$$

where $E(T)$ is the expected value of travel time T, $E(SDE)$ is the expected value of the "scheduled delay" (i.e., cost or penalty) when arriving early, $E(SDL)$ is the expected value of the scheduled delay when arriving late, P_L is the probability of arriving late, and S is the variance of the travel time. Note that T, $E(SDE)$, $E(SDL)$, P_L and S are calculated as if the driver departs in time interval i. If we denote departure time by t_d, and the desired arrival time (e.g., work-start time, for morning commute to work) by t_a, then we can express SDE as

$$SDE = max[t_a - (t_d + T),0] \qquad (3.3)$$

and SDL as

$$SDL = max[(t_d + T) - t_a,0] \qquad (3.4)$$

So, to estimate the values of the utilities u_i, one must first estimate the values of all these auxiliary characteristics.

3.2.5 Expected Travel Time, Scheduled Delays and Probability of Arriving Late

The first of these auxiliary values – the expected value $E(T)$ of the traffic time T – is the most straightforward to compute: we can find it by simply applying a standard traffic assignment procedure (e.g., the one implemented in TransCAD) to the original O-D matrices.

To estimate $E(SDE)$ and $E(SDL)$, in addition to the travel time, one must also know the departure time t_d and the desired arrival time t_a.

Let us start our analysis with the departure time t_d. For simplicity, for all the traffic originating during a certain time interval, as a departure time, we take the midpoint of the corresponding time interval. For example, for all the traffic originating between 7:00 a.m. and 7:15 a.m., we take t_d =7:07.5 a.m.

The analysis of the desired arrival time t_a is slightly more complicated. The desired arrival time depends on the time of the day. In the morning, the desired arrival time is the time when the drivers need to be at work or in school. During the evening rush hour, the desired arrival time is the time by which the drivers want to return home, etc. In terms of traffic congestion, the most crucial time period is the morning rush hour, when for most drivers, the desired arrival time is the work-start time. In view of this, in the following text, we will refer to all desired arrival times as work-start times.

The work-start time usually depends on the destination zone. For example, in El Paso, most zones have the same work-start time with the exception of a few zones such as:

- the Fort Bliss zones where the military workday starts earlier, and
- the university/college zone(s) where the school day usually starts somewhat later.

For every zone, we therefore usually know the (average) work-start time, i.e., the (average) desired arrival time for all the trips with the destination in this zone.

Of course, the actual work-start time for different drivers arriving in the zone may somewhat differ from the average work-start time for this zone. To take this difference into consideration, we assume that the distribution of the actual works-start time follows a bell-shaped distribution around the average. Considering the discrete time intervals, e.g., time moments separated by 15 minute time intervals, it makes sense to assume that:

- for the 40% of the drivers, the actual work-start time is the average for this zone,
- for 20%, the work-start time is one time interval (15 minute) later;
- for another 20%, the work-start time is one time interval (15 minutes) earlier,
- for 10%, it is two time intervals later, and
- for the remaining 10%, it is two time intervals earlier.

For example, if the average work-start time for a zone is 8:00 a.m., and the selected time interval is 15 minutes, then the assumed work-start times are as follows

- for 10% of the drivers, the work-start time is 7:30 a.m.;
- for 20% of the drivers, the work-start time is 7:45 a.m.;
- for 40% of the drivers, the work-start time is 8:00 a.m.;
- for 20% of the drivers, the work-start time is 8:15 a.m.; and, finally,
- for 10% of the drivers, the work-start time is 8:30 a.m..

For each of these five groups, the corresponding value of *SDE* can be estimated from

$$SDE(t_a) = max[t_a - (t_d + T), 0] \tag{3.5}$$

To get the desired value of *E(SDE)*, one need to combine the values $SDE(t_a)$ at the different t_a with the corresponding probabilities. For example, when the average work-start time is 8:00 a.m., the expected value of *SDE* is equal to

$$E(SDE) = 0.1*SDE(7{:}30) + 0.2*SDE(7{:}45) + 0.4*SDE(8{:}00) + 0.2*SDE(8{:}15) + 0.1*SDE(8{:}15) \tag{3.6}$$

Similarly, one can estimate the expected value *E(SDL)* of the delay *SDL*. By adding the probabilities corresponding to different work-start times, one can also estimate the probability P_L of being late.

3.2.6 Variance of the Travel Time

The previous sub-section describes how to estimate $E(T)$, $E(SDE)$, $E(SDL)$ and P_L. To compute the utility value u_i, we need one more characteristic: the variance S of the route travel time. Let us analyze how we can estimate the variance S.

In a deterministic network (DN), once we know the capacities of all the road links and the traffic demand (i.e., the values of the O-D matrix), we can apply a DUE algorithm to uniquely determine the route travel times for all O-D pairs. In practice, the travel time can change from day to day. Some changes in travel time are caused by incidents, weather, special events and etc. Since incidents are the major source of travel time delays, and in the absence of the other data, it is reasonable to estimate the variance S of the route travel time caused by the incidents.

For this analysis, the analyst needs to have records of incidents which occurred during a certain period of time (e.g., 90 days). The record of each incident typically includes the location and time of the incident, and the number of lanes in the corresponding link which was closed because of this incident. To estimate S corresponding to a certain time interval (e.g., from 8:00 a.m. to 8:15 a.m.), the analyst should only consider the incidents which occurred during this time interval. Based on the incident location, one can find the link on which this incident occurred. The incident decreases the capacity of this link. This decrease can be estimated based on the original number of lanes and on the number of lanes closed by this incident.

If all the lanes are closed by the incident, then the capacity of the link goes down to 0. A reader should be cautioned that TransCAD does not allow us to enter 0 value for link capacity. To overcome this problem, the capacity should be set to the smallest possible value (such as 1 vehicle per hour). For all practical purposes, this is equivalent to setting this capacity to 0.

Let us now provide heuristic arguments for estimating the decrease in capacity in situations in which some lanes remain open. Let us start with the simplest case of a 1-lane road. In reality, depending on the severity of an incident, the factor from 0 to 1 describing the decreased capacity can take all possible values from the interval [0,1]. The incident record only marks whether the incident actually led to the lane closure or not. In other words, instead of the actual value of the capacity-reduction factor, the record only shows, in effect, 0 or 1, with

- 0 corresponding to the closed lane, and
- 1 corresponding to the open lane.

In yet another terms, we approximate the actual value of the factor by 0 or 1. It is reasonable to assume that:

- factors 0.5 or higher get approximated by 1 (lane open), while
- factors below 0.5 are approximated by 0 (lane closed).

So, the incident records in which the lane remained open correspond to all possible values of the capacity-reduction factor from the interval [0.5,1]. As a reasonable average value of this factor for the case when the lane remained open, we can therefore take the midpoint of this interval, i.e., the value 0.75.

In multi-lane roads, an incident usually disrupts the traffic on all the lanes. It is therefore reasonable to assume that if no lanes were closed, then the capacity of each lane was decreased to 75% of its original value. Thus, for minor incidents in which no lanes were closed, we set the resulting capacity to 3/4 of the original capacity of the link.

For a 2-lane link, if one lane is closed and another lane remains open, then we have one lane with 0 capacity and one lane with 3/4 of the original capacity; the resulting capacity is 3/4 of the capacity of a single lane, i.e., 3/8 of the original capacity of the 2-lane road. Since this number comes from a heuristic estimate, the capacity reduction factor is only approximately equal to 3/8 = 0.375. Experts tend to estimate on a 7 plus/minus 2 scale. This means that in the interval [0,1], they usually distinguish at most 9 different values with a distance of approximately 10% between them. These values can represent the actual value with an accuracy of 5% or even less. Thus, the approximate value 0.375 can mean the actual value from 0.325 to 0.425. Since the number 0.375 is only approximate, we can simplify our computations if, instead of this rather complex number, we use the simplest fraction from this interval, i.e., 1/3.

For a 3-lane road, if one lane is closed this means that we retain only 2/3 of the incident-reduced 75% capacity, i.e., 1/2 of the original capacity. If two lanes are closed, this means that we retain only 1/3 of the reduced capacity, i.e., 1/4 of the original capacity.

Similar values can be estimated for 4-lane roads and, if necessary, for roads with a larger number of lanes.

Based on the above logic, the remaining link capacity due to incidents, expressed in the number of equivalent lanes, is listed in Table 3.1.

Table 3.1: Capacity of links affected by incidents

Remaining capacity (number of lanes)		Number of lanes closed by incident			
		1	2	3	4
No. of original lanes	1	0	-	-	-
	2	0.75	0	-	-
	3	1.50	0.75	0	-
	4	2.25	1.50	0.75	0

For each recorded incident occurring at a given time interval, we replace the original capacity in the incident-affected link by the correspondingly reduced value, and solve the traffic assignment problem. As a result, for each O-D pair, we get a new value of the O-D (or route) travel time. Using the output of the traffic assignment, the O-D travel times may be estimated by means of the “cost matrix” function in TransCAD.

Thus, for each O-D pair and for each time interval, for each day d during the period where incidents were observed D (e.g., 90 days), we have a value of the O-D travel time $t(d)$:

- if there was no incident during the time interval on this day, the value of the travel time comes from the original traffic assignment (without incident);
- for the days on which there was an incident during the given time interval, the travel time comes from the analysis of the network with the correspondingly reduced capacity.

Based on these $t(d)$ value, we compute the mean value E of the travel time as

$$E = \frac{1}{D}\sum_{d=1}^{D} t(d) \tag{3.7}$$

and then the variance S as

$$S = \frac{1}{D-1}\left[\sum_{d=1}^{D}\left(t(d)-E\right)^2\right] \tag{3.8}$$

3.2.7 Development of Algorithm: Idea and Its Limitations

In the two previous sections, we described how we can compute the characteristics which are needed to estimate the utility related to each departure time. Let us now assume that we know the original O-D matrices for each time interval i. For each time interval i, we can use the corresponding O-D matrix and solve the traffic assignment problem corresponding to this time interval. From the resulting traffic assignment, we can compute the values of the desired auxiliary characteristics $E(T)$, $E(SDE)$, $E(SDL)$, P_L and S and thus, estimate the expected utility u_i of departing at this time interval i. The logit formula enables us to compute the probability P_i that the driver will actually select departure time interval i.

The probability P_i means that out of N drivers who travel from the given origin zone to the given destination zone, $N \times P_i$ leave during the ith time interval. The rest of the $N \times (1 - P_i)$ drivers will change their departure time to leave in other intervals, with the corresponding probabilities given by the logit model. Similarly, some other drivers who have originally estimated to depart at other time intervals (they are counted in the original O-D matrices for other time intervals), may switch to the ith time interval. The updated number of drivers between an O-D pair who depart during the ith time interval can be computed by adding the summing the products of the corresponding values in the original O-D matrix and the corresponding probability, from all the time intervals.

These new O-D matrices take into account the departure time choice. However, they are not the ultimate O-D matrices. Indeed, since we have changed the O-D matrices, we thus changed the traffic assignments at different intervals of time; this will lead to different values of utilities u_i and probabilities P_i.

As an example, let us assume that there is an O-D pair for which the free-flow route travel time is 30 minutes. Let us also assume that for the corresponding destination, everyone needs to be at work at 8 a.m. Let us also assume that at present, there is not much traffic congestion between the origin and destination zones, so everyone leaves around 7:30 a.m. and gets to work on time. Since we are estimating the distribution of traffic flow over time intervals based on the existing traffic, we will thus conclude that

- in the O-D matrix corresponding to the time interval that include 7:30 a.m., we will have all the drivers, while
- in the O-D matrices corresponding to earlier or later time intervals, we will have no drivers at all.

Let us now apply these O-D matrices to traffic assignment. Due to this higher traffic volume along some links, the traffic time will drastically exceed 30 minutes, so all the drivers leaving at 7:30 a.m. will be, for example, 15 minutes late.

On the other hand, drivers who happen to leave at 7:15 a.m. encounter practically no traffic – because there was no one needing to drive at this time in the original O-D matrix, so their travel time is exactly 30 minutes, and they get to work by 7:45 a.m., which is 15 minutes early. As we have seen in the above empirical formula (and in full accordance with common sense), the penalty for being 15 minutes late is much higher than the penalty of being 15 minutes early. As a result, the utility corresponding to leaving at 7:15 a.m. is higher than the probability of leaving at 7:30 a.m. Hence, in accordance with the logit formula, the probability that a driver will select to leave at 7:15 a.m. is much higher than the probability that this driver will leave at 7:30 a.m.

So, in the new O-D matrices, most drivers will leave at 7:15 a.m., and the values corresponding to leaving at 7:30 a.m. will be much lower. If the drivers really follow the pattern corresponding to the new O-D matrix, then the traffic congestion corresponding to 7:30 a.m. will be much lighter than before, so the utility of leaving at 7:30 a.m. will become higher and thus, the probability of leaving at 7:30 a.m. will increase again. It is reasonable to expect that if we repeat this procedure several times, we will eventually reach the desired stable values of the O-D matrix.

Let us describe these ideas in precise term. In essence, we have described a procedure which transforms the original set of O-D matrices $\mathbf{M}$ into a new set of O-D matrices $F(\mathbf{M})$, a set which takes into account departure time choice based on the traffic assignments generated by the original O-D matrices. To completely take into account the departure time choice means to find the O-D matrices which already incorporate the departure time choice, i.e., the matrices *M* which do not change after this transformation: $F(\mathbf{M}) = \mathbf{M}$.

At first glance, it seems reasonable to find these "stable" O-D matrices $\mathbf{M}$ by using a reasonable iterative procedure:

- we start with the set of first-approximation O-D matrices $\mathbf{M}_1$ which are obtained by multiplying the new O-D daily matrix by the original K-factors;
- then, we apply the transformation F again and again: $\mathbf{M}_2 = F(\mathbf{M}_1)$, $\mathbf{M}_3 = F(\mathbf{M}_2)$, …, until the procedure converges, i.e., until the new set of matrices $\mathbf{M}_{i+1}$ becomes close to the previous set $\mathbf{M}_i$.

This procedure seems even more reasonable if we recall that a similar iterative procedure is successfully used in TransCAD to find the traffic assignment. However, we found out that this seemingly reasonable procedure often does not converge.

This lack of convergence can be illustrated on a "toy" example in which we have a single origin, single destination, and two possible departure times. Similarly to the above example, let us assume that the work starts at 8 a.m., that the free-flow traffic time is 30 minutes, and that we consider two possible departure times 7:30 a.m. and 7:15 a.m. Again, just like in the above example, we assume that the original O-D matrices are based on the existing low-congestion networks in which everyone leaves at 7:30 a.m. and nobody leaves at 7:15 a.m. In other words, we assume that the K-factor for 7:30 a.m. is 1, and the K-factor for 7:15 a.m. is 0. We also assume that there are high penalties for being late and for spending too much time in traffic.

In accordance with the above iterative procedure, we start with the O-D matrices $\mathbf{M}_1$ in which everyone leaves for work at 7:30 a.m., and nobody leaves for work at 7:15 a.m. The only difference with the current situation is that we are applying the same K-factors to the future, more heavy traffic.

- For those departing at 7:15 a.m., there is no traffic, so the travel time is equal to the free-flow travel time of 30 minutes.
- The drivers departing at 7:30 a.m. face a much heavier traffic, so we get a traffic congestion. As a result of this congestion, the travel time increases to 45 minutes.

So,

- drivers who leave at 7:15 a.m. spend only 30 minutes in traffic and arrive 15 minutes early, while
- drivers who leave at 7:30 a.m. spend 45 minutes on the road and are 15 minutes late.

Since we assumed that the penalties for being late are heavy, the expected utility of leaving at 7:15 a.m. is much higher than the expected utility of leaving at 7:30 a.m.. Thus, the probability of leaving at 7:15 a.m. is overwhelmingly higher than the probability of leaving at 7:30 a.m.. As a result, we arrive at the new O-D matrices $\mathbf{M}_2 = F(\mathbf{M}_1)$ in which almost everyone leaves at 7:15 a.m. and practically no one leaves at 7:30 a.m..

For these new O-D matrices $\mathbf{M}_2$:

- for those departing at 7:30 a.m., there is no traffic, so the travel time is equal to the free-flow time of 30 minutes;
- the drivers departing at 7:15 a.m. face a much heavier traffic, so we get a traffic congestion; as a result of this congestion, the travel time increases to 45 minutes.

So,

- drivers who leave at 7:30 a.m. spend only 30 minutes in traffic and arrive on time, while
- drivers who leave at 7:15 a.m. spend 45 minutes on the road.

Since we assumed that the penalties for spending extra time on the road are heavy, the expected utility of leaving at 7:30 a.m. is much higher than the expected utility of leaving at 7:15 a.m.. Thus, the probability of leaving at 7:30 a.m. is overwhelmingly higher than the probability of leaving at 7:15 a.m. As a result, we arrive at the new O-D matrices $\mathbf{M}_3 = F(\mathbf{M}_2)$ in which almost everyone leaves at 7:30 a.m. and practically no one leaves at 7:15 a.m..

In other words, we are back to the original O-D matrices $\mathbf{M}_3 \approx \mathbf{M}_1$. These "flip-flop" changes continue without any convergence. How can we modify the above idea so as to enhance convergence? This leads us to propose the method discussed in the following sub-section.

3.2.8 Development of Algorithm: A More Realistic Approach

We started with the O-D matrices $\mathbf{M}_1$ which describe the existing traffic behavior. We want to predict how a change in traffic volume and in road network will affect the driver's behavior. To do that, let us analyze

- how the actual drivers change their behavior if the road congestion and road conditions change, and
- how we can simulate this behavior in a computer model so as to predict these changes.

At first, the drivers simply try to follow the same traffic patterns as before, i.e., depart at the same times as before. In terms of the computer representation of the drivers' behavior, this means that the proportion of the drivers departing at different time intervals remains the same as in the original traffic. In other words, this behavior corresponds to what we described as the first approximation $\mathbf{M}_1$ – when we take the new daily O-D matrix and multiply it by the K-factors corresponding to the original traffic.

As we have mentioned, due to the change in traffic volume and in road capacity, this first-approximation behavior may lead to congestion and delays. When drivers realize this, they will change their departure time so as to avoid these new delays. The drivers will use the traffic patterns and delays caused by $\mathbf{M}_1$ to decide on the new departure times. The resulting change in the O-D matrix is what we described in the previous section as a transformation *F*. In other words, the resulting O-D matrix is $\mathbf{M}_2 = F(\mathbf{M}_1)$.

The change of departure times, as reflected by the move from the original O-D matrices $\mathbf{M}_1$ to the new O-D matrices $\mathbf{M}_2$, will again change the traffic patterns and delay times, so again, there will be a need to change the departure times based on the new traffic delays.

In these terms, the above iterative process $\mathbf{M}_{i+1} = F(\mathbf{M}_i)$ corresponds to the situation when the drivers only use the experience of their most recent traffic behavior and ignore the rest of the traffic history. Let us illustrate this idea on the above "toy" example.

In this example, the drivers used to go to work at 7:30 a.m. For the original traffic volume, this was a reasonable departure time because it allowed them to be at work exactly at the desired time 8:00 a.m., and to spend as little time on the road as possible – exactly 30 minutes, the free-flow traffic time.

When the traffic volume increases, in Day 1 of this new arrangement, the drivers follow the same departure time as before, i.e., they all leave for work at 7:30 a.m. Since the traffic volume has increased, this departure time no longer leads to the desired results – most of the drivers are 15 minutes late for work.

Since in the first day, most drivers were 15 minutes late, on the second day they leave 15 minutes earlier, at 7:15 a.m., so as to be at work on time. They do reach work on time, but at the expense of driving 15 minutes longer than they used to. A few drivers, however, still leave at 7:30 a.m.. To their pleasant surprise, they experience a smooth and fast ride and arrive at work exactly on time.

The other drivers learn about the negative experience of those who left at 7:15 a.m. and of the positive experience of those who left at 7:30 a.m. In our iterative model, we assume that when the drivers decide on departure time at Day 3, they only take into account delays on the previous Day 2. Under this assumption, to select the departure time on Day 3, the drivers only use the Day 2 experience. On Day 2, departing at 7:30 a.m. certainly led to much better results that leaving for work at 7:15 a.m. So, under this assumption, on Day 3, most drivers will switch to 7:30 a.m. departure time. As a result, most of them will be again 15 minutes late for work, with the exception of those who left home earlier, at 7:15 a.m. Since on Day 3, leaving at 7:15 a.m. was clearly much preferable than leaving for work at 7:30 a.m., on the next Day 4, most drivers will again leave at 7:15 a.m., etc.

In this analysis, we get the same non-converging fluctuations as we had in the previous section, but this time, we understand the reason for these fluctuations: the fluctuations are caused by the simplified assumption that the drivers' behavior is determined only by the most recent experience.

In reality, when the drivers choose departure times, they take into account not only the traffic congestion on the day before, but also traffic congestion on several previous days. It is reasonable to assume that all these previous days are weighted equally. Let us describe this assumption in precise terms. We start with the set $\mathbf{M}_1$ of O-D matrices which describe the number of drivers leaving at different time intervals on Day 1, when the drivers follow their original departure times. Similarly, let us denote the set of O-D matrices describing the drivers on Day *i* by $\mathbf{M}_i$.

Suppose that we already know the O-D matrices $\mathbf{M}_1$, $\mathbf{M}_2$,…, $\mathbf{M}_i$ which describe the number of drivers leaving at different time intervals at days 1, …, *i*. Since the drivers weigh all these previous days equally, they estimate the expected traffic $\mathbf{E}_i$ as the average of the previous traffics:

$$\mathbf{E}_i = \frac{1}{i}\left[\mathbf{M}_1 + \mathbf{M}_2 + ... + \mathbf{M}_i\right] \qquad (3.9)$$

The drivers use this expected traffic $\mathbf{E}_i$ to make their departure time choices. We have already described the corresponding procedure, and we have denoted the resulting transformation of O-D matrices by *F*. So, we can conclude that the O-D matrices $\mathbf{M}_{i+1}$ corresponding to the new departure times have the form $\mathbf{M}_{i+1} = F(\mathbf{E}_i)$.

Thus, we arrive at a new iterative procedure that takes into account departure time choice when making traffic assignments. This procedure has the following steps,

- Start with the O-D matrices $\mathbf{M}_1$ which describe the original departure times; these O-D matrices can be obtained by multiplying the daily O-D matrix by the the K-factors;
- For *i* = 2, 3, …, repeat the following steps:
    - Compute $\mathbf{E}_i$ according to Equation (3.9); and then
    - Compute $\mathbf{M}_{i+1} = F(\mathbf{E}_i)$
- After the iterations have stopped, use the resulting set of O-D matrices to describe the resulting traffic assignments.

Our experiments on the “toy” road network and on the actual El Paso road network confirmed that this procedure converges. An important question is when to stop the iterations. More iterations lead the solution closer to the desired “equilibrium” traffic assignment. However, each iteration requires a reasonably large amount of computation time on TransCAD, so it is desirable to limit the number of iterations.

To find a reasonable stopping criterion, let us recall that the main objective of our traffic assignment task is to evaluate the network performance with the future year traffic in order for planners to make decisions on road projects. Thus, the objective is to deal with the O-D matrices which describe future drivers’ behavior. The only way to get such future matrices is by prediction. At best, we can predict the accuracy of the future traffic with the accuracy of 10-15%. Thus, it makes sense to stop iterations when we have already achieved this same order of accuracy, i.e., when the difference between the O-D matrices $\mathbf{E}_i$ (based on which we make the plans at moment $i+1$) and the resulting matrices $\mathbf{M}_{i+1}$ is smaller than (or equal to) 10-15% of the size of the matrix entries themselves.

As a measure of the difference between the matrices $\mathbf{E}_i$ and $\mathbf{M}_{i+1}$, it is reasonable to take the root mean square difference, i.e., the value $\delta(\mathbf{E}_i, \mathbf{M}_{i+1})$ determined by the formula

$$\delta(\mathbf{E}_i, \mathbf{M}_{i+1}) = \frac{1}{TZ^2} \sum_{t=1}^{T} \sum_{o=1}^{Z} \sum_{d=1}^{Z} \left(e_{od}^t - m_{od}^t\right)^2 \tag{3.10}$$

where T is the number of time intervals, Z is the number of zones in the network; t, o and d denote the indices for time interval, origin (row) and destination (column) of the O-D matrices respectively; e_{od}^t and m_{od}^t are the elements in the $\mathbf{E}_i$ and $\mathbf{M}_{i+1}$ matrices respectively. Similarly, as a measure of the size of a set $\mathbf{E}_i$ of matrices, it is reasonable to take its root mean square value, i.e., the value $rms(\mathbf{E}_i)$ determined by the formula

$$rms(\mathbf{E}_i) = \sqrt{\frac{1}{TZ^2} \left[\sum_{t=1}^{T} \sum_{o=1}^{Z} \sum_{d=1}^{Z} \left(e_{od}^t\right)^2 \right]} \tag{3.11}$$

To speed up computations, we only compute the sizes $rms(\mathbf{M}_1)$ and $rms(\mathbf{M}_2)$ for the first two iterations, and use the largest of the two resulting sizes as an estimate for the size in general. In other words, we stop the traffic assignment and departure time choice adjustments when

$$\delta(\mathbf{E}_i, \mathbf{M}_{i+1}) \le max\{rms(\mathbf{M}_1), rms(\mathbf{M}_2)\} \tag{3.12}$$

3.2.9 Development of Algorithm: Resulting Algorithm and Final Remarks

In this section, we have described the algorithm for taking into account departure time choice when making traffic assignments. The advantage of this algorithm is that it converges. However, from the computational viewpoint, this algorithm has a limitation. To implement the above algorithm, we must store the sets of O-D matrices $\mathbf{M}_1$, $\mathbf{M}_2, \ldots, \mathbf{M}_i$ corresponding to different iterations. For a large city-wide road network, we need to store information about many O-D pairs at several different time intervals. For example, the standard El Paso network has 681 zones, so we need to store the information about each of the 681x681 O-D pairs at each of, say, 12 15-minute time intervals, and we must store as many different pieces of this information as there are iterations. Storing, accessing, and processing all this information requires a large amount of computation time.

It is therefore desirable to reformulate the above algorithm in such a way as to avoid this excessive storage. We will show that such a simplification is indeed possible. The idea for this simplification comes from the fact that once we know the previous average value

$$\mathbf{E}_i = \frac{1}{i}\left[\mathbf{M}_1 + \mathbf{M}_2 + \ldots + \mathbf{M}_i\right] \tag{3.13}$$

And we have computed the new matrices $\mathbf{M}_{i+1} = F(\mathbf{E}_i)$, we do not need to repeat all the additions to compute the new average:

$$\mathbf{E}_{i+1} = \frac{1}{i+1}\left[\mathbf{M}_1 + \mathbf{M}_2 + \ldots + \mathbf{M}_i + \mathbf{M}_{i+1}\right] \tag{3.14}$$

Indeed, the expression for $\mathbf{E}_{i+1}$ can be reformulated as follows:

$$\mathbf{E}_{i+1} = \frac{1}{i+1}\left[i\mathbf{E}_i + \mathbf{M}_{i+1}\right] = \frac{1}{i+1}\left[i\mathbf{E}_i + F(\mathbf{E}_i)\right] \tag{3.15}$$

Taking into account that $\mathbf{E}_1 = \mathbf{M}_1$, we arrive at the following algorithm:

- we start with the O-D matrix $\mathbf{E}_1$ which describes the original departure times; this O-D matrix can be obtained if we multiply the original daily O-D matrix by the K-factor;
- Compute $rms(\mathbf{E}_1)$
- Repeat for i = 2, 3, …,
  - Compute $F(\mathbf{E}_i)$
  - Compute $\mathbf{E}_{i+1} = \frac{1}{i+1}\left[i\mathbf{E}_i + F(\mathbf{E}_i)\right]$
- Stop when $\delta(\mathbf{E}_i, F(\mathbf{E}_i)) \le max\{rms(\mathbf{E}_1), rms(\mathbf{E}_2)\}$
- Use the resulting set of O-D matrices $\mathbf{E}_i$ to represent the traffic demand and the resulting traffic assignment to describe the predicted traffic conditions.

CHAPTER 4

DEVELOPMENT OF ROUTE CHOICE MODELS

As reviewed in Chapter 2 (Section 2.3.1), the route choice behavior of drivers in a SN may be classified as risk averse, risk prone or risk neutral, each with a respective form of route disutility functions. For risk averse and risk prone drivers, the route disutility functions are exponential functions of the route travel time. For risk neutral drivers, the route disutility is a linear function of the average route travel time. For each route disutility function, there is a corresponding form of equivalent link disutility (ELD) function. This Chapter presents the derivation of the ELD functions for the risk neutral and risk averse route choice behavior. It also discusses the advantages of the ELD functions derived in this research over those reviewed in Section 2.3.1. This Chapter also demonstrates a method to estimate the coefficient of the derived ELD function for risk averse drivers based on the survey data gathered in El Paso, TX.

4.1 Risk Averse Behavior

4.1.1 Desirability of Using Equivalent Link Disutility Functions

According to the SN-DUE model, a driver selects a route with the minimum value of the expected disutility $E[DU_r]$. If we "rescale" the disutility function, i.e., consider an auxiliary function $A_r = g(E[DU_r])$ for some monotonically increasing function $g(x)$, then minimizing $E[DU_r]$ is equivalent to minimizing A_r. We will use this property to simplify the decision making in the SN-DUE model.

In particular, for risk averse drivers, following Equation (2.3), we have $E[DU_r] = b_1(A_r - 1)$, where

$$A_r = E[exp(\omega t_r)] \tag{4.1}$$

Therefore, $A_r = g(E[DU_r])$ for $g(x) = (x/b_1)+1$. Since b_1 >0, the function $g(x)$ is monotonically increasing and therefore, minimizing $E[DU_r]$ is equivalent to minimizing A_r .

The route travel time t_r is composed of link travel times t_i: $t_r = \sum_{i=1}^{L} t_i$. In a SN, link travel times (t_i) are considered to be independent random variables. Thus, the auxiliary expression $A_r = E[exp(\omega t_r)]$ can be expressed as

$$A_r = E[exp(\omega t_r)] = E[exp(\omega(t_1 + t_2 + ... + t_L))] = E[exp(\omega t_1)exp(\omega t_2)...exp(\omega t_L)]$$

$$= E[exp(\omega t_1)] \cdot E[exp(\omega t_2)] \cdot ... \cdot E[exp(\omega t_L)] \quad (4.2)$$

Drivers will select the route that minimizes $E[DU_r]$; this is equivalent to minimizing A_r. Since $ln(x)$ is a monotonically increasing function, this choice is, in its turn, equivalent to selecting the route that minimizes $ln(A_r)$. Here

$$ln(A_r) = ln\{E[exp(\omega t_1)]\} + ln\{E[exp(\omega t_2)]\} + ... + ln\{E[exp(\omega t_L)]\} \quad (4.3)$$

Let us perform one more rescaling, to make this expression similar to that of the DN. A DN can be viewed as a particular case of a SN, in which all travel times t_i and t_r are deterministic. In a DN, the above expression reduces to

$$ln(A_r) = ln[exp(\omega t_1)] + ln[exp(\omega t_2)] + ... + ln[exp(\omega t_L)] = \omega(t_1 + t_2 + ... + t_L) = \omega t_r \quad (4.4)$$

In a DN, we select a route with the smallest route travel time t_r. For convenience, let us rescale the objective function $ln(A_r)$ one more time so that for DN, the rescaled objective function will coincide with t_r. Specifically, we consider $du_r = \frac{1}{\omega} ln(A_r)$ instead of $ln(A_r)$, both for the DN and for the SN. In this case, for the DN we have $du_r = t_r$.

In the general SN case, since $g(x) = \frac{x}{\omega}$ is a monotonically increasing function, selecting a route based on du_r is equivalent to selecting a route based on $ln(A_r)$, and thus equivalent to selecting a route based on $E[DU_r]$. From Equation (4.3), we conclude that the new objective function du_r can be expressed as $du_r = DU_1 + ... + DU_L$, where $DU_i = \frac{1}{\omega} ln\{E[exp(\omega t_i)]\}$. Thus, the drivers preference in SN-DUE is equivalent to selecting a route with the smallest value of the sum $du_r = \sum_{i \in r} DU_i$. So we get the desired equivalence with the ELD function $DU_i = \frac{1}{\omega} ln\{E[exp(\omega t_i)]\}$. Therefore, selecting a route in a SN is very similar to selecting a route in a DN, but with link disutility $DU_i = \frac{1}{\omega} ln\{E[exp(\omega t_i)]\}$ instead of link travel time.

4.1.2 Equivalent Link Disutility Functions

Let us reformulate this expression for DU_i in terms of mean and variance of t_i. In a SN the actual travel time t_i in link *i* can be expressed as the sum of the mean travel time $\bar{t}_i$ and the deviation from its mean:

$$t_i = \bar{t}_i + \left(t_i - \bar{t}_i\right) \tag{4.5}$$

It follows that

$$exp\left(\omega t_i\right) = exp\left(\omega \bar{t}_i\right) exp\left(\omega\left(t_i - \bar{t}_i\right)\right) \tag{4.6}$$

Hence

$$E\left[exp\left(\omega t_i\right)\right] = exp\left(\omega \bar{t}_i\right) E\left[exp\left(\omega\left(t_i - \bar{t}_i\right)\right)\right] \tag{4.7}$$

Usually $\omega\left(t_i - \bar{t}_i\right)$ is small, so we can expand the exponential function into the Taylor series and only keep the first three terms in this expansion

$$exp\left(\omega\left(t_i - \bar{t}_i\right)\right) = 1 + \omega\left(t_i - \bar{t}_i\right) + \frac{\omega^2\left(t_i - \bar{t}_i\right)^2}{2} + \ldots \tag{4.8}$$

Therefore

$$E\left[exp\left(\omega\left(t_i - \bar{t}_i\right)\right)\right] \approx 1 + \omega E\left[t_i - \bar{t}_i\right] + \frac{\omega^2}{2} E\left[\left(t_i - \bar{t}_i\right)^2\right] \tag{4.9}$$

By definition, $E\left[t_i - \bar{t}_i\right]=0$ and $E\left[\left(t_i - \bar{t}_i\right)^2\right] = \sigma_{t_i}^2$ which is the variance of t_i. Substituting Equation (4.9) into Equation (4.7), we obtain

$$E\left[exp\left(\omega t_i\right)\right] = exp\left(\omega \bar{t}_i\right)\left[1 + \frac{\omega^2}{2}\sigma_{t_i}^2\right] \tag{4.10}$$

The link disutility function thus becomes

$$\begin{aligned} DU_i &= \frac{1}{\omega} ln\left\{E\left[exp\left(\omega t_i\right)\right]\right\} = \frac{1}{\omega} ln\left\{exp\left(\omega \bar{t}_i\right)\left[1 + \frac{\omega^2}{2}\sigma_{t_i}^2\right]\right\} \\ &= \bar{t}_i + \frac{1}{\omega} ln\left[1 + \frac{\omega^2}{2}\sigma_{t_i}^2\right] \end{aligned} \tag{4.11}$$

Using the Taylor series expansion of $ln\left(1+z\right) = z + \ldots$ we obtain

$$DU_i \approx \bar{t}_i + \frac{\omega}{2}\sigma_{t_i}^2 \tag{4.12}$$

We have shown that, if the all drivers in a network follow the same risk averse behavior, solving for DUE in a SN is similar to solving for DUE in a DN, except that we replace t_i in a

DN with DU_i in a SN. Note that the first term $\bar{t}_i$ in DU_i is the same as Equation (2.1), the BPR function. Thus, it can be said that, in a SN with risk averse behavior, the additional term in the route choice decision for drivers is the link travel time variance, scaled by a factor $\omega/2$. The magnitude of ω reflects the sensitivity of the drivers in avoiding the risk. Risk averse drivers will avoid links that have high $\sigma_{t_i}^2$. Note that, if σ_{t_i} =0, the SN-DUE model is reduced to a DN-DUE model.

4.2 Risk Prone Behavior

4.2.1 Desirability of Using Equivalent Link Disutility Functions

According to the SN-DUE model, a driver selects a route with the smallest possible value of the expected disutility $E[DU_r]$

$$E[DU_{r'}] = \min_{r \in R} \{E[DU_r]\} \tag{4.13}$$

For risk prone drivers, according to Equation (2.3), $E[DU_r] = b_2(1 - B_r)$ where

$$B_r = E[exp(-\varphi t_r)] \tag{4.14}$$

Thus, minimizing $E[DU_r]$ is equivalent to maximizing B_r. Since the link travel times t_i are independent random variables, we conclude that for a route consisting of L links, we have

$$B_r = E[exp(-\varphi t_r)] = E[exp(-\varphi t_1)] \cdot E[exp(-\varphi t_2)] \cdot \ldots \cdot E[exp(-\varphi t_L)] \tag{4.15}$$

Selecting a route according to Equation (4.12) is equivalent to selecting a route that maximizes B_r. This choice, in its turn, is equivalent to selecting the route that minimizes $du_r = -\frac{1}{\varphi} ln(B_r)$. Here

$$du_r = -\frac{1}{\varphi} ln\{E[exp(-\varphi t_1)]\} - \frac{1}{\varphi} ln\{E[exp(-\varphi t_2)]\} - \ldots - \frac{1}{\phi} ln\{E[exp(-\varphi t_L)]\} \tag{4.16}$$

Thus, for risk prone behavior, the drivers preference in SN-DUE is equivalent to selecting a route with the smallest value of the sum $du_r = \sum_{i \in r} DU_i$. So we get the desired equivalence with the equivalent link disutility function $DU_i = -\frac{1}{\varphi} ln\{E[exp(-\varphi t_i)]\}$. Therefore, selecting a route in a SN is very similar to selecting a route in a DN, but with link disutility $DU_i = -\frac{1}{\varphi} ln\{E[exp(-\varphi t_i)]\}$ instead of link travel time.

4.2.2 Equivalent Link Disutility Functions

Let us reformulate this expression for DU_i in terms of mean and variance of t_i. By following the same procedure as in the risk averse case, we can show that

$$-\frac{1}{\varphi}ln\{E[exp(-\varphi t_i)]\} = -\frac{1}{\varphi}ln\left\{exp(-\varphi\bar{t}_i)\left[1+\frac{\varphi^2}{2}\sigma_{t_i}^2\right]\right\} = \bar{t}_i - \frac{1}{\varphi}ln\left[1+\frac{\varphi^2}{2}\sigma_{t_i}^2\right] \tag{4.17}$$

Therefore, we can write

$$DU_i = \bar{t}_i - \frac{1}{\varphi}ln\left[1+\frac{\varphi^2}{2}\sigma_{t_i}^2\right] \tag{4.18}$$

Using the Taylor series expansion for $ln(1+x)$, we obtain

$$DU_i \approx \bar{t}_i - \frac{\varphi}{2}\sigma_{t_i}^2 \tag{4.19}$$

Equation (4.19) may be interpreted as follows. A risk prone driver will consider the average link travel times $(\bar{t}_i)$ as well as the variance of link travel times $(\sigma_{t_i}^2)$ in his/her route choice decision. If there are choices of two links with the same average travel time, a risk prone driver prefers the link with the higher variance. The higher the variance, the more favorable the link is to the risk prone driver. Therefore, the link disutility function has the link variance term, weighted by $(-\varphi/2)$.

4.3 Desired Properties of Equivalent Link Disutility Functions

A route *r* is made up of a series of *L* connected links *i=1,…,L*. We have already shown that we can assign, to every link *i*, a value DU_i in such a way that the drivers preference is equivalent to selecting a route with the smallest value of the sum $du_r = \sum_{i=1}^{L} DU_i$. In other words, the equivalent link disutility function satisfies the property

(P1) *It must be mathematically consistent with the route disutility function, in the sense that it leads to the same routing decision (it may however have a different form than the route disutility function).*

Property P1 ensures that the equivalent link disutility function describes the same route choice behavior as the original route disutility function.

It is also desirable that the equivalent link disutility function satisfies the following properties:

(P2) *If we sub-divide a link into a series of shorter links, the equivalent disutility of the original link must be equal to the sum of the equivalent disutilities of the shorter links*.

(P3) *The equivalent link disutility function must be a monotonically increasing and continuously differentiable function of link volume*.

Property P2 ensures that drivers' route choice and network flow remain the same irrespective of the resolution of network representation. Property P3 ensures that the equivalent link disutility function is consistent with common sense: the higher the link volume, the less preferable it is to the drivers, and small changes in the link volume lead to small changes in the driver's preference.

The consistency in UE flow patterns irrespective of the resolution in network representation is important in many practical applications. Many transportation planning models divide the geographical area to be analyzed into zones, depending on the land-use patterns. The zones in the geographical border (or buffer zones) are usually larger than the zones in the central business district. Naturally, the modeling details are often sized according to the zone dimension. Zones covering larger areas are likely to have longer links. On the other hand, smaller zones are likely to have shorter links and higher node density. Many traffic assignment algorithms use the geographical and topological information of the nodes and links converted from a GIS database. To be geographically correct in representing a curved road segment which has a uniform geometry, intermediate nodes are inserted between the two ends of the segment so that it can be represented by a series of piecewise linear links. If the additive property of the link disutility is not preserved, such division of a link into a series of smaller links may produce different UE flow patterns after traffic assignment.

A consistent equivalent link disutility function can be placed instead of the deterministic link travel time function in the existing traffic assignment models (such as TransCAD (Caliper, 2005b)) and thus enable us to use these models for SN-DUE applications.

We first use a commonly used deterministic link travel time function to illustrate the concepts of P2 and P3. As we have mentioned, the most popular deterministic link travel time function used by transportation modelers is the BPR function in Equation (2.1). The t_i^f is computed by dividing l_i, the length of link *i*, by u_i^f, the free-flow speed of link *i*. For a route *r* which is made up a series of *L* links $(i = 1,...,L)$, the route travel time is $t_r = \sum_{i=1}^{L} t_i$. In short, the route travel time is the arithmetic sum of the link travel times, with the latter represented by the BPR function.

Since α >0 and β >0, t_i is a monotonically increasing and continuously differentiable function of v_i, i.e., the BPR function satisfies P3.

We now illustrate the concept of P2. Suppose that we now divide link *i* into *n* consecutive sub-links $\{i_1, i_2, ..., i_n\}$, with lengths $\{l_{i_i}, l_{i_2,...}, l_{i_n}\}$. Then, the volume, capacity, and free-flow speed of the sub-links are same as that of link *i*, i.e., $v_{i_1} = v_{i_2} = ... = v_{i_n} = v_i$, $c_{i_1} = c_{i_2} = ... = c_{i_n} = c_i$, and $u^f_{i_1} = u^f_{i_2} = ... = u^f_{i_n} = u^f_i$. The free-flow travel times of the sub-links are thus $\{t^f_{i_1}, t^f_{i_2}, ..., t^f_{i_n}\} = \left\{\frac{l_{i_1}}{u^f_i}, \frac{l_{i_2}}{u^f_i}, ..., \frac{l_{i_n}}{u^f_i}\right\}$. The travel time in link *i*, computed from the sum of the travel times in its sub-links, is

$$t_{i_1} + t_{i_2} + ... + t_{i_n} = t^f_{i_i}\left[1+\alpha\left(\frac{v_i}{c_i}\right)^\beta\right] + ... + t^f_{i_n}\left[1+\alpha\left(\frac{v_i}{c_i}\right)^\beta\right] = \left(t^f_{i_1} + ... + t^f_{i_n}\right)\left[1+\alpha\left(\frac{v_i}{c_i}\right)^\beta\right]$$

$$= \left(\frac{l_{i_1} + ... + l_{i_n}}{u^f_i}\right)\left[1+\alpha\left(\frac{v_i}{c_i}\right)^\beta\right] = \left(\frac{l_i}{u^f_i}\right)\left[1+\alpha\left(\frac{v_i}{c_i}\right)^\beta\right] = t^f_i\left[1+\alpha\left(\frac{v_i}{c_i}\right)^\beta\right] = t_i \qquad (4.20)$$

Therefore, if we divide an original link into shorter links and compute the travel times of the shorter links, then the sum of the travel times on the shorter links is the same as the original link travel time. Thus, by using the BPR function, the additive property of the link travel time is preserved, and the BPR function satisfies property P3.

4.4 Simpler Equivalent Link Disutility Functions

4.4.1 General Expression for Risk Averse, Risk Prone and Risk Neutral Behavior

Let us use the property P2 to derive expression for the equivalent link disutility functions in terms of link volume and link capacity. In a SN, t_i, the travel time in link *i*, is a random variable. For this random variable t_i, the average travel time $\bar{t}_i$ can be estimated by the BPR function:

$$\bar{t}_i = t^f_i\left[1+\alpha\left(\frac{v_i}{c_i}\right)^\beta\right] \qquad (4.21)$$

Note that, according to this formula, when v_i =0, we have $\bar{t}_i = t_i^f$. Moreover, in the absence of traffic flow, i.e., when v_i =0, the link travel time t_i should be equal to t_i^f (with probability=1.0). Other than these restrictions on the average and on the free-flow travel time, we are not making any other explicit assumptions about the distribution of t_i ; in this sense, the conclusions of this section are distribution-free.

It is natural to assume that, DU_i , the equivalent disutility of link *i* should depend on the free-flow travel time t_i^f and the relative average delay $d = \left(\bar{t}_i - t_i^f\right)/t_i^f$, i.e.,

$$DU_i = F\left(t_i^f, d\right) \tag{4.22}$$

where

$$d = \frac{\bar{t}_i - t_i^f}{t_i^f} = \alpha\left(\frac{v_i}{c_i}\right)^\beta \tag{4.23}$$

for some function $F\left(t_i^f, d\right)$. So, to describe an equivalent link disutility function, we must find the appropriate function $F\left(t_i^f, d\right)$.

One would expect a link which has a longer uncongested travel time to have a higher equivalent disutility; so, $F\left(t_i^f, d\right)$ must be an increasing function of t_i^f . One would also expect that as the link becomes more congested, the equivalent disutility would increase; so, $F\left(t_i^f, d\right)$ must also be an increasing function of *d*. In addition, the function $F\left(t_i^f, d\right)$ must satisfies the following conditions:

(i) In the deterministic case, we want our equivalent link disutility function to reduce to the standard link travel time function. We have already mentioned that when $v_i = 0$, then the travel time is deterministically determined $t_i = \bar{t}_i = t_i^f$, therefore

$$F\left(t_i^f, 0\right) = t_i^f \tag{4.24}$$

(ii) We would like the equivalent link disutility function to satisfy the property P2: If we sub-divide a link into a series of shorter links, the equivalent disutility of the original link must be equal to the sum of the equivalent disutilities of the shorter links. If we sub-divide a link into two sub-links with free-flow travel times $t_{i_1}^f$ and $t_{i_2}^f$ respectively, then $v_{i_1} = v_{i_2} = v_i$, and $c_{i_1} = c_{i_2} = c_i$; so by Equation (4.22), the relative average delay *d* for both sub-links is the same as for the original link. Thus the desired property P2 takes the following form

$$F\left(t_{i_i}^f + t_{i_2}^f, d\right) = F\left(t_{i_1}^f, d\right) + F\left(t_{i_2}^f, d\right) \tag{4.25}$$

Let us describe all the functions $F\left(t_i^f, d\right)$ which satisfy these conditions. First we analyze Equation (4.25). We fix a value d and introduce an auxiliary function $G(a) = F(a, d)$. In terms of this new function, Equation (4.25) takes the form

$$G(a+b) = G(a) + G(b) \tag{4.26}$$

We also know that $F\left(t_i^f, d\right)$ is an increasing function of t_i^f and therefore, $G(a)$ is an increasing function of *a*. It is known (Aczel, 2006) that every monotonically increasing function $G(a)$ which satisfies Equation (4.25) has the form $G(a) = k \cdot a$ for some *k*>0. For different *d*, the coefficient *k* may in general be different: $k = k(d)$. Thus we conclude that

$$DU_i = F\left(t_i^f, d\right) = t_i^f k(d) \tag{4.27}$$

From Equation (4.24), we know that for *d*=0 we have $F\left(t_i^f, d\right) = t_i^f$. Therefore $k(0)$=1.

For typical values of α and β (see Equation (4.24)), we have $d << 1$. Thus we can use the Taylor series expansion

$$k(d) = 1 + a_1 d + a_2 d^2 + \ldots \tag{4.28}$$

and ignore the higher order terms, i.e., use an expression $k(r) = 1 + a_1 d + a_2 d^2$. Substituting the formula for *d* (Equation (4.23)) into this expression, we conclude that

$$DU_i \approx t_i^f \left[1 + a_1 \alpha \left(\frac{v_i}{c_i} \right)^{\beta} + a_2 \alpha^2 \left(\frac{v_i}{c_i} \right)^{2\beta} \right] \tag{4.29}$$

Furthermore, for the standard values of α =0.15, β =4, and the normal range of v_i / c_i, the term $\alpha^2 (v_i / c_i)^{2\beta}$ is usually negligible. Therefore we may simplify Equation (4.29) to

$$DU_i = t_i^f \left[1 + a_1 \alpha \left(\frac{v_i}{c_i} \right)^{\beta} \right] \tag{4.30}$$

Equation (4.30) can also be expressed as

$$DU_i = \bar{t}_i + t_i^f \left[(a_1 - 1) \alpha \left(\frac{v_i}{c_i} \right)^{\beta} \right] \tag{4.31}$$

Hence, we may view DU_i as consisting of two components: the "deterministic" component $\bar{t}_i$ which has the same value given by the BPR function, and the "stochastic" component $t_i^f[...]$ which is due to the uncertainty in link travel time. Then, a_1 describes the sensitivity of the driver in respond to this uncertainty. Note that, Equation (4.30) can be used to represent risk averse, risk prone and risk neutral drivers, depending on the value of a_1. When a_1=1, drivers do not consider travel time uncertainty in route choice, and Equation (4.30) is reduced to the BPR function as in Equation (2.1).

4.4.2 Conditions for Risk Averse Behavior

We have earlier derived Equation (4.12) as an ELD function that represents the route choice behavior of risk averse drivers. Comparing Equations (4.12) with (4.30), the latter is easier to implement in DUE algorithms as one does not need to know the $\sigma_{t_i}^2$ of every link. However, the condition of $\sigma_i^2 \geq 0$ imposes a restriction on the a_1 value. By equating the last term on the right-hand-side of Equations (4.12) and (4.30), and with $\sigma_i^2 \geq 0$

$$\sigma_i^2 = \frac{2}{\omega} t_i^f (a_1 - 1)\alpha \left(\frac{v_i}{c_i} \right)^{\beta} \geq 0 \tag{4.32}$$

As all other terms in Equation (4.32) are positive, it follows that $a_1 \geq 1$. For risk averse drivers, we refer to this sensitivity parameter a_1 as the risk averse coefficient.

4.4.3 Conditions for Risk Prone Behavior

The bound of a_1 for risk prone behavior may be derived in the similar fashion. Comparing Equations (4.19) with (4.30) and by setting $\sigma_i^2 \geq 0$, we obtain

$$\sigma_i^2 = \frac{2}{\omega} t_i^f (a_1 - 1)\alpha \left(\frac{v_i}{c_i} \right)^{\beta} \leq 0 \tag{4.33}$$

As all other terms in Equation (4.33) are positive, it follows that $a_1 \leq 1$, for risk prone drivers.

4.5 Modeling Route Choice Behavior in Stochastic Networks

We have already shown that the property P1 is satisfied. In terms of our ELD function DU_i, this property means that the driver preferences should be equivalent to selecting a route with the smallest value of the sum $du_r = \sum_{i=1}^{L} DU_i$.

Thus, the Equation (4.30) provides a convenient way of solving the SN-DUE model using a DUE algorithm, such as the Frank-Wolf algorithm in TransCAD (Caliper, 2005b), provided that DU_i is a convex function of v_i. This property of DU_i holds e.g. when $a_1 \geq 0$. Therefore, we can treat the SN-DUE model like a DN-DUE model simply by replacing the t_i and t_r in the DN-DUE model by DU_i and du_r respectively. In fact, we only need to replace t_i by DU_i in the solution algorithm!

To use Equation (4.30) in a DUE algorithm, one only needs to know the value of a_1. In principle, every driver should have his/her individual a_1 value. To describe the general behavior of the driving population, an average value of a_1 may be used. The following section describes a method to estimate the average a_1 value from a questionnaire survey.

4.6 Estimation of Risk Averse Coefficient

By expressing Equation (4.30) in terms of d (as defined in Equation (4.23), we obtain

$$DU_i = t_i^f \left[1 + a_1 d\right] = t_i^f \left[1 + a_1 \left(\frac{\bar{t}_i - t_i^f}{t_i^f}\right)\right] \tag{4.34}$$

In a hypothetical link that has a constant travel time

$$DU_i = t_i^f \tag{4.35}$$

Consider the case where there are only two parallel links connecting an O-D pair, with link i=1 having a constant travel time t_1^f, while link i=2 having a travel time according to Equation (4.34). For link i=2, the values of t_2^f and $\bar{t}_2$ may be prescribed as the minimum and average travel times respectively. Given the values of t_2^f and $\bar{t}_2$, we may ask a driver to specify the value of t_1^f such that he/she does not have any preference on one link over another. Under this condition

$$t_1^f = t_2^f\left[1 + a_1\left(\frac{\bar{t}_2 - t_2^f}{t_2^f}\right)\right] \tag{4.36}$$

We may then solve for a_1.

A questionnaire survey has been conducted in the city of El Paso, Texas, to estimate the average a_1 value among the driving population. In this survey, participants were presented with the scenario of morning commute to work that has a fixed work-start time with a penalty for late arrival. The complete survey form is attached in the Appendix. There are two questions in the survey. Question 1 has t_2^f =20 minutes and $\bar{t}_2$ =30 minutes while Question 2 has t_2^f =35 minutes and $\bar{t}_2$ =50. In each of the questions, participants were given a set of possible t_1^f values at 5-minute increments. Each person was asked to select the closest t_1^f value in each question that satisfies Equation (4.36), that is, he/she do not have preference between link 1 (which has a constant time t_1^f) and link 2 (which has an uncertain travel time). The two questions with different travel times were designed to check the consistency in the route choice behavior. They also help to find average a_1 values for different trip lengths. The t_2^f , $\bar{t}_2$ values posed in the two questions are the typical ranges found in El Paso. Survey responses were collected from 202 drivers. There were 404 a_1 values computed from Equation (4.36). The survey response (t_1^f values) and the estimated a_1 values are all listed in the Appendix. The average value of a_1 is 1.4356. This indicates that an average driver is risk averse (since a_1>1) in the morning commute to work. The value of a_1=1.4356 is used in the traffic assignment for risk averse drivers in the SN-DUE model in the remaining chapters of this report.

CHAPTER 5

TRAFFIC ASSIGNMENT WITH A FIXED ORIGIN-DESTINATION MATRIX

This chapter concerns the implementation of the SN-DUE models (i.e., user equilibrium traffic assignment in a SN for risk averse drivers) when the traffic demand is specified in a O-D matrix. That is, the traffic assignment is performed for one time period when the trip rates (in vehicles per hour) between all the O-D pairs in the O-D matrix remained unchanged through the time period. This assumes that drivers do not change their departure times in response to traffic congestion or travel time reliability. The O-D matrix is typically given as an hourly matrix, e.g., the morning peak hour of 8:00 a.m. to 9:00 a.m.

The ELD function for the implementation of the SN-DUE model has been derived in Chapter 4. One of the purposes of this chapter is to demonstrate the difference in the results of traffic assignment in the SN-DUE model (which uses the ELD function) and the DN-DUE model (which uses the BPR function). A relatively small test network and the El Paso network in the 2005 scenario are used in the illustrations.

5.1 Implementation in TransCAD

This traffic assignment model belongs to the SN-DUE model discussed in Section 2.2. It is recommended that this type of traffic assignment be conducted for the morning peak commuting hour because

- most of the drivers have good knowledge of the travel times in alternate routes
- most of the drivers have a fixed time of arrival at work (work-start time) with a late arrival penalty

Because of the need to arrive in time for work, drivers in the morning peak hour tends to exhibit risk averse behavior when the travel time in the network is uncertain. This behavior has been shown in the result of the route choice survey reported in Chapter 4.

In Chapter 4, an ELD function in the form of Equation (4.30) was derived. The a_1 value of 1.4359 has been estimated from a route choice survey. To model the SN-DUE, one simply replaces the BPR function in the DN-DUE, the standard traffic assignment model in a deterministic network, with the ELD function while still using the same DUE algorithm to solve the problem. In fact, the ELD function is very similar to the BPR function, except for addition of the a_1 term in front of α. Therefore, one can simply use the BPR function, but replace the α value with the $a_1\alpha$ value to model and solve the SN-DUE problem like a DN-DUE model! This Chapter takes the advantage of this property to make use of the default functions provided by TransCAD to solve the SN-DUE problem.

The traffic assignment model provided by TransCAD belongs to the DN-DUE model. In TransCAD, the Frank-Wolfe algorithm has been provided to solve the DUE problem, while the BPR function describes the deterministic travel time in a DN (Caliper, 2005b).

A software Travel Time Reliability Program Suite has been developed as part of this research for implementation with Version 4.8 of TransCAD. This program suite has several programs, of which the following programs may be necessary to solve the SN-DUE model, and to analyze the results:

- Adjust O-D Matrix
- Adjust Link Capacity
- Traffic Assignment with Fixed O-D
- Capacity Reliability Curve

Instructions on how to use these programs are explained in the accompanying User's Guide.

Adjust O-D Matrix

This program contains instructions on how to convert an O-D matrix that has trips over a longer time period to an O-D matrix for trips over a shorter time period. Very often, the O-D matrix used in transportation planning contains estimated trips over a 24-hour period. This 24-hourly O-D matrix needs to be converted into the O-D matrix for the morning peak hour for input into the SN-DUE model. A typical way to convert a 24-hourly O-D matrix to an hourly O-D matrix is to multiply the original by the K-factor.

Adjust Link Capacity

Since the traffic demand is given in an hourly O-D matrix, the link capacity must also be in unit of vehicles per hour. Some network models in TransCAD have link capacity expressed in terms of vehicles per day. The Adjust Link Capacity program is to convert the link capacity from vehicles per day to vehicles per hour. The conversion from daily capacity to hourly capacity is not as simple as dividing the earlier by 24. The conversion factor depends on the facility type.

Traffic Assignment with Fixed O-D

Once the hourly O-D matrix has been created in a TransCAD matrix file and hourly link capacity updated in the link attributes in the TransCAD database, the SN-DUE model is ready to be solved. The Traffic Assignment with Fixed O-D program provides a set of instructions for users to make use of the standard traffic assignment functions in TransCAD to solve the SN-DUE model. Note that the only difference in the procedure is to enter the value of $a_1\alpha$=1.4359x0.15=0.2123 instead of α=0.15, as shown in Figure 5.1.

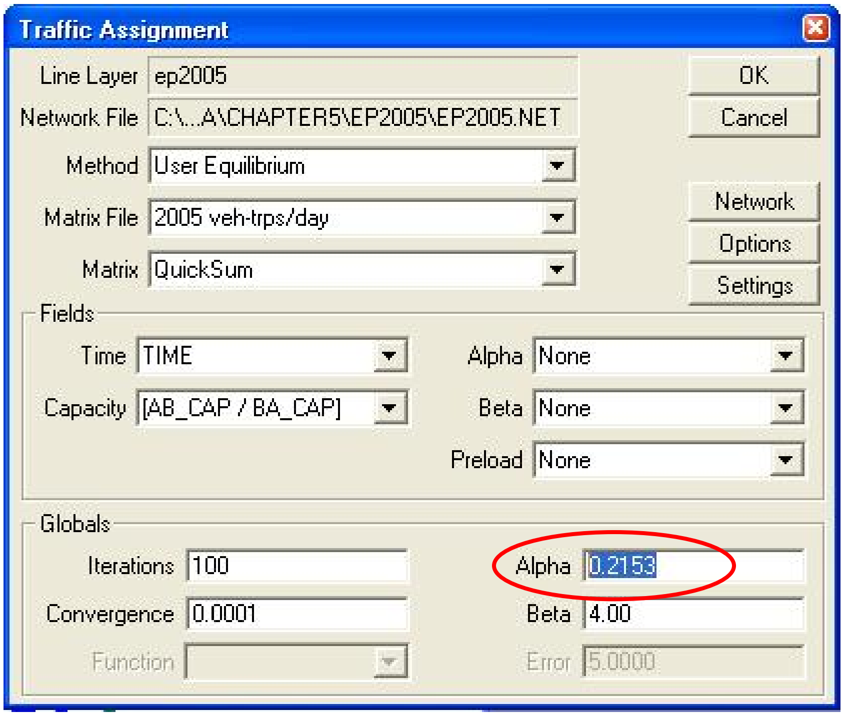


Figure 5.1: Screenshot of traffic assignment parameters in TransCAD

Capacity Reliability Curve

The Capacity Reliability Curve program helps to plot the capacity reliability curves discussed in Section 2.5. The program plots two charts:

- (% of links with $v_i > c_i$) versus μ
- (% of lane-miles with $v_i > c_i$) versus μ

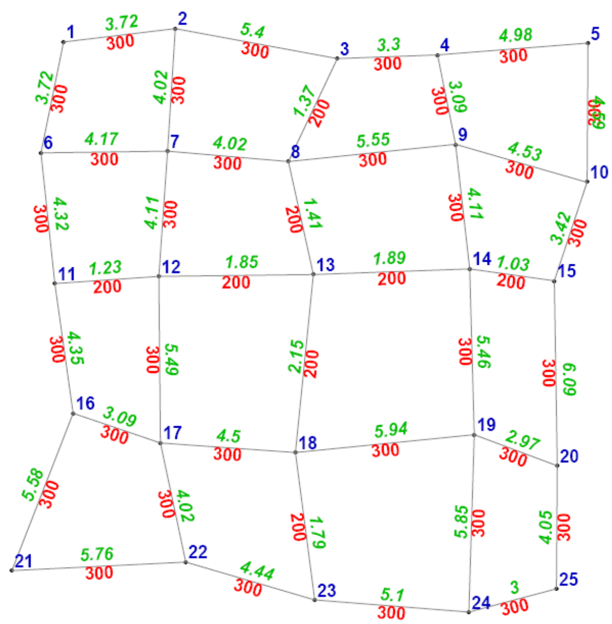
These charts show the network performance or level of service when the traffic demand during the peak hour (the hourly O-D matrix) is increased/decreased by a factor of μ.

The Capacity Reliability Curve program essentially has two iterative loops. The outer loop sets the values of μ based on the range specified by the user. For each μ value, the inner loop multiplies the hourly O-D matrix by μ, and solve the SN-DUE model for the new O-D matrix.

5.2 Test Network

In this section, a test network, adopted from Dial (2006), is used to illustrate the application the ELD function in a SN-DUE model (using the value of a_1=1.4356 obtained in the survey) and compare the results against the DN-DUE model.

The test network has been coded into TransCAD. The 25 nodes, 40 two-way links, t_i^f and one-way link capacity c_i are shown in Figure 5.2. The links with capacity of 300 vph have free-flow speeds of 20 mph while those links with capacity of 200 vph have free-flow speeds of 55 mph. Only nodes 7, 9, 17, 19 are O-D nodes. The O-D matrix is shown in Table 5.1. TransCAD uses the Frank-Wolfe algorithm to solve the DUE problem (Caplier, 2005b). After network coding, a DUE assignment was performed in TransCAD using the setting as reported in Dial (2006). After our DUE assignment, majority of the links have the same v_i and t_i values as reported in Dial (2006). Of the few links that have different v_i and t_i values, the maximum differences are 1 vph and 0.04 minutes, respectively. We attribute the small differences due to the Frank-Wolfe algorithm's implementation details.



All links are two-way links.
Free-flow link travel time is shown above each link (in green, italic, in minutes)
Directional link capacity is shown below each link (in red, in vph)

Figure 5.2: Test network - free-flow travel time and link capacity

Table 5.1: Fixed O-D matrix of text network

Trips (vehicles per hour)		Destination Node			
		7	**9**	**17**	**19**
Origin Node	**7**	0	500	500	500
	9	500	0	500	500
	17	500	500	0	500
	19	500	500	500	0

5.2.1 Deterministic Network-Deterministic User Equilibrium Model

The DN-DUE model was first implemented for this network. The standard values of α =0.15 and β =4 were used in the BPR function. To be consistent with the practice of the Texas Department of Transportation, the Frank-Wolfe algorithm was run for 100 iterations. Figure 5.3 shows the directional volume-capacity ratios (v_i/c_i) after 100 iterations. Since the O-D matrix is symmetrical and the links have the same t_i^f and c_i values in both directions, the resulting v_i/c_i and t_i are the same in both directions of a link. The t_i values are displayed in Figure 5.4.

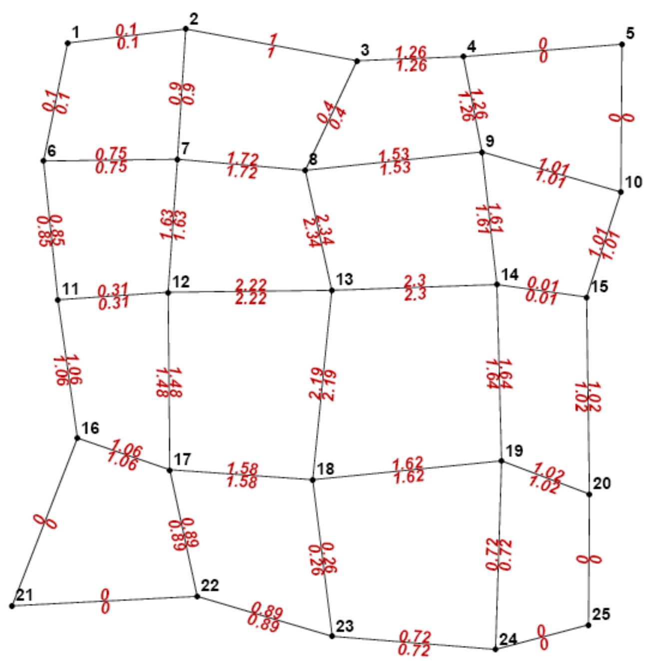
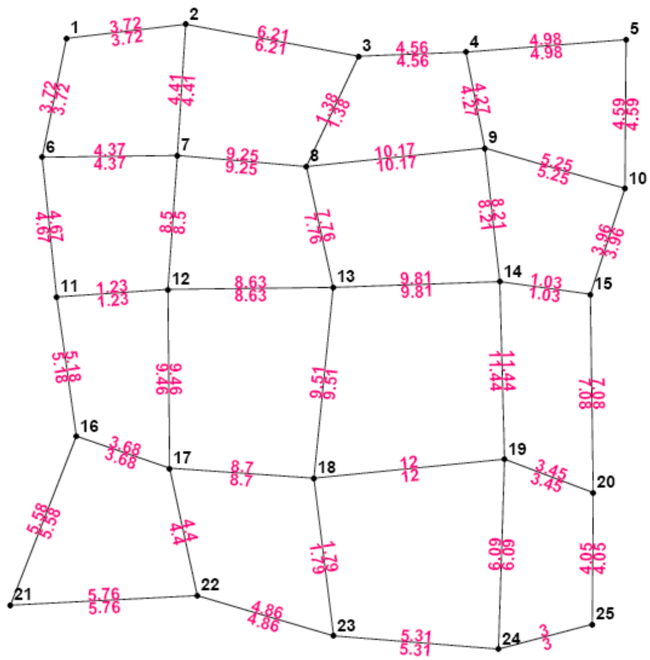


Figure 5.3: Test network with fixed O-D matrix - V-C ratio after traffic assignment with BPR function



Link travel time is in minutes

Figure 5.4: Test network with fixed O-D matrix - link travel time after traffic assignment with BPR function

5.2.2 Stochastic Network-Deterministic User Equilibrium Model

In the SN-DUE model, we simply replaced the BPR function in the DN-DUE model by the ELD function. Put simply, one only needs to change the value of α =0.15 in the BPR function to $a_1\alpha$ =1.4356x0.15=0.2153. Figures 5.5 and 5.6 show the directional v_i/c_i and average directional link travel time ($\bar{t}_i$), respectively, after 100 iterations.

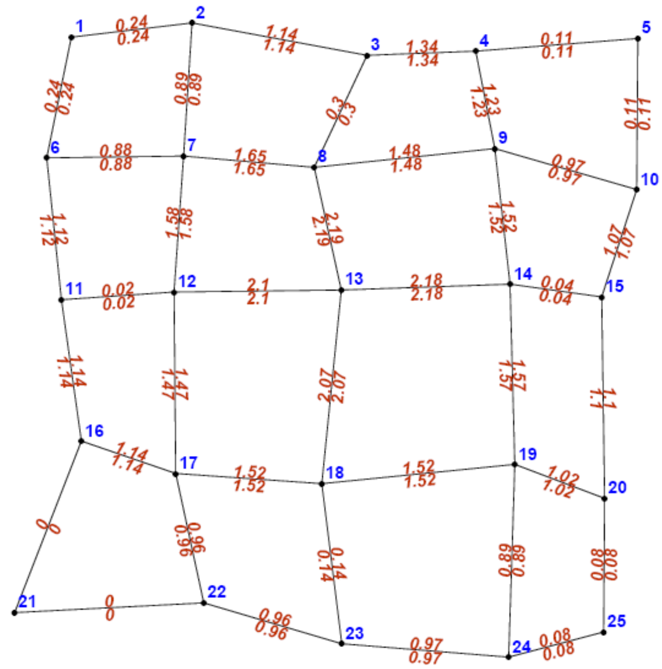
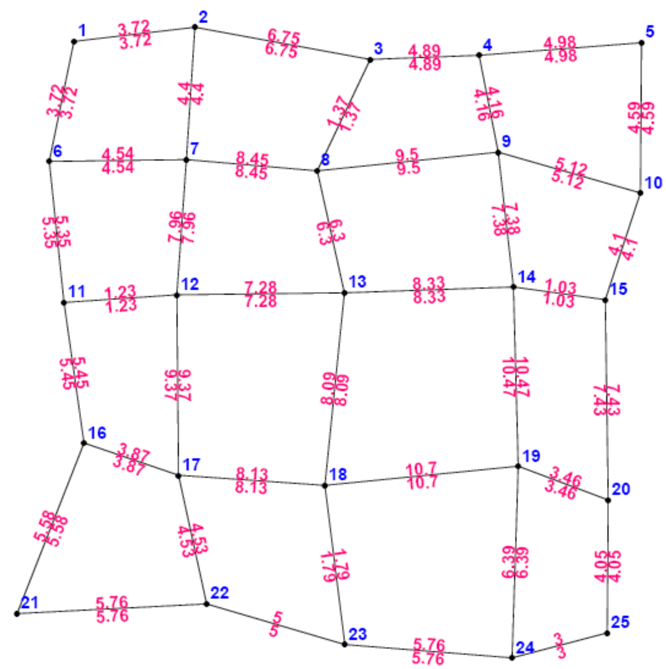


Figure 5.5: Test network with fixed O-D matrix - V-C ratio after traffic assignment with ELD function



Link travel time is in minutes

Figure 5.6: Test network with fixed O-D matrix - link travel time after traffic assignment with ELD function

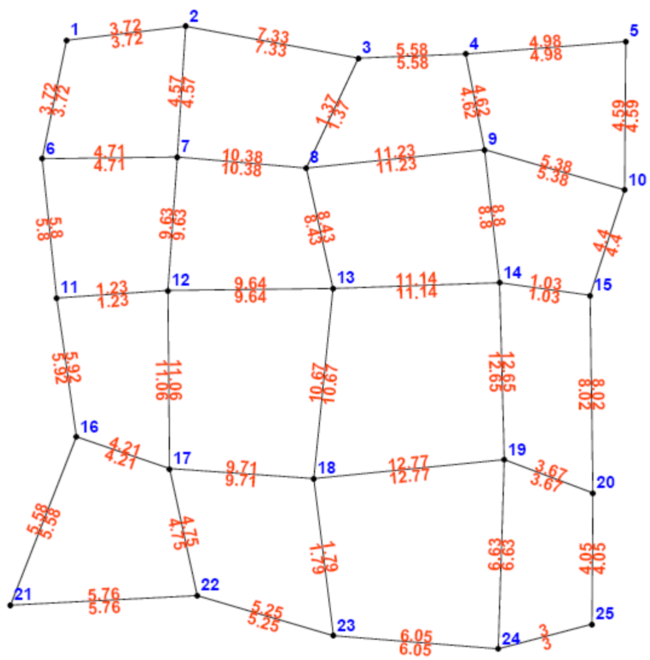
5.2.3 Comparison of Volume-Capacity Ratio

Figures 5.3 and 5.5 show the v_i/c_i of the links in the test network, after traffic assignments with the BPR and ELD functions, respectively. Compared to Figure 5.3, Figure 5.5 has 17 links with relatively lower v_i/c_i, 3 links with the same v_i/c_i ratio and 20 links with higher v_i/c_i. With the BPR function, there are 10 links with v_i/c_i >1.5 in Figure 5.3. The v_i/c_i of these links have been reduced after the trips are assigned with the ELD function. For example, link 8-13 in Figure 5.3 has the maximum v_i/c_i =2.34 in the network. In Figure 5.5, this link still has the maximum v_i/c_i in the network but the value has become 2.19. With the ELD function, risk averse drivers are more sensitive to v_i/c_i (the later is proportional to travel time variation) and therefore they will avoid links which have high volume, resulting in a more "uniform" distribution of traffic in the network.

5.2.4 Comparison of Link Travel Time

Figure 5.4 shows the t_i (for a DN-DUE model), computed by using Equation (2.1), while Figure 5.6 show the $\bar{t}_i$ (for a SN-DUE) computed by using Equation (4.22). For links that have high v_i/c_i in Figure 5.3, there are reductions from t_i in Figure 5.4 to $\bar{t}_i$ in Figure 5.6 (due to the fact the magnitude of change is proportional to v_i/c_i to the power of β =4). Links with relatively low v_i/c_i in Figure 5.3 show no or only a marginal increase from t_i in Figures 5.4 to $\bar{t}_i$ in Figure 5.6. This is the overall effect of re-routing some traffic from links with high volumes (and hence high travel time variance) to links with low volumes (with more certain travel times).

One point worth noting is that, in the DN-DUE model, the used routes between an O-D pair have the same route travel time that is less than the travel time of any unused route. However, in our SN-DUE model, all the used routes between an O-D pair have the same route disutility that is less than the disutility of any unused route. Therefore in the SN-DUE model, only the route disutility, not the route travel time, is in equilibrium. For risk averse drivers, the link disutility (DU_i) is always greater than the average link travel time $(\bar{t}_i)$. Therefore, route disutility is always greater than the route travel time. To illustrate this, the link disutilities of the test network after traffic assignment with the ELD function is plotted in Figure 5.7. Readers can compare Figure 5.7 with Figure 5.6 to see that $DU_i \geq \bar{t}_i$, $\forall i$. Note that the difference between DU_i and $\bar{t}_i$ is greater when the v_i/c_i ratio is higher.



Link disutility is in minutes

Figure 5.7: Test network with fixed O-D matrix - link disutility after traffic assignment with ELD function

5.2.5 Comparison of O-D Travel Time

Table 5.2 shows the O-D travel times along the shortest-time paths of the DN-DUE model, after 100 iterations of traffic assignment with the BPR function. Table 5.3 shows the O-D travel times along the shortest-disutility paths of the SN-DUE model, after 100 iterations of traffic assignment with the ELD function. As mentioned, in the SN-DUE model, drivers select the route between an O-D pair that has the smallest disutility. The routes with the smallest disutility may not be the same as the route with the shortest travel time. To illustrate this point, consider the route between nodes 7 and 17 in the test network. In Figure 5.7, the shortest-disutility path between nodes 7 and 17 is by nodes 7-6-11-16-17, with a route disutility of 20.64 minutes. In Figure 5.6, this route has an average travel time of 19.21 minutes. However, if one examines Figure 5.6 carefully, the shortest-time path between nodes 7-17 is via nodes 7-12-17, with an average route travel time of 17.33 minutes, a saving of 1.88 minutes! In this case, along the route of nodes 7-12-17, links 7-12 and 12-17 have v_i/c_i of 1.58 and 1.47, respectively, which are higher than the v_i/c_i of the links along route of nodes 7-6-11-16-17 (see Figure 5.6). A higher v_i/c_i ratio indicates a higher link travel time variance. This reflects that in a SN, a risk averse driver would rather select a route which has a higher average route travel time but smaller travel time variance over a route with a smaller average travel time but higher travel time variance.

Table 5.2: Test network with fixed O-D matrix - O-D travel time after traffic assignment with BPR function

Travel Time (minutes)		Destination Node			
		7	**9**	**17**	**19**
Origin Node	**7**	-	19.42	17.90	38.26
	9	19.42	-	36.01	19.65
	17	17.90	36.01	-	20.65
	19	38.26	19.65	20.65	-

Table 5.3: O-D Test network with fixed O-D matrix - travel time after traffic assignment with ELD function

Travel Time# (minutes)		Destination Node			
		7	**9**	**17**	**19**
Origin Node	**7**	-	17.95	19.21 (17.33)	40.32
	9	17.95	-	38.31 (31.93)	17.85
	17	19.21 (17.33)	38.31 (31.93)	-	18.83
	19	40.32	17.85	18.83	-

O-D travel time is calculated along the shortest-disutility path. If the shortest-time path is different from the shortest-disutility path, the O-D travel time along the shortest-time path is shown in parenthesis.

The route travel times between the O-D pairs in Tables 5.2 and 5.3 are of interest in this comparison. For the O-D pairs between nodes 7-17 and 17-7, the shortest-disutility paths are not the same as the shortest-time paths. This has been discussed in the previous paragraph. Another two O-D pairs, nodes 9-17 and 17-9 also have their shortest-disutility paths differ from their respective shortest-time paths. For comparison purpose, the O-D travel times for these four O-D pairs along the respective shortest-time paths are included in Table 3 in parentheses. For these four O-D pairs, it is expected that the O-D travel times for the SN-DUE model in Table 5.3 are greater than those obtained with the DN-DUE model in Table 2. For the other O-D pairs, no consistent patterns of greater or smaller O-D travel time between same O-D pair in Tables 5.2 and 5.3 have been found.

5.2.6 Comparison of Network Performance

The network performance is evaluated by comparing the total vehicle-miles traveled (VMT) and total vehicle-hours traveled (VHT) after 100 iterations of the Frank-Wolfe algorithm. For the DN-DUE model, the VMT is 32119 veh-miles and the VHT is 2545.08 veh-hrs. For the SN-DUE model, the corresponding statistics are 32876 veh-miles and 2425.68 veh-hrs respectively. This reflects the fact that risk averse drivers prefer a longer route with a lower travel time variance than a shorter route with a higher travel time variance. The overall effect of redistribution of flow has resulted in a smaller VHT. The SN-DUE model has a total disutility of 2849.03 veh-hrs.

5.3 El Paso Network

In this section, the El Paso network is used as a realistic network to mimic the actual transportation planning process. The network files, which are based on the network geometry and traffic demand in year 2005, in the TransCAD format have been provided by the El Paso MPO through the TxDOT El Paso District. The network consists of 681 zones, 4836 links and 3060 nodes. The 4836 links consist of both one-way links and two-way links (1073 one-way links and 3763 two-way links). The links in the network are shown in Figure 5.8. The total lane-miles in the network is 4295.30 lane-miles. The TransCAD database files include directional 24-hour capacities (in vehicles/day) and a 24-hour O-D matrix (also in vehicles/day) for the year 2005. This network is denoted as EP2005 network for the rest of this report.

Figure 5.8: EP2005 network as seen in TransCAD

5.3.1 Data Preparation

Traffic assignment for risk averse drivers (i.e., the SN-DUE model) were applied to the EP2005 network to simulate the traffic distribution in the network in year 2005 during the morning commuting hour when there is uncertainty in the link travel time. The ELD function with a_1 =1.4356, from the survey of El Paso drivers (see Section 4.6) was used to model the risk averse behavior of the drivers.

The O-D matrix and link capacities that were supplied with the EP2005 network database were in vehicles/day. Before performing the traffic assignment, these O-D matrix and capacity were converted into the peak hour trip rate and hourly capacity respectively.

The El Paso Gateway 2030 MTP report (EPMPO, 2006) was used to deduce the peak hour. Figure 5.9 is the hourly traffic distribution in a typical weekday in El Paso, reproduced from the Gateway 2030 MTP report. From this figure, the morning peak hour was determined to be 7:00 a.m. to 8:00 a.m. The K-factor for each of the 24 hours was also provided by EPMPO. The K-factor for 7:00 a.m. to 8:00 a.m. is 0.1175. This factor was used as an input to the Adjust O-D matrix to create the hourly O-D matrix of 7:00 a.m. to 8:00 a.m. from the 24-hour O-D matrix.

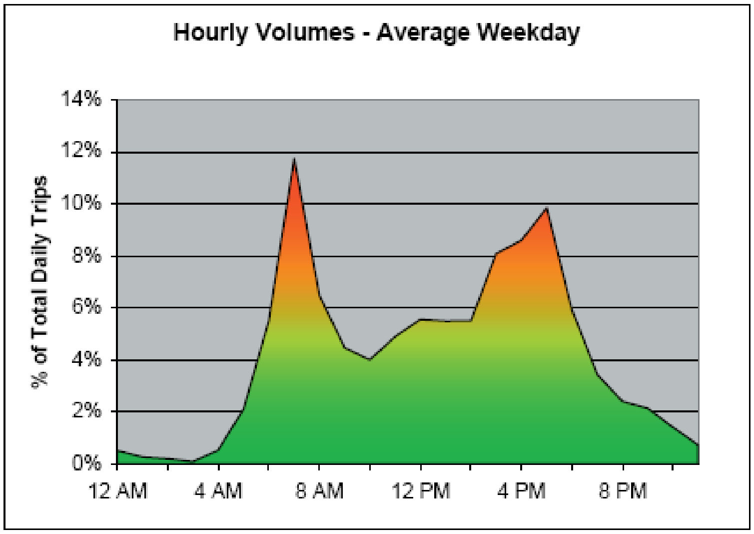


Figure 5.9: Hourly distribution of traffic in El Paso (from ELMPO (2006))

The hourly capacities for the different facility types were estimated from the typical values found in Highway Capacity Manual 2000 (TRB, 2000). These estimated values are shown in Table 5.4. The link capacities (the AB_CAP, BA_CAP and TOT_CAP columns) in the EP2005 database were updated with the values listed in Table 5.4 and converted into vehicles/hour by means of the Adjust Link Capacity program.

Table 5.4: Estimated hourly capacities of different facility types

Facility type number	Facility type	Hourly capacity (veh/hr/lane)
0	Conn	1500
1	B Hwy	2200
2	FrwyR	2400
3	Expy	2200
4	PartD	1800
5	PartU	1800
6	Dart	1600
7	Uart	1600
8	CollD	1500
9	CollU	1500
11	Frtg	2000
12	Ramp	2200
13	Xmtn	1800
14	FrwyC	2400

After the hourly O-D matrix was created and link capacity adjusted, the SN-DUE model was implemented as per instructions given in the Traffic Assignment with Fixed O-D program. The following sub-sections present the results and compare the network performance against the SN-DUE model (which used the BPR function).

5.3.2 Total Vehicle-Miles Traveled and Total Vehicle-Hours Traveled

Table 5.5 compares the total vehicle-miles traveled (VMT) and total vehicle-hours traveled (VHT) in the EP2005 network during the morning peak hour of 7:00 a.m. to 8:00 a.m., after the traffic assignments using the ELD and BPR functions. The total VMT of SN-DUE model is slightly smaller than the total VMT of the DN-DUE model, but the total VHT of SN-DUE model is slightly higher than the total VHT of the DN-DUE model. The marginal differences are less than 0.6% which is not large enough to draw any conclusion.

Table 5.5: EP2005 network with fixed O-D matrix – total VMT and total VHT

	SN-DUE (ELD function)	DN-DUE (BPR function)
Total VMT (veh-miles)	1813151	1813325
Total VHT (veh-hr)	61903	61529

5.3.3 V-C Ratios at Hotspots

Hotspots are potential bottlenecks or important locations in the network at which the traffic conditions are closely monitored. Ten hotspots have been identified in the EP2005 network. The traffic conditions at these locations are measured by the V-C ratios at the respective links. Table 5.6 compares the V-C ratios at the hotspots between the SN-DUE and SN-DUE models. Of the 20 V-C ratios compared, the SN-DUE model has lower V-C ratios at 15 out of the 20 links. This again, is a reflection that with the ELD function in the SN-DUE model, traffic avoids the links which have high V-C ratios.

Table 5.6: EP2005 network with fixed O-D matrix – V-C ratio at hotspots

Location of hotspots	**Link ID**	**V-C ratio**	
		SN-DUE (ELD)	**DN-DUE (BPR)**
I-10 north of Sunland Park	1538 (EB)	0.7085	0.7056
	1542 (WB)	**0.7957**	0.7985
I-10 between Sunland Park & Executive Center	1534 (EB)	**0.8653**	0.8771
	1535 (WB)	**0.7641**	0.7647
I-10 west of US-54	1924 (EB)	**0.7527**	0.8162
	2927 (WB)	**0.7265**	0.7336
I-10 east of US-54	216 (WB)	**0.7420**	0.7609
	217 (EB)	**0.7524**	0.7583
I-10 west of Loop 375	3580 (WB)	**0.7122**	0.7334
	3583 (EB)	0.4387	0.4102
Paisano north of Executive Center	1623 (EB)	0.0258	0.0074
	1623 (WB)	0.1934	0.1835
Cesar Chavez northwest of Midway	579 (EB)	**0.7081**	0.7113
	579 (WB)	**0.7008**	0.7034
I-10 west of Horizon	3647 (WB)	**0.4774**	0.4815
	4759 (WB)	**0.4702**	0.4721
Mesa south of Sunland Park	1908 (EB)	**0.6052**	0.6131
	1908 (WB)	**0.6025**	0.6213
Mesa north of Shuster	1835 (EB)	0.2583	0.2364
	1835 (WB)	0.2931	0.2861

5.3.4 Lane-Mile Distribution of V-C Ratios

Since the EP2005 network has 4836 links, it is impractical to compare the link-by-link V-C ratio like in the test network. Instead, the lane-mile distribution by V-C ratios were plotted and analyzed.

After traffic assignment, the V-C ratio (in the AB_voc and BA_voc columns of the ASN_LinkFlow.bin file), length and number of lanes of all the links were copied onto a new Miscosoft Excel worksheet for post processing. First, data for the opposite directions of two-way links were separated. That is, a two-way link was separated into two one-way links. At the end of this step, all the data are in the form of one-way links. For each of the (one-way) links, the lane-miles was computed. The one-way data were then sorted in increasing order of V-C ratio. The V-C ratios were next divided into intervals (e.g., from 0 to 1, at increments of 0.1). For each interval of V-C ratios, the lane-miles of the links with V-C ratios that fell into this interval were summed. Figure 5.10 plots the lane-mile distribution of V-C ratio (percent lane-miles in the network in the vertical axis versus V-C ratio in the horizontal axis) obtained from the SN-DUE model. The DN-DUE model was also implemented for the EP2005 network, with the same O-D matrix and hourly link capacities. The lane-miles distribution of V-C ratio is also plotted in Figure 5.10. Table 5.7 lists the percent of lane-miles in each interval of V-C ratio, for the SN-DUE and DN-DUE models.

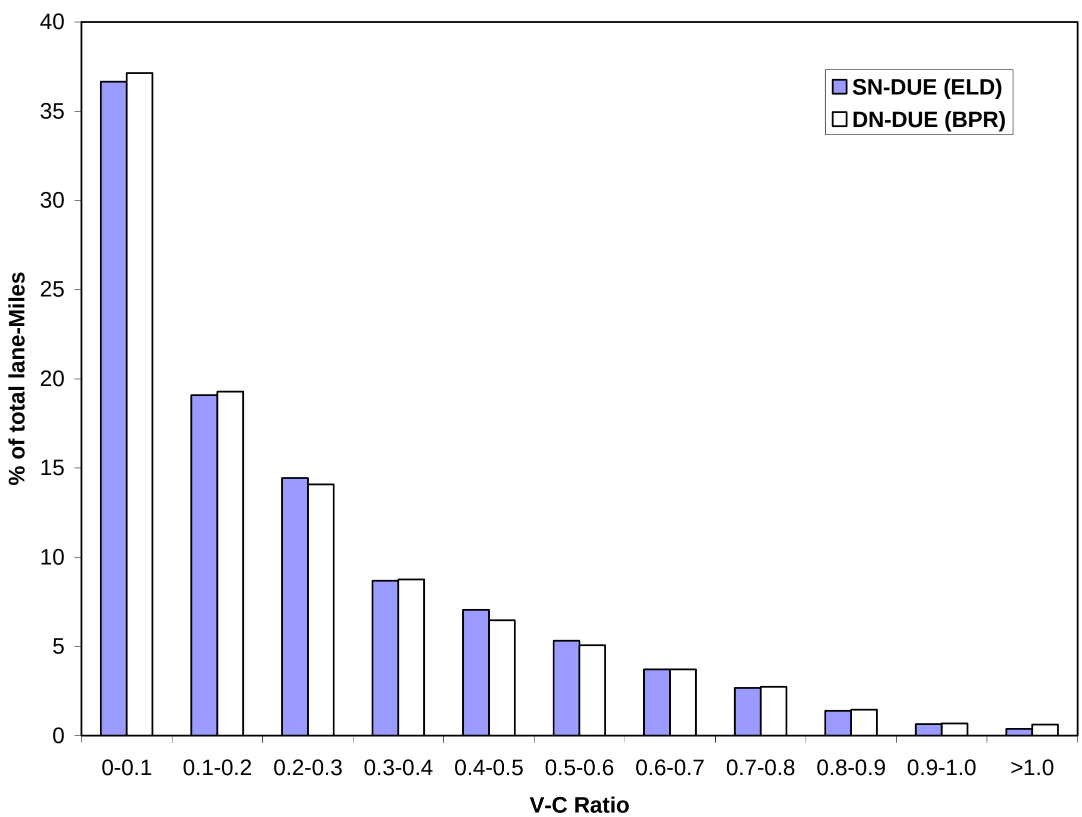


Figure 5.10: EP2005 network with fixed O-D matrix - lane-miles distribution of V-C ratio for all links

Table 5.7: EP2005 network with fixed O-D matrix – lane-miles distribution of V-C ratio for all links

V-C Ratio	SN-DUE (ELD function)		DN-DUE (BPR function)	
	Lane-miles	% lane-miles	Lane-miles	% lane-miles
0-0.1	1574.53	36.66	1594.93	37.13
0.1-0.2	819.56	19.08	828.27	19.28
0.2-0.3	620.17	14.44	604.84	14.08
0.3-0.4	372.94	8.68	376.03	8.75
0.4-0.5	302.48	7.04	277.42	6.46
0.5-0.6	228.14	5.31	217.87	5.07
0.6-0.7	159.27	3.71	159.41	3.71
0.7-0.8	115.13	2.68	117.67	2.74
0.8-0.9	59.68	1.39	62.44	1.45
0.9-1.0	27.56	0.64	29.65	0.69
>1	15.86	0.37	26.79	0.62
Total	4295.30	100.00	4295.30	100.00

The SN-DUE model used the ELD function in the traffic assignment while the DN-DUE model used the BPR function in the traffic assignment. From Figure 5.10 and Table 5.7, the SN-DUE model has more lane-miles within the V-C ratio range of 0.2 to 0.6, but has fewer lane-miles with V-C ratio of more then 0.6, compared to the DN-DUE model. This is consistent with the finding reported in the test network that, when the ELD function is used, traffic will be distributed from the links which are more congested to the link which are less congested. As drivers shift to the links that have very low V-C ratios, the V-C ratios of these links may increase to the next V-C ratio interval in Figure 5.10 and Table 5.7. This explains why the lane-miles with V-C ratio of less than 0.2 are fewer with the SN-DUE model than the DN-DUE model.

The changes in the V-C ratios are more obvious for the freeway links. Figure 5.11 plots the lane-mile distribution by V-C ratios for only the freeway links (functional classes 1, 2, 3 and 14). Table 5.8 compares the number and percentage of freeway lane-miles at the various V-C ratio intervals. With the exception of the V-C ratio between 0.3 and 0.4, the SN-DUE model (which uses the ELD function) results in fewer percentages of freeway lane-miles with very high and very low V-C ratios, compared to the DN-DUE model (which uses the BPR function). Note that in both models, no freeway link has a volume that exceeds the capacity.

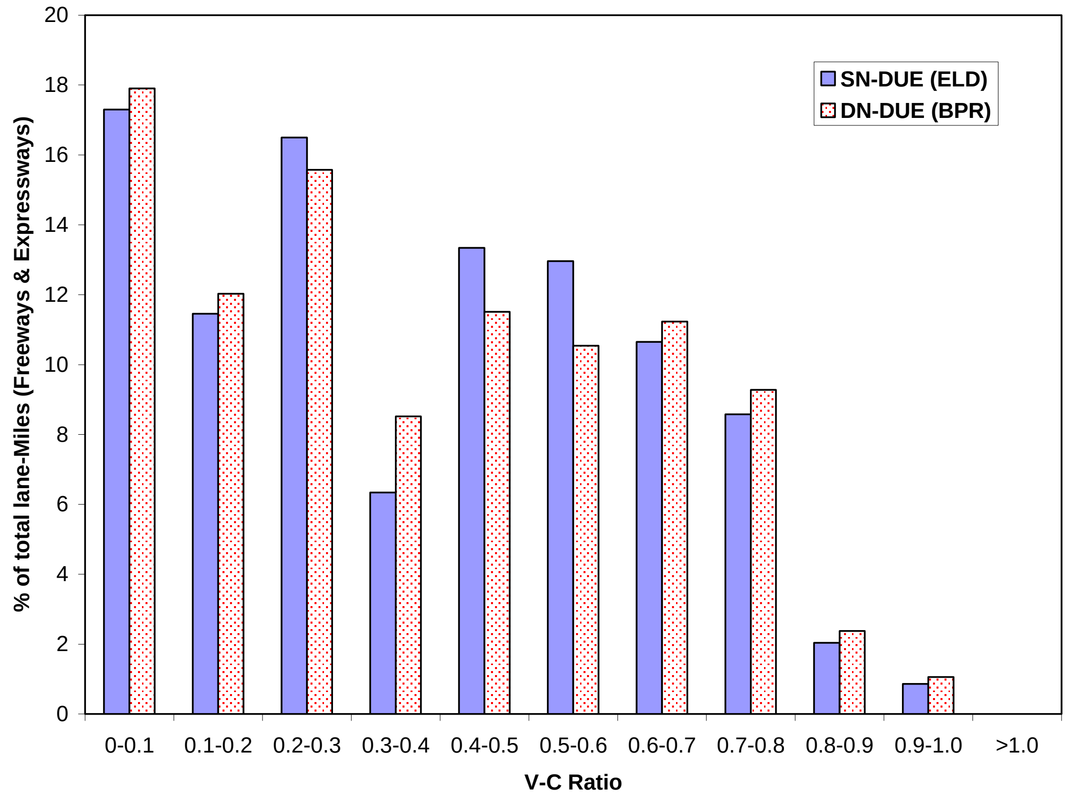


Figure 5.11: EP2005 network with fixed O-D matrix - lane-miles distribution of V-C ratio for freeway links

Table 5.8: EP2005 network with fixed O-D matrix – lane-miles distribution of V-C ratio for freeway links

V-C Ratio	SN-DUE (ELD function)		DN-DUE (BPR function)	
	Lane-miles	**% lane-miles**	**Lane-miles**	**% lane-miles**
0-0.1	101.04	17.30	104.56	17.90
0.1-0.2	66.89	11.45	70.23	12.02
0.2-0.3	96.33	16.49	90.95	15.57
0.3-0.4	37.02	6.34	49.74	8.52
0.4-0.5	77.91	13.34	67.22	11.51
0.5-0.6	75.68	12.96	61.56	10.54
0.6-0.7	62.20	10.65	65.57	11.23
0.7-0.8	50.10	8.58	54.18	9.28
0.8-0.9	11.88	2.03	13.88	2.38
0.9-1.0	5.02	0.86	6.18	1.06
>1	0.00	0.00	0.00	0.00
Total	584.07	100.00	584.07	100.00

5.3.5 Distribution of Trip Travel Time

The distribution of O-D trip travel time is next analyzed. Table 5.8 lists the total number of trips and percentage of the total trips that have trip travel times that belong to the respective 5-minute intervals. Figure 5.12 plots the percentage distribution of trip length in 5-minute intervals. From the Figure 5.12 and Table 5.9, it is observed that the SN-DUE model has more trips with travel time equal or greater than 15 minutes and fewer trips with travel time less than 15 minutes, compared to the DN-DUE model. The average trip travel time in the SN-DUE model is 12.1984 minutes, while the average trip travel time in the DN-DUE model is 12.1246 minutes. The increase in average trip travel time in the SN-DUE model is 4.4 seconds per trip in order to avoid links which have high travel time uncertainty.

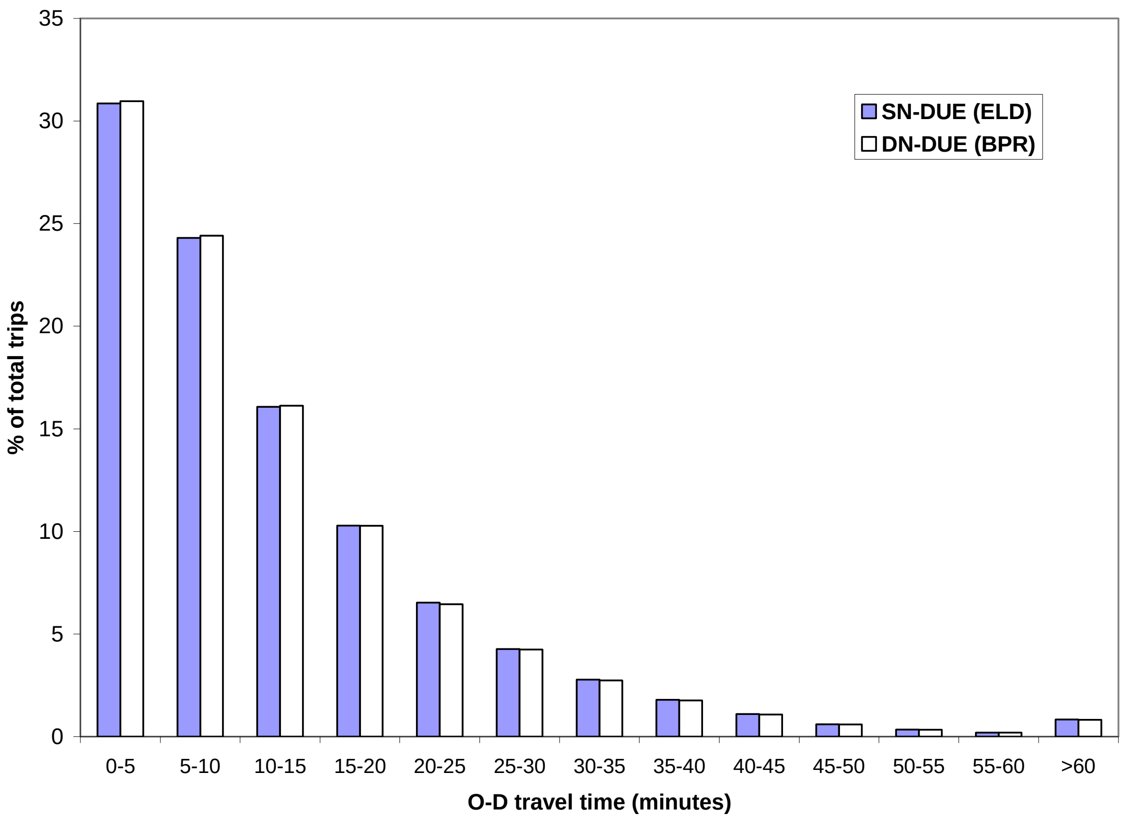


Figure 5.12: EP2005 network with fixed O-D matrix – distribution of trip travel time

Table 5.9: EP2005 network with fixed O-D matrix –distribution of trip travel time

O-D travel time (minutes)	SN-DUE (ELD function)		DN-DUE (BPR function)	
	No. of trips	% of total trips	No. of trips	% of total trips
0-5	93955	30.86	94275	30.96
5-10	74005	24.31	74312	24.41
10-15	48927	16.07	49085	16.12
15-20	31337	10.29	31295	10.28
20-25	19898	6.54	19643	6.45
25-30	12996	4.27	12929	4.25
30-35	8487	2.79	8346	2.74
35-40	5480	1.80	5387	1.77
40-45	3349	1.10	3283	1.08
45-50	1835	0.60	1802	0.59
50-55	1062	0.35	1023	0.34
55-60	606	0.20	594	0.20
>60	2547	0.84	2508	0.82
Total	304482	100.00	304482	100.00

5.3.6 Capacity Reliability

Figure 5.13 plots the capacity reliability curves of the SN-DUE model and DN-DUE model for the EL2005 network. The data used to plot these curves are obtained after running the Capacity Reliability Curve program. The capacity reliability curve indicates the change in the network's level of service (in this case, percentage of total lane-miles that has V-C ratio of more than 1). The x-axis of the graph has the matrix multiplication factor μ that ranges from 0.8 to 1.5, at 0.1 increments, with μ=1 corresponds to the 2005 O-D matrix between 7:00 a.m. and 8:00 a.m. (the 2005 base demand). μ=0.8 means the traffic demand is only 80% of the 2005 base demand, while μ=1.5 represents a 50% increase from the base demand. As expected, when the traffic demand increases, the percentage of lane-miles in the network that will reach capacity increases. The magnitude of percentage of lane-miles with V-C ratio >1 is higher and the rate of increase is much faster for the DN-DUE model than the SN-DUE model. This indicates that with the ELD function (in the SN-DUE model), drivers tend to select the links which are not as congested and avoid the links which have high V-C ratio. With such a route choice behavior, we can expect a network which can accommodate more vehicles without having too many links that reach capacity level. The curves also indicate that the EP2005 network modeled by SN-DUE has more capacity reliability than the DN-SUE counterpart.

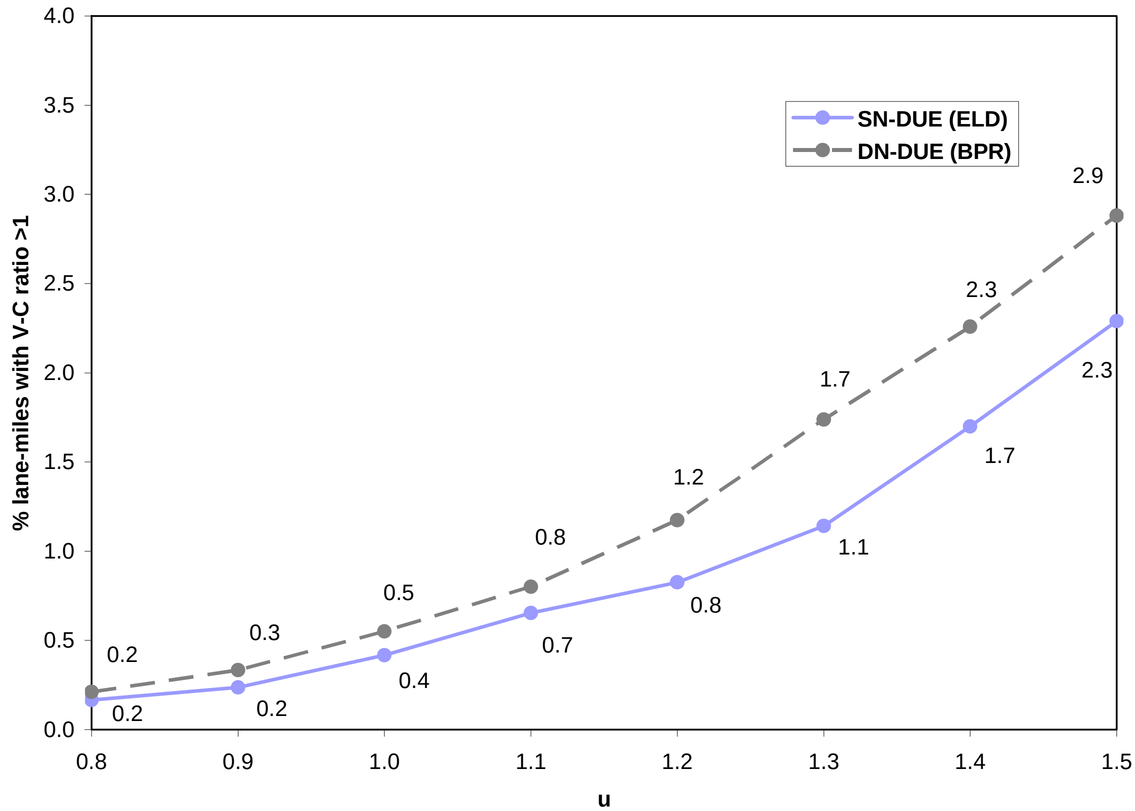


Figure 5.13: EP2005 network – capacity reliability curves

The results in Figure 5.13 assume that traffic input into the network (the O-D matrix) is increased by a constant factor consistently across all the zones while the network remains unchanged. It implies the growth of population and economic activities are uniform in the network and no expansion of the road facility. If the land-use plan in the network is known and the forecasted O-D matrix in the future year is available, the capacity reliability curve may be modified as the one presented in Figure 5.14. In this analysis, it is assumed that the traffic demand continues to grow and new road facilities are added over the years. The forecasted 24-hour O-D matrices and expanded road networks for the years 2015, 2025 and 2030 are provided by TxDOT. For each of these matrices, the Adjust O-D Matrix program was used to generate the hourly O-D matrix between 7:00 a.m. and 8:00 a.m., using the same K-factor=0.1175. Traffic assignments were carried out using the hourly O-D matrices for years 2015, 2025 and 2030, respectively. Therefore, Figure 5.14 plots the year instead of plotting μ in the x-axis, and the forecasted O-D matrix for the corresponding years were used in the traffic assignments. Figure 5.14 show results that are consistent with Figure 5.12. The SN-DUE model exhibits better capacity reliability than the DN-DUE model.

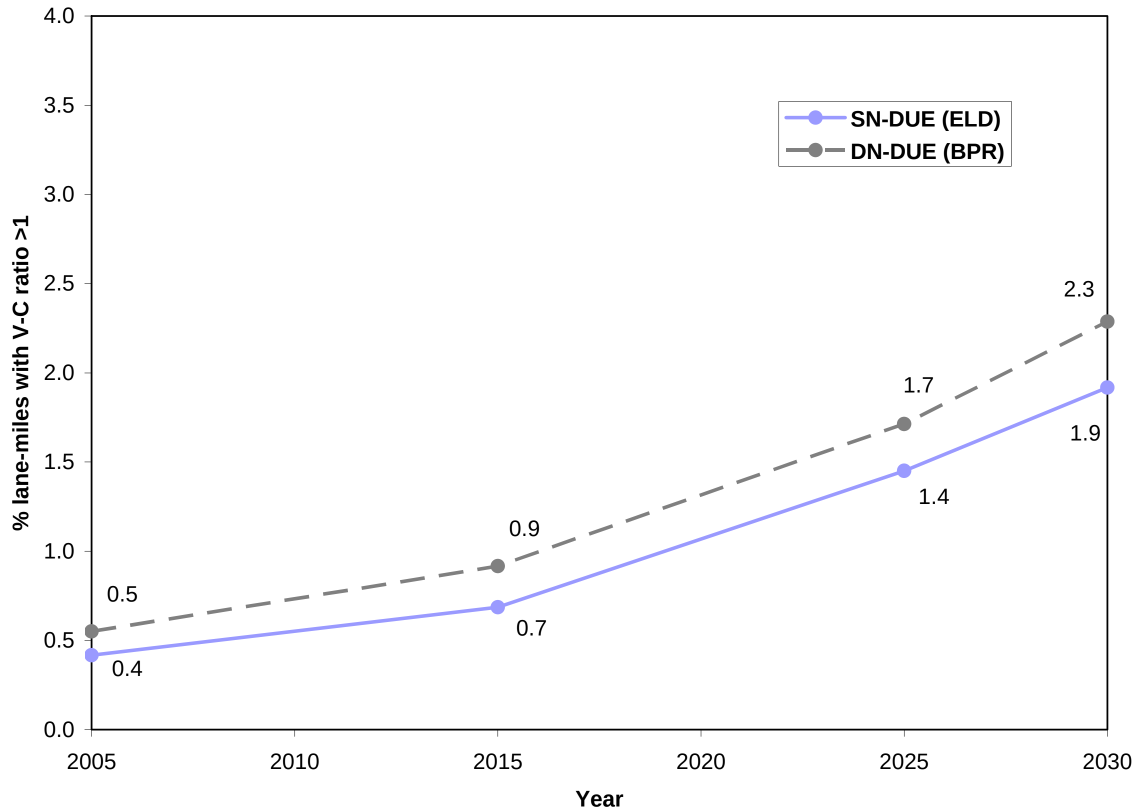


Figure 5.14: EP2005 network – forecasted capacity reliability curves

CHAPTER 6

TRAFFIC ASSIGNMENT WITH DEPARTURE TIME CHOICE

This chapter describes how to implement the concept of traffic assignment with departure time choice, as proposed in Chapter 3. The main ideas and algorithms behind this assignment have been described in Section 3.2. The chapter also describes the results of applying the corresponding algorithms to the El Paso 2005 network.

6.1 Implementation in TransCAD

Section 3.2 has described how to take into account departure time choice when making traffic assignments. The corresponding algorithm has been coded as part of our Travel Time Reliability Program Suite for implementation in TransCAD. Detailed instructions on how to use the corresponding functions are given in the software's accompanying User's Guide.

Several programs from this suite are related to the task of traffic assignment with departure time choice:

- Adjust O-D Matrix
- Adjust Link Capacity
- Set Variance of O-D Travel Time
- Traffic Assignment with Departure Time Choice
- Plot VMT & VHT
- Plot Hotspots

Of these six programs, the first three programs

- Adjust O-D Matrix
- Adjust Link Capacity
- Set Variance of O-D Travel Time

prepare the data needed for traffic assignment with departure time choice. The program

- Traffic Assignment with Departure Time Choice

actually performs this traffic assignment. The last two programs

- Plot VMT & VHT
- Plot Hotspots

enable the analyst to plot the results of this traffic assignment.

A brief description of the functions of these programs are given below.

<u>Adjust O-D Matrix</u>

This program contains instructions on how to convert an O-D matrix that has trips over a longer time period into an O-D matrix for trips over a shorter time period. Usually, the O-D matrix used in transportation planning contains estimated trips over a 24-hour period. For traffic assignment with departure time choice, we need to subdivide this daily traffic into shorter (15-minute, 30-minute, or 1 hour) time intervals. To compute the O-D matrices corresponding to different time intervals, the original daily O-D matrix is multiplied by the values of the corresponding K-factors. Since TransCAD already has a built-in function to perform such an operation, this description simply explains how to use the TransCAD function to generate the necessary O-D matrices.

To use these instructions, the analyst must have the values of the K-factors that correspond to the different time intervals. Usually, transportation agencies have K-factors for different hour-long time intervals. To obtain the values of the K-factors for shorter (30 minutes and 15 minutes) time intervals, linear interpolation as described in Section 3.2 may be used.

As a result of following the instructions presented by this program, the analyst should have a set of O-D matrices which correspond to different time intervals within the selected time period. For example, if the analyst selects a morning rush hour time period from 6:00 a.m. to 9:00 a.m., and time intervals of 15 minutes, then there should be 12 O-D matrices corresponding to the following 12 time intervals:

1. from 6:00 a.m. to 6:15 a.m.;
2. from 6:15 a.m. to 6:30 a.m.;
3. from 6:30 a.m. to 6:45 a.m.;
4. from 6:45 a.m. to 7:00 a.m.;
5. from 7:00 a.m. to 7:15 a.m.;
6. from 7:15 a.m. to 7:30 a.m.;
7. from 7:30 a.m. to 7:45 a.m.;
8. from 7:45 a.m. to 8:00 a.m.;
9. from 8:00 a.m. to 8:15 a.m.;
10. from 8:15 a.m. to 8:30 a.m.;
11. from 8:30 a.m. to 8:45 a.m.;
12. from 8:45 a.m. to 9:00 a.m.;

Adjust Link Capacity

This program is used to change the capacity of all the links in a network. From the viewpoint of traffic assignment with departure time choice, the main use of this program is to transform all the capacity values from vehicles per day to vehicles per hour.

The need for this transition comes from the fact that for one-hour and shorter time intervals, the traffic demand in the corresponding O-D matrix is usually given in vehicles per hour. So, to properly use these O-D matrices in TransCAD, the model must have link capacity values also described in the same unit of vehicles per hour. However, some network models in TransCAD have link capacity expressed in terms of vehicles per day. The Adjust Link Capacity program enables us to convert link capacity from vehicles per day to vehicles per hour.

At first glance, it may seem easy to calculate the hourly capacity by simply dividing the daily capacity by 24. However, in reality, the corresponding conversion factors may be different from 24; the actual value of the conversion factor depends on the type of the road facility. In view of this fact, the Adjust Link Capacity program enables the analyst to separately adjust link capacities for different road types. For this adjustment, the analyst must know the values of vehicles per lane per hour for different road facility type.

Set Variance of O-D Travel Time

This program computes the variance of route travel time for all O-D pairs in a network. It assumes that the variance is caused by lane blocking incidents which can only occur one at a time in the network. The algorithm for computing this variance is given in Section 3.2.

The Set Variance of O-D Travel Time program must have O-D matrix files that correspond to the different time intervals and the geographic file with the correspondingly adjusted capacities. Thus, in order to run Set Variance of O-D Travel Time program, the analyst may have to first run the programs Adjust O-D Matrices and Adjust Link Capacity.

The Set Variance of O-D Travel Time program must also have an incident database (*.bin) file that contains, for each incident,

- the incident start time;
- the link ID of the incident location; and
- the number of lanes closed by this incident.

The program also asks for the number of days during which the incident data was collected.

Based on all the information, for each time interval, the program creates a matrix which contains the incident-caused variance of each O-D travel time during the given time interval. For example, if we use twelve consecutive 15-minute time intervals for the period from 6:00 a.m. to 9:00 a.m., then

- the first matrix contains the travel time variance for all O-D pairs during the 6:00 a.m. to 6:15 a.m. time interval;
- the second matrix contains the travel time variance for all O-D pairs during the 6:15 a.m. to 6:30 a.m. time interval;
- etc.

Traffic Assignment with Departure Time Choice

This program actually computes the traffic assignment with departure time choice. It follows the algorithm presented in Section 3.2. To run this program, we must have:

- the O-D matrix files that correspond to different time intervals;
- the geographic file with the correspondingly adjusted capacities; and
- the variance of O-D travel time matrices that correspond to different time intervals.

The, to run this program, we must first run the programs in the following order

- Adjust O-D Matrices;
- Adjust Link Capacity; and

- Set Variance of O-D Travel Time.

The program asks for the (average) work-start times at different zones. Specifically, it asks for the default work-start time, and then allows the user to input the work-start times for the zones in which the work-start time is different.

By default, this program assumes that the analyst is dealing with risk averse drivers whose behavior can be characterized by the value a_1 = 1.4356. It also enables the user to change this value if necessary.

After receiving all the input data, the program iteratively adjusts the O-D matrices to take into account the departure time choice. After the iterations have converged, the program returns the adjusted O-D matrices and the corresponding traffic assignment files.

Plot VMT & VHT

This program uses the output of the Traffic Assignment with Departure Choice Program to plot the total vehicle-miles traveled (VMT) and total vehicle-hours traveled (VHT) as a function of time interval. The program produces the two corresponding plots. It also produces a text file which contains the values of the data points used to plot the curves.

Plot Hotspots

This program uses the output of the Traffic Assignment with Departure Choice Program to plot, for a given link, the V-C ratio versus time interval. The program prompts the user for the link ID of the "hotspot". For this hotspot, the program produces a plot ─ with one or two curves depending on whether the selected link is a one-way or a two-way link. The program also produces a text file which contains the values of the data points used to plot the curve(s).

After the plotting is done, the program gives the user an option of inputting a link ID of another hotspot.

6.2 El Paso Network

In this section, we use the same EP2005 network as in Chapter 5.

6.2.1 Data Preparation

The test of traffic assignment with departure time choice in the EP2005 network used the morning rush hours traffic, from 6:00 a.m. to 9:00 a.m., with 15-minute time intervals. During this time period, the following values of the hourly K-factors (in Table 6.1) are provided by EPMPO (2006):

Table 6.1: Hourly K-factors provided by EPMPO

Hour	K-factor
6:00 a.m.	0.055012
7:00 a.m.	0.117510
8:00 a.m.	0.064856
9:00 a.m.	0.044771

By using linear interpolation (as described in Section 3.2), the following K-factors have been obtained:

Table 6.2: Fifteen-minute K-factors

Hour	K-factor
6:00 a.m.	0.055012
6:15 a.m.	0.070637
6:30 a.m.	0.086261
6:45 a.m.	0.101886
7:00 a.m.	0.117510
7:15 a.m.	0.104347
7:30 a.m.	0.091183
7:45 a.m.	0.078020
8:00 a.m.	0.064856
8:15 a.m.	0.059835
8:30 a.m.	0.054814
8:45 a.m.	0.049792
9:00 a.m.	0.044771

To find the incident-related variance of O-D travel times, the records of all the incidents which occurred in El Paso during the 15-day period from May 30, 2006 to June 13, 2006, during the time period of the day (6:00 a.m. to 9:00 a.m.) were used. The Set Variance of O-D Travel Time program was used to generate the variance of O-D travel time matrices that correspond to each time interval.

6.2.2 Convergence of Iterative Process

In accordance with the algorithm described in Section 3.2, the interpolated K-factors were used to subdivide the 24-hour O-D matrix into $\mathbf{E}_1$, a set of 12 O-D matrices corresponding to the 12 selected 15-minute time intervals. The root mean square value $rms(\mathbf{E}_1)$ of the resulting set $\mathbf{E}_1$ of O-D matrices was 3.2306.

The iterative algorithm described in the same Section 3.2 stopped when the root mean square difference $\delta(\mathbf{E}_i, F(\mathbf{E}_i))$ between the O-D matrices $\mathbf{E}_i$ used to plan the traffic assignment and the O-D matrices $F(\mathbf{E}_i)$ describing the resulting departure time choice does not exceed 10% of $rms(\mathbf{E}_1)$, i.e., does not exceed 0. 3230629. The program converged after 10 iterations.

6.2.3 Total VMT and VHT

For the EP2005 network, the Traffic Assignment with Departure Time Choice program produces the following results. The value of a_1 =1.4356 has been used in the program to describe the risk averse behavior in the ELD function.

Table 6.3 shows the total VMT and VHT obtained in the traffic assignment output files for the 12 15-minute intervals. The original output values from the traffic assignment files are presented in columns 2 and 4. Note that, these values are in vehicle-miles per hour for total VMT and vehicle-minutes per hour for total VHT. This is because, by default, the units of the 15 minute O-D matrices are vehicles per hour, the link capacity is in vehicles per hour, the output units of link flow are vehicles per hour. The VMT of a link is the product of the total link flow (in vehicles per hour) and link length (in miles). Therefore, the units of total VMT in the traffic assignment output files are vehicle-miles per hour. The unit of link travel time in TransCAD is in minutes. The VHT of a link is the sum of the products of direction link flow (in vehicles per hour) and directional link travel times (in minutes). Therefore, the units of total VHT in the traffic assignment output files are vehicle-minutes per hour.

Using the values in the traffic assignment output files will lead to gross overestimations of the total VMT and VHT. This is because each traffic assignment is meant for traffic in a time interval. In this case, the input and results of each traffic assignment is valid for only 15 minutes. Therefore, the reported total VMT and VHT in columns 2 and 4 in Table 6.3 must be divided by a factor of 4 to scale to the same time span.

After scaling, the total VMT and VHT over all the intervals are summed to give the total VMT and VHT over three hours (from 6:00 a.m. to 9:00 a.m.). A check can be made by comparing the hourly average VMT and VHT against the corresponding values reported in Table 5.5. The hourly average values reported in Table 6.3 are lower than the corresponding values in Table 5.5, but they are of the same order of magnitude. The hourly total VMT and VHT in Table 6.3 are lower because these are the average values of three hours which include before and after the morning peak hour.

Table 6.3: Traffic assignment with departure time choice – Total VMT and VHT

1	2	3	4	5
Time interval	**Total VMT (vehicle-miles per hour)**	**Total VMT (vehicle-miles per 15-minute)**	**Total VHT (vehicle-minutes per hour)**	**Total VHT (vehicle-hours per 15-minute)**
1	676561	169140	1217938	5075
2	717604	179401	1319436	5498
3	1207969	301992	2350412	9793
4	2241939	560485	4669014	19454
5	3145151	786288	6992634	29136
6	3200821	800205	7318455	30494
7	2038697	509674	4478473	18660
8	715099	178775	1507949	6283
9	241893	60473	501842	2091
10	131330	32833	267069	1113
11	94071	23518	188598	786
12	78024	19506	155074	646
Total	-	3622290	-	129029
Hourly average	-	1207430	-	43010

Figure 6.1 plots the change in total VMT over the time intervals. The figure also includes the total VMT computed from the Traffic Assignment with Fixed O-D program for comparison. Essentially, the latter data points are the results of using the 15-minute O-D matrices to perform traffic assignment with a fixed O-D matrix approach, without the changing driver's departure time. It can be seen that, without or before adjusting the departure time, the total VMT peaks at interval 5 (7:00 a.m. to 7:15 a.m.). This reflects that to some degree, the K-factor has already captured the peak 15 minutes. However, with departure time choice, the peak pattern is more severe and it spread over a longer time span (7:00 a.m. to 7:30 a.m.). Another point to note is that, when the average work start-time is set to 8:00 a.m., most of the risk averse drivers will adjust their departure times to earlier, causing the curve to have very small values when the time intervals have passed the average work-start time.

It is important to emphasize that the input O-D matrices (derived from the 24-hour matrices and the interpolated K-factors) are based on the current year conditions. Therefore, it is not reasonable to run the model with departure time choice. An analyst running the traffic assignment with departure time choice model with existing and valid input data will produce the new O-D matrices and results that are biased (and not realistic). Therefore, this model is more appropriately used to model the network conditions in the future years, when traffic congestion is expected to influence a driver's departure time decision.

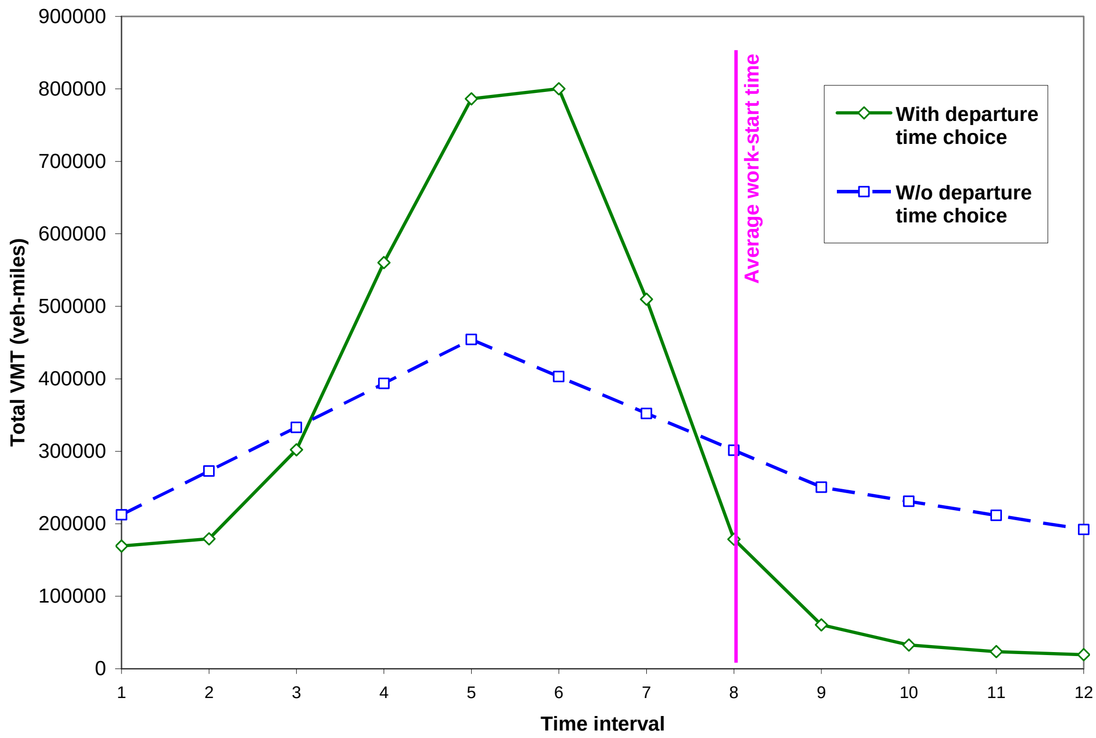


Figure 6.1: Traffic assignment with departure time choice – total VMT

Figure 6.2 plots the change in total VHT over the time intervals. Both curves, with and without departure time choices, follow the same shape as in the total VMT.

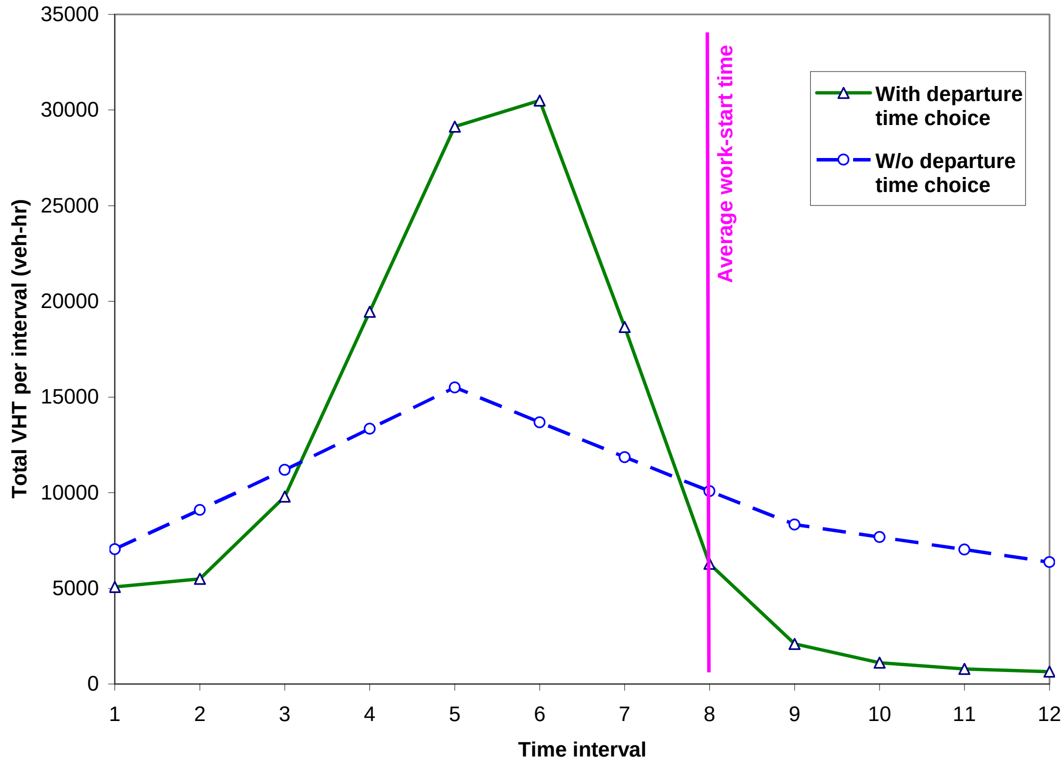


Figure 6.2: Traffic assignment with departure time choice – total VHT

6.2.4 Analysis for the Peak Time Interval

Chapter 5 of this report presents a detailed analysis of the network characteristics after traffic assignment with a fixed O-D matrix. The analysis includes:

- V-C ratio at hotspots
- lane-mile distribution by V-C ratio
- distribution of trip travel time

The analysis can be repeated for the network of interest in any time interval, by processing the data at the corresponding traffic assignment output file. To perform such analysis, it is recommended that the analyst examine the total VMT and VHT curves, and select the time interval with the highest VMT and VHT. In the examples in Figures 6.1 and 6.2, the interval of interest is interval 6 (7:15 a.m. to 7:30 a.m.). As the analysis procedure is the same as described in Chapter 5, it will not be repeated here. However, readers are cautioned that, when the traffic assignment results are analyzed, the results are only valid during the short time interval.

6.2.5 V-C Ratios at Hotspots

The Plot Hotspot program allows the user to analyze the change in V-C ratio over time in selected links. As examples, this program has been used to plot the V-C ratios of the following important links in the EP2005 network:

- Westbound I-10 east of US-54
- Eastbound I-10 west of Executive Center Drive
- Eastbound Mesa Street north of Shuster
- Westbound Mesa Street north of Shuster

These first two links are one-way freeway links that connect the commuters to the downtown. The eastbound Mesa Street is an alternate route for commuters from the west side of El Paso to travel to the downtown area without using the freeway. Since Mesa Street is coded as a two-way in the TransCAD model, the V-C ratio of westbound Mesa Street is also plotted for comparison. Westbound of Mesa Street is also an important link for drivers who travel from the east side of El Paso to UTEP and the medical centers nearby.

The V-C ratio curves are shown in Figure 6.3. All the four curves peak at interval 5 (7:00 a.m. to 7:15 a.m.). It is also noticed that traffic at Mesa Street in both directions is almost zero before 6:15 a.m. and after 8:15 a.m. The shape of the V-C curves follow closely to the total VMT and VHT curves plotted in Figures 6.1 and 6.2.

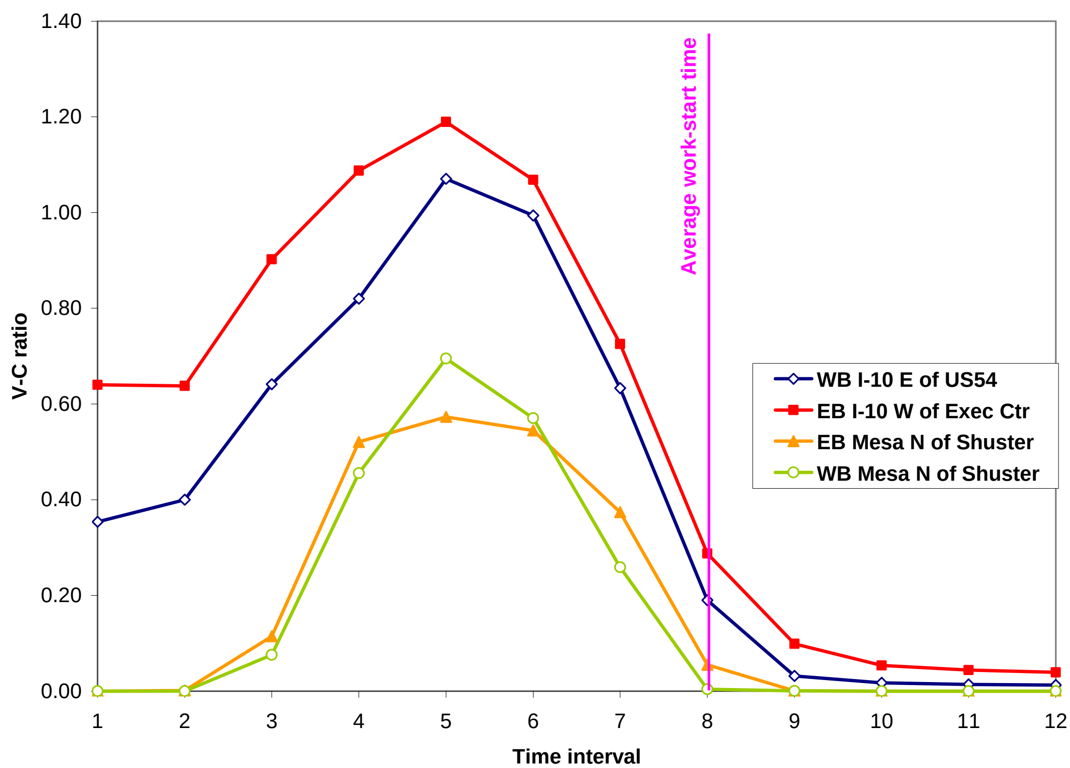


Figure 6.3: Traffic assignment with departure time choice – V-C ratios at hotspots

CHAPTER 7

APPLICATION IN PROJECT EVALUATION

This chapter illustrates how the concept of the SN-DUE model can be applied to evaluate a transportation project proposal. The traffic conditions in two networks are to be compared in this evaluation. The base network is the EP2005 network as described in Chapter 5. A new project, the Southern Relief Route (SRR), has been added to the EP2005 network. This network with SRR is called EP2005SRR in this Chapter. The traffic loading used in the evaluation is the 7:00 a.m. to 8:00 a.m. O-D matrix. This is the same O-D matrix used in Chapter 5. In our analysis, it is assumed that the SRR is completed and opened to traffic in year 2005.

The departure time choice analysis performed in Chapter 6 is based on a set of 15-minute O-D matrices constructed based on several assumptions. As no detailed information on the future 15-minute O-D matrices in the morning peak period is available, it was decided that analysis would not be performed for departure time choice.

Since no further information on the future year's road expansion (in other part of the road network) is provided, the capacity reliability analysis is performed with the same network as in 2005. This is unlike Chapter 5 where the capacity reliability curves were plotted for future years' O-D matrices and future years' road expansion.

7.1 El Paso Network with Southern Relief Route

The TransCAD road network database for the EL2005SRR network has been provided by TxDOT El Paso District. This network, with the addition of SRR, has 4923 links and 4340.69 lane-miles. A TransCAD screenshot of the entire network is shown in Figure 7.1, while an enlarged view of the SRR is highlighted in Figure 7.2.

Figure 7.1: EP2005SRR network as seen in TransCAD

Figure 7.2: SRR in EP2005SRR network
(the SRR is highlighted in yellow)

As usual, the capacity of all the links in the network were first adjusted from the 24-hourly capacity to hourly capacity, according to the values listed in Table 5.4.

Note that, SRR is a toll road with a toll rate of $0.14/mile. To perform traffic assignment with toll, the Planning → Advanced Traffic Assignment → Multimodal Multi-Class Assignment option in TransCAD Version 4.8 was used. In addition, to simulate the risk averse behavior of the drivers, the α value of 0.2153 has been used (to reflect the used of ELD function with a_1 =1.4356).

7.2 V-C Ratios at Hotspots

The V-C ratios at the 10 hotspots in the network are first analyzed. The value of the V-C ratios at the same links from the EP2005 and EP2005SRR networks are tabulated side by side in Table 7.1.

In the scenario simulated for the 7:00 a.m. to 8:00 a.m. traffic, the two hotspots along I-10 in the west side of El Paso (north of Sunland Park and between Sunland Park and Executive Center) have lower V-C ratios. This is because the proposed SRR starts at Sunland Park interchange. The portion of I-10 north of Sunland Park interchange has been widened with increased capacity. Along I-10 between Sunland Park and Executive Center, the freeway has been widened, and some of the traffic which originally used I-10 is diverted to the parallel SRR route. The V-C ratio of eastbound I-10 west of US-54 has also decreased significantly. This shows that the diversion of some of the eastbound traffic from I-10 to SRR not only benefits I-10 on west side of the downtown, but also has positive effect on the traffic on I-10 east of the downtown area.

In Table 7.1, one of the hotspots is at Paisano north of Executive Center. This section of Paisano in EL2005 has been converted to part of SRR. Therefore, in the EP2005SRR network, this link attracts more traffic and hence leads to an increase in V-C ratio. The V-C ratios of approximately 0.7 in both directions indicate that the SRR is well utilized during the morning peak hour.

Table 7.1: EP2005 network with and without SRR – V-C ratio at hotspots

Location of hotspots	**Link ID**	**V-C ratio**	
		EP2005 (ELD)	**EP2005SRR (ELD)**
I-10 north of Sunland Park	1538 (EB)	0.7085	**0.5480**
	1542 (WB)	0.7957	**0.4765**
I-10 between Sunland Park & Executive Center	1534 (EB)	0.8653	**0.5246**
	1535 (WB)	0.7641	**0.5820**
I-10 west of US-54	1924 (EB)	0.7527	**0.3220**
	2927 (WB)	0.7265	0.7125
I-10 east of US-54	216 (WB)	0.7420	0.7362
	217 (EB)	0.7524	0.7618
I-10 west of Loop 375	3580 (WB)	0.7122	0.7141
	3583 (EB)	0.4387	0.3322
Paisano north of Executive Center	1623 (EB)	0.0258	**0.6973**
	1623 (WB)	0.1934	**0.7265**
Cesar Chavez northwest of Midway	579 (EB)	0.7081	0.7115
	579 (WB)	0.7008	0.7082
I-10 west of Horizon	3647 (WB)	0.4774	0.4769
	4759 (WB)	0.4702	0.4691
Mesa south of Sunland Park	1908 (EB)	0.6052	0.6284
	1908 (WB)	0.6025	0.6602
Mesa north of Shuster	1835 (EB)	0.2583	0.2546
	1835 (WB)	0.2931	0.2818

7.3 Total Vehicle-Miles Traveled and Total Vehicle-Hours Traveled

Table 7.2 compares the total VMT and total VHT in the EL2005 network with and without SRR. As expected, with the SRR, the total VHT has reduced from 61903 vehicle-hours to 61841 vehicle-hours, a saving of 62 vehicle-hours between 7:00 a.m. to 8:00 a.m. The total VMT has also been reduced by 2243 vehicle-miles. This shows that the SRR not only provides congestion relief (spreading vehicles from I-10 Freeway), but also provides a more direct route from the west side of El Paso to the downtown area.

A comparison is also made if the evaluation of EP2005 and EP2005SSR network would lead to a different conclusion if DN-DUE model is used (i.e., if the BPR function is used in traffic assignment instead of the ELD function). Using the BPR function in traffic assignment with a fixed O-D matrix, the EP2005SRR has relatively smaller total VMT and total VHT, than the EP2005 network. The conclusions are consistent with the earlier findings using the ELD function.

Table 7.2: EP2005 network with and without SRR – total VMT and total VHT

	EP2005 (ELD function)	**EP2005SRR (ELD function)**
Total VMT (veh-miles)	1813151	1810908
Total VHT (veh-hr)	61903	61841
	(BPR function)	**(BPR function)**
Total VMT (veh-miles)	1813325	1810875
Total VHT (veh-hr)	61529	61470

7.4 Lane-Mile Distribution of V-C Ratios

Table 7.3 and Figure 7.3 show the percentage distribution of total lane-miles at the various V-C ratios. With the addition of SRR, there is a lower percentage of lane-miles with V-C ratios greater than 0.6. This indicates that SRR is attracting traffic away from the competing congested routes that have high V-C ratios. With the SRR, the network has more lane-miles with moderate range of V-C ratio (between 0.2 to 0.6). Overall, the EL2005SRR network appears less congested than the EP2005 network. However, there are more links (although they are of small number) in the EP2005SRR network which have V-C ratios greater than 1.

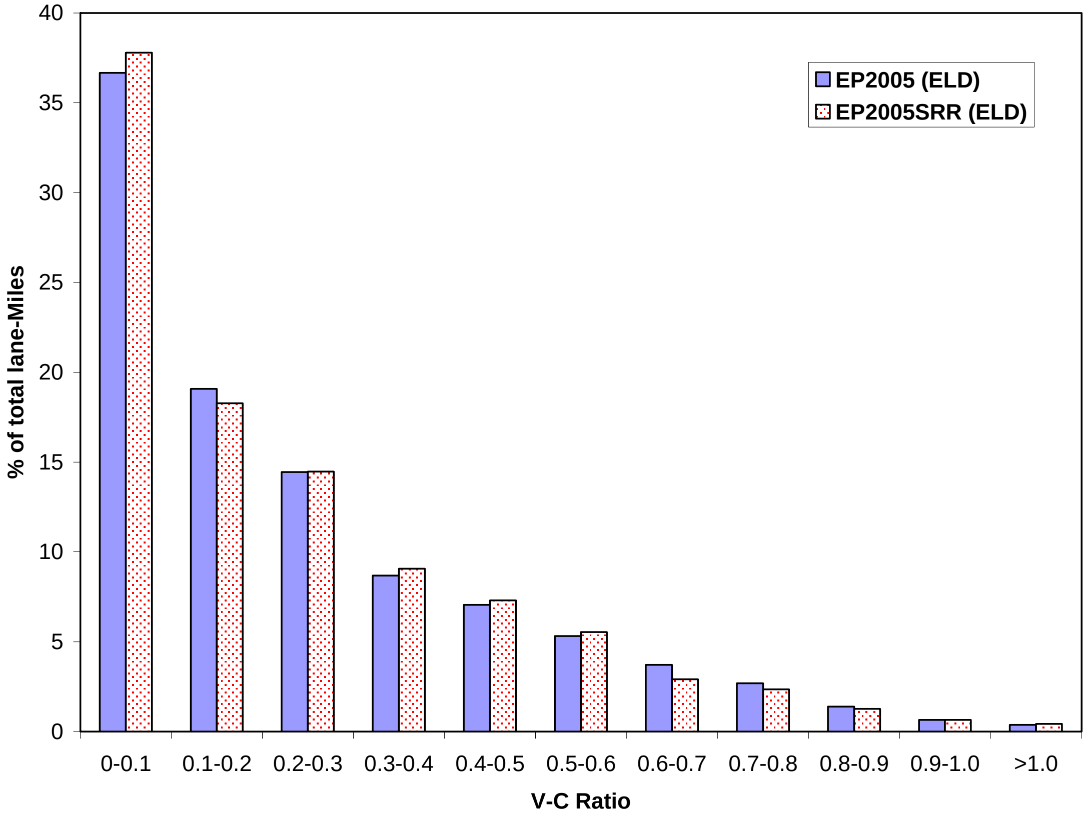


Figure 7.3: EP2005 network with and without SRR – lane-mile distribution of V-C ratio

Table 7.3: EP2005 network with and without SRR – lane-mile distribution of V-C ratio

V-C Ratio	EP2005 (ELD)		EP2005SRR (ELD)	
	Lane-miles	% lane-miles	Lane-miles	% lane-miles
0-0.1	1574.53	36.66	1640.08	37.78
0.1-0.2	819.56	19.08	793.14	18.27
0.2-0.3	620.17	14.44	627.81	14.46
0.3-0.4	372.94	8.68	393.26	9.06
0.4-0.5	302.48	7.04	316.72	7.30
0.5-0.6	228.14	5.31	240.49	5.54
0.6-0.7	159.27	3.71	126.34	2.91
0.7-0.8	115.13	2.68	102.12	2.35
0.8-0.9	59.68	1.39	54.74	1.26
0.9-1.0	27.56	0.64	27.94	0.64
>1	15.86	0.37	18.07	0.42
Total	4295.30	100.00	4340.69	100.00

Figure 7.4 and Table 7.4 shows the lane-mile distribution of V-C ratio for the freeway links only. The freeway links are facility types (functional classes) 1, 2, 3 and 14. The SRR project actually adds 11.57 lane-miles in the network. In Figure 7.4, the percent lane-mile is plotted as the y-axis to normalize against the difference in the total freeway lane-miles. The changes in the V-C ratios basically fall into two groups. With the SRR, there are fewer percentages of lane-miles with V-C ratios of 0.6 to 0.9, and more lane-miles with V-C ratios of 0.4 to 0.6. A similar trend of V-C ratio being shifted from the range of 0.1 to 0.3 to less than 0.1 has also been observed. The SRR has an effect in reducing some of the freeway lane-miles from high V-C ratios. This indicates that the SRR is spreading the traffic among the freeway lane-miles.

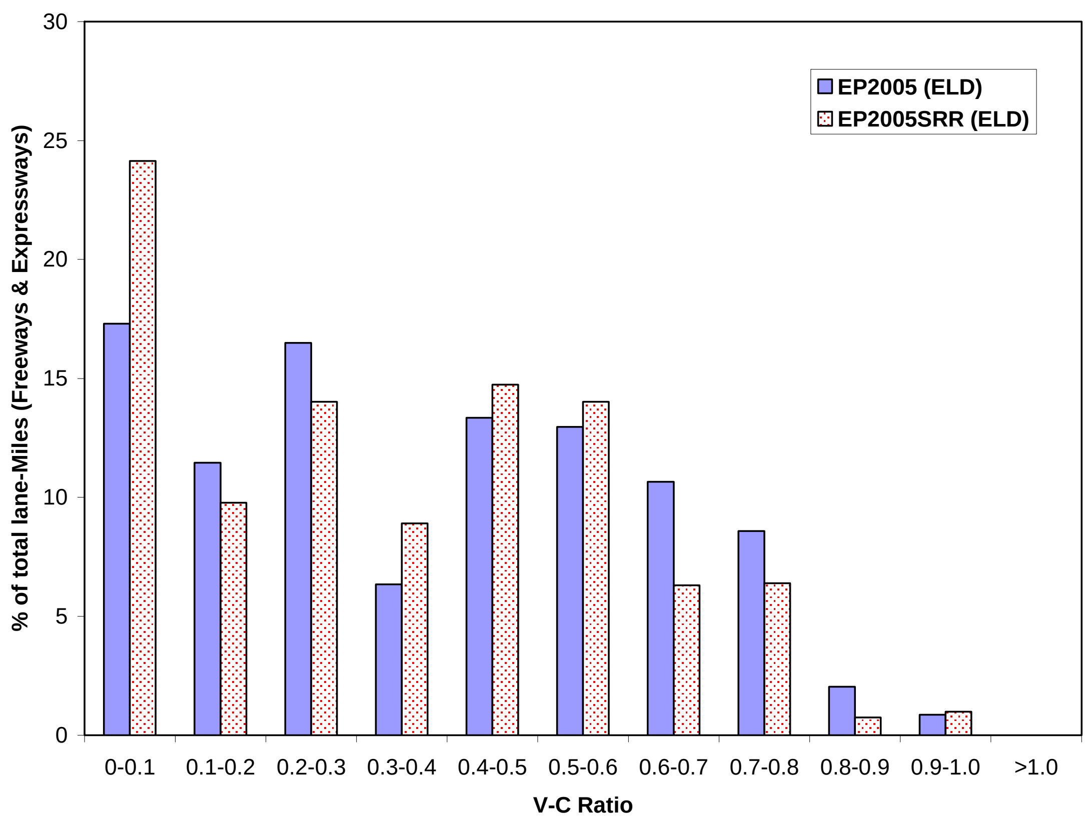


Figure 7.4: EP2005 network with and without SRR – lane-mile distribution of V-C ratio for freeway links

Table 7.4: EP2005 network with and without SRR – lane-mile distribution of V-C ratio for freeway links

V-C Ratio	EP2005 (ELD function)		EP2005SRR (ELD function)	
	Lane-miles	% lane-miles	Lane-miles	% lane-miles
0-0.1	101.04	17.30	143.74	24.13
0.1-0.2	66.89	11.45	58.21	9.77
0.2-0.3	96.33	16.49	83.48	14.02
0.3-0.4	37.02	6.34	53.04	8.91
0.4-0.5	77.91	13.34	87.77	14.74
0.5-0.6	75.68	12.96	83.45	14.01
0.6-0.7	62.20	10.65	37.56	6.31
0.7-0.8	50.10	8.58	38.01	6.38
0.8-0.9	11.88	2.03	4.45	0.75
0.9-1.0	5.02	0.86	5.88	0.99
>1	0.00	0.00	0.00	0.00
Total	584.07	100.00	595.59	100.00

7.5 Distribution of Trip Travel Times

Table 7.5 and Figure 7.5 show the distribution of trip travel time in 5-minute increments. The EP2005SRR network has relatively more trips with travel times of less than 15 minutes and relatively fewer trips with travel times of more than 20 minutes, compared to the EL2005 network. The EL2005 network has an average trip travel time of 12.1984 minutes while the EP2005SRR network has an average trip travel time of 12.1861 minutes, a saving of only 0.738 second per trip. The savings in the average trip travel time caused by the SRR is not that significant because it has been averaged out by trips in the network not using the SRR.

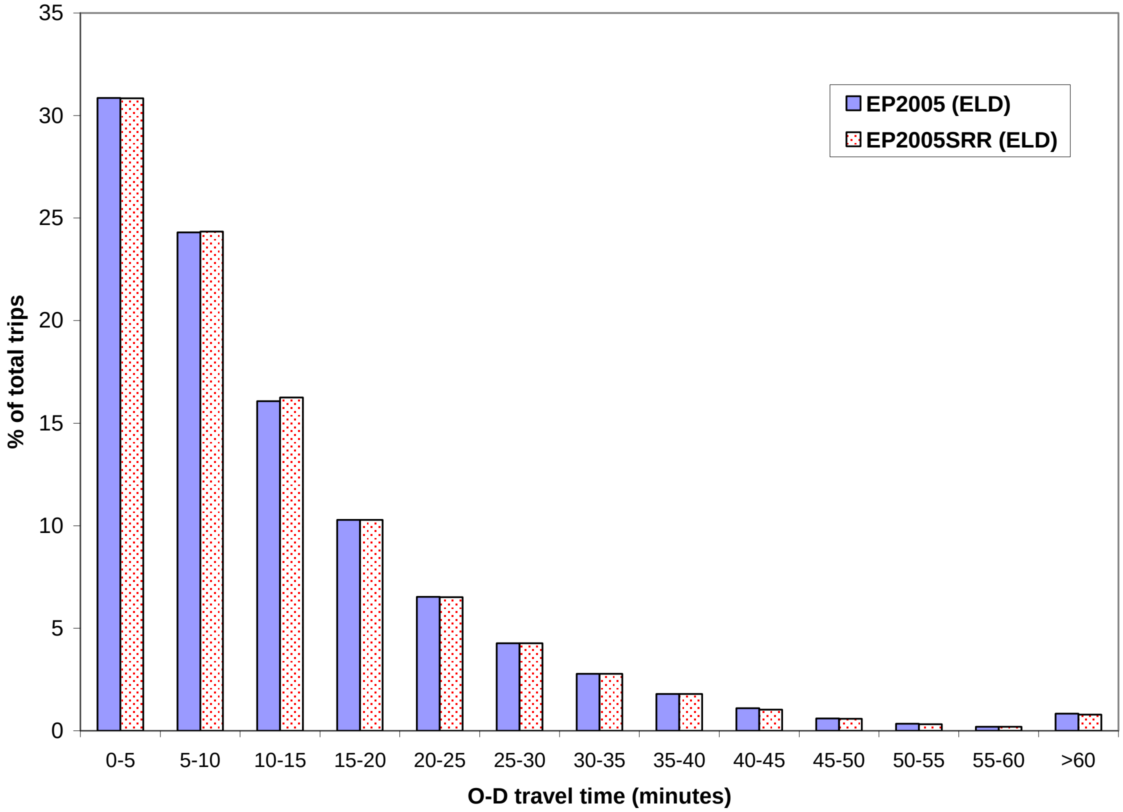


Figure 7.5: EP2005 network with and without SRR – distribution of trip travel time

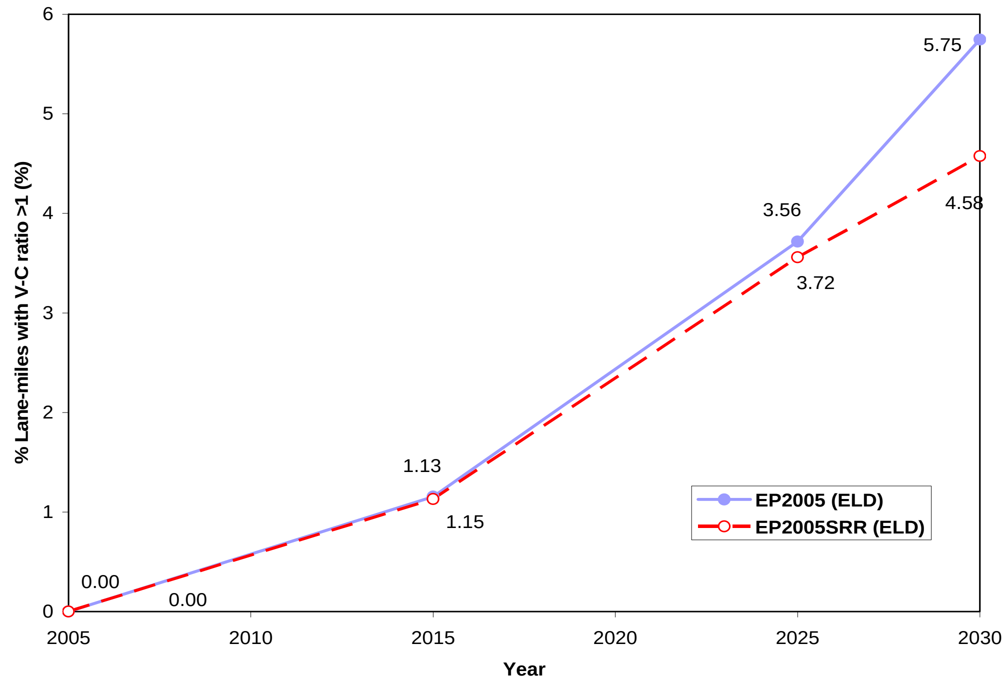
Table 7.5: EP2005 network with and without SRR – distribution of trip travel time

O-D travel time (minutes)	**EP2005 (ELD)**		**EP2005SRR (ELD)**	
	No. of trips	**% of total trips**	**No. of trips**	**% of total trips**
0-5	93955	30.86	93892	30.84
5-10	74005	24.31	74109	24.34
10-15	48927	16.07	49509	16.26
15-20	31337	10.29	31326	10.29
20-25	19898	6.54	19849	6.52
25-30	12996	4.27	12975	4.26
30-35	8487	2.79	8461	2.78
35-40	5480	1.80	5461	1.79
40-45	3349	1.10	3120	1.02
45-50	1835	0.60	1790	0.59
50-55	1062	0.35	992	0.33
55-60	606	0.20	593	0.19
>60	2547	0.84	2406	0.79
Total	304482	100.00	304482	100.00

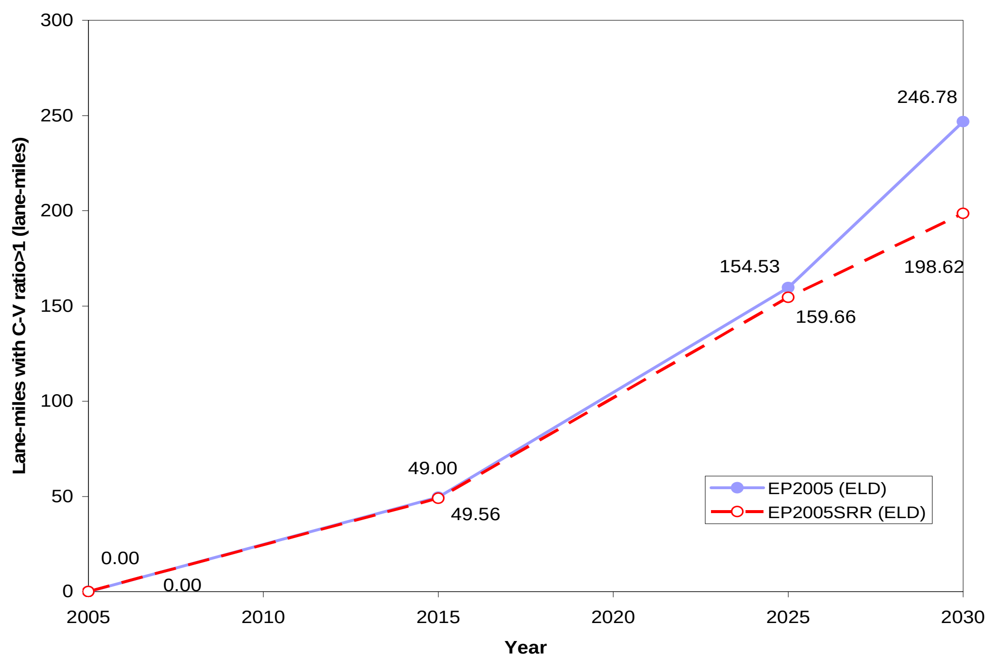
7.6 Capacity Reliaility

The capacity reliability of the EP2005 and EP2005SRR networks are compared in this section. Unlike in Chapter 5, where the EP2005, EP2015, EP2015 and EP2030 networks were provided together with the projected O-D matrices in the corresponding years, the future year's network with the SRR is not available. Therefore, both the EP2005 and EP2005SRR networks are assumed to be the same over the years, i.e., no capacity expansion. Nevertheless, the projected O-D matrices in the years 2005, 2015, 2025 and 2030 were used. Traffic assignments were performed with the ELD function for years 2005, 2015, 2025 and 2030. Since the SRR is a toll road, it is also assumed that the toll rate of $0.14 per mile remain unchanged over the years.

Figure 7.6(a) plots the increase in percent lane-miles in the network with V-C ratio greater than 1 over the analyzed years. Since the EP2005 and EP2005SRR networks have different total lane-miles (4295.30 lane-miles in EP2005 and 4340.69 lane-miles in EP2005SRR), the absolute value of lane-miles with V-C ratios greater than 1 is also plotted in Figure 7.6(b). From 2005 to 2015, both networks have almost identical capacity reliability. This is because, in the earlier years, the remarkable improvement in V-C ratios are all centered around the parallel routes of SRR, which form only a small fraction of lane-miles in the entire network. In 2025 and 2030, the percent and number of lane-miles with V-C ratios greater than 1 have increased relatively at a faster pace. The percent and absolute values are higher than the modeling results reported in Chapter 5. This is because, in the EP2005 and EP2005SRR network, no capacity expansion is coded in the northeast region of El Paso, but the forecasted O-D matrix loaded more vehicles into the network from this area. Comparing the two curves in the same figure, the EP2005SRR network actually has better capacity reliability, because it has fewer lane-miles with V-C ratio greater than 1 in years 2025 and 2030.



(a) by percent lane-miles



(b) by absolute value of lane-miles

Figure 7 6: EP2005 network with and without SRR – forecasted capacity reliability curves

7.7 Summary

In this chapter, the use of traffic assignment with a fixed O-D matrix, with the ELD function (which represents the route choice behavior of risk averse drivers) has been used to evaluate a transportation proposal: the addition of the SRR in the El Paso network. A comparative evaluation of the EP2005 network and EP2005SRR network (which is the EP2005 network with the addition of SRR) under the same traffic demand in the morning peak hour has been made.

The evaluation has found that the EP2005SRR network has resulted in slightly lower total VMT, total VHT and average trip travel time. The improvement is marginal because most of the improvements in traffic flow are concentrating around the SRR and its parallel freeway. The EL2005SRR has fewer lane-miles with high level congestion as the level of traffic grows in the future years, especially beyond 2015. The analysis at the hotspots also reveals that most of the reductions in V-C are along portions of the major freeway which is parallel to the SRR, but the rest of the network has relatively small changes in the volumes.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATION FOR FUTURE RESEARCH

8.1 Conclusions

This research has produced the following important findings:

From the literature review, it was found that a driver's route choice in response to travel time reliability (or more correctly, travel time uncertainty) may be modeled by three types of behavior: risk averse, risk neutral and risk prone. In each type of behavior, the driver selects the least-disutility route. The route disutility is an exponential function of the average route travel time.

Based on past research, traffic assignment models may be classified into four types based on the assumptions on link travel time and the driver's perception of the link travel time. Based on this classification, the Stochastic Networks-Deterministic User Equilibrium (SN-DUE)) model is recommended for use in modeling route choice in a network with travel time uncertainty in the morning commute, which is usually the most congested hour.

Our literature review also found a calibrated model that describes the driver's choice of departure time to work when the route travel time is uncertain. This model has been incorporated into the traffic assignment model developed in this research.

The existing definition and method of computing capacity reliability has been reviewed. The definition has been modified and incorporated into this research to provide a quantitative measure of a network's level of service when the traffic assignment model considers travel time uncertainty and driver's response to travel time uncertainty. The definition is further modified to predict the level of service when the traffic demand and network facility changes over the years.

Based on the findings in the literature review, the research team has proposed two traffic assignment approaches in a network with travel time uncertainty during the morning peak hour:

- Traffic assignment with a fixed Origin-Destination (O-D) matrix
- Traffic assignment with departure time choice

Both approaches incorporate the route choice behavior in response to travel time uncertainty. The second model further incorporates a driver's departure time choice in response to traffic congestion along the route.

This research team has derived Equivalent Link Disutility (ELD) functions (as reported in Chapter 4) that correspond to each of the three types of route choice behavior. The link disutility functions have two components: a deterministic component that is described by the

BPR function, and a stochastic component proportional to the link travel time variance. The research team has proven that these derived expressions are the more general cases of those found in literature review (which are only applicable under some conditions). However, their functional forms are difficult to implement in traffic assignment models. As an alternative, the research team has derived simpler ELD functions, with mathematical properties consistent with the earlier derived ELD expressions, so that they can be easily implemented in the traffic assignment model. The simpler ELD function is similar to the BPR function, except with an additional factor to account for the different risk taking behavior of the driver. In summary, to perform traffic assignment in the morning commuting hour with travel time reliability consideration, the analyst only needs to use the traditional static traffic assignment model, but simply replace the BPR function with the simpler ELD function. In TransCAD, this can be done easily by changing the value of alpha in the BPR function.

A driver survey has been conducted in El Paso to illustrate how the risk averse coefficient in the simple ELD function can be estimated. The estimated coefficient has shown that for the morning commute to work, on the average, drivers are risk averse.

The traffic assignment with a fixed O-D approach has been implemented in TransCAD. Two networks, a 25-node test network and the El Paso network (in year 2005) have been used to illustrate the difference in the results with and without travel time reliability considerations. It has been shown that, with the risk averse behavior (that considers travel time uncertainty), drivers tend to avoid highly congested links and prefer the less congested links (which may have longer average travel time). This leads to a more uniform distribution of Volume-Capacity (V-C) ratios across the network. Because of this, the total Vehicle-Hours Traveled (VHT) is likely to increase.

The traffic assignment with departure time choice approach has also been implemented in TransCAD, using the two networks, for the morning peak period of 6:00 a.m. to 9:00 a.m. The implementation results have demonstrated that this approach was able to adjust the departure times of the drivers to meet their work-start times. However, because this approach requires O-D matrices in smaller time intervals and the work-start time of each of the zones, further work on data collection needs to be done to bring this approach closer to practical implementation.

The traffic assignment with a fixed O-D approach (with the ELD function) has been applied to comparatively evaluate the El Paso network with and without the Southern Relief Route (SRR). The different ways of presenting and comparing the results of traffic assignment, such as comparing the total VMT, total VHT, distribution of V-C ratio, distribution of trip length, and V-C analysis at hotspots, have been demonstrated in this case study.

A program suite (named Travel Time Reliability) has been written in the GISDK language for use with TransCAD Version 4.8 as an Add-in. This program suite has eight programs which, when used in combinations, allows an analyst to conduct traffic assignment with a fixed O-D matrix and traffic assignment with departure time choice, in a network with travel time uncertainty. It also assists the analyst in preparing the input data and visualizing the traffic assignment results. A User's Guide which accompanies this software has been written.

8.2 Recommendations for Future Research

Although this research has developed traffic assignment models for stochastic networks with travel time reliability consideration, there are still several issues that need to be addressed for more accurate implementation. These issues, discussed below, warrant further research.

The average link travel time in a stochastic network is assumed to follow the BPR function. Although the BPR function is the most accepted and used function by researchers and practitioners, it was proposed in the 1960s, when the driving population, their behavior, vehicle performance and classes, level of traffic congestion, etc, were different from today. Furthermore, this function has not been calibrated extensively with field data. Our experiences in modeling with the BPR function suggest that it underestimates the level of congestion compared to field observations. An updated function or functions are necessary to represent the different types of Texas roadway facilities in order to produce more accurate modeling results for transportation planning decisions. How the updated function, if in a different form, affects the derivation of ELD function needs to be studied.

In Chapter 4, the ELD functions for risk averse, risk neutral and risk prone behaviors have been derived. In reality, there exist fractions of the driving population who are risk averse, risk neutral and risk prone. In the analysis and illustrations presented in Chapters 5, 6 and 7, the research team have assumed that in the morning commute, when work-start times become constraints, all the drivers in the network are (on the average) risk averse. This simplification enables us to model the SN-DUE model as an DN-DUE model. An extension would be to model the network with different proportions of risk averse, risk neutral and risk prone drivers. This approach is called multi-class traffic assignment, which is an emerging area of transportation research.

In the traffic assignment with departure time choice model, a time interval of 15 minutes has been used. A time interval must be short enough to represent users' departure time decision interval and long enough for the users to complete their trips. The time interval of 15 minutes is recommended as a compromise. Our results show that the average trip travel time of approximately 12 minutes is less than the 15-minute time interval. The sensitivity of the choice of time interval on the total VMT, total VHT and V-C ratio at hotspots needs to be investigated, but this is beyond the scope and time of this project.

A related issue in the selection of departure time interval is the availability of O-D matrices. The original O-D matrices used as the inputs to the traffic assignment models with departure time choice (in Chapter 6) were constructed with interpolated K-factors. The O-D matrices can be more accurate if traffic counts at the same resolution as the time interval at representative locations in the network are available.

An important input in the traffic assignment with departure time choice model is the work-start time. In the model developed in this research, the average work-start time of each zone has been assumed based on the researchers' knowledge of the El Paso network and input from the Project Advisory Committee. The work-start time is further assumed to follow a discrete probability distribution with probability of 0.1, 0.2, 0.4, 0.2, 0.1 for five time intervals, with the probability of 0.4 being the time interval of the average work-start time. These assumptions were made because no data of existing work-start time is available from TxDOT or El Paso MPO. In the future, when possible, data on work-start time should be gathered for each of the zones.

At present, the Capacity Reliability program developed in this project can only work with a network without any tolled links. For a network with toll links, the traffic assignment task and computation of percent lane-miles with V-C ratio greater than 1 have to be performed manually. Such automation can be made in the future when time and budget are available.

Another application of the traffic assignment approaches developed in this project is to model the network's capacity reliability due to the loss in capacity in a link, for example, a bridge collapse or freeway closure. Due to the constraint in time, this has not been investigated in this project, but should be explored in future applications.

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APPENDIX A

ESTIMATION OF RISK AVERSE COEFFICIENT:

SURVEY FORM AND RESULTS

Route Choice Behavior Survey

UTEP is conducting a research project titled "Strategies to Improve Travel Time Reliability" which is funded by the Texas Department of Transportation (TX DOT). An objective of this research is to conduct surveys to see how travelers perceive between a route with an uncertain travel time and a route which has a constant travel time.

This survey will not require you to disclose any confidential information. We appreciate your time in taking part in this survey by answering the following two questions. Thank you.

Kelvin Cheu, PhD
Associate Professor
Department of Civil Engineering

<u>Question #1</u>

Suppose that you live in location A and work at location B. You are to report to work every weekday at 8:00 a.m.

There are two routes you can take from A to B: Routes 1 & 2. Route 1 has an uncertain travel time but Route 2 has a fixed travel time.

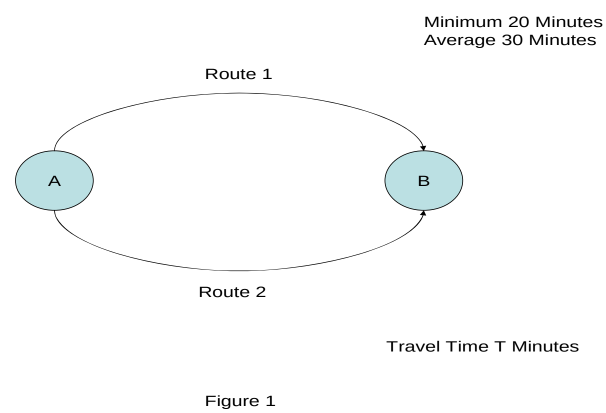

Figure A1: Network for survey question 1

The travel time on Route 1 is unreliable, and depends on the traffic conditions on that day. We only know that it has a *minimum* travel time of 20 minutes on a good day, but on the *average*, the travel time is 30 minutes.

The travel time on Route 2 is very reliable and is *constant* at *T* minutes.

If $T \leq 20$ minutes, the travel time on Route 2 is less than or equal to that of Route 1. In this case you will most likely choose Route 2.

When $T > 20$ minutes, Route 1 can have a shorter travel time than Route 2. Route 2 becomes less attractive as *T* increases.

When *T*=30 minutes, the *constant* travel time on Route 2 is the same as the *average* travel time on Route 1. If you leave home at 7:30 a.m. and use Route 2, you will reach you office at 8:00 a.m. But with Route 1, you have a 50% chance of arriving before 8:00 a.m. and a 50% chance of arriving later than 8:00 a.m.

Given that you have to reach your office by 8:00 a.m., you may prefer to use Route 2 that has a longer but more reliable travel time. What is the value of *T* so that you would consider both routes having the same quality? That is, what is the value of *T* so that you do not have any preference of one route over the other?

Answer (please circle one): *T* = 30, 35, 40, 45, 50, 55, 60 minutes

Question #2

Consider the similar problem as in Question #1, but for 2 routes (Routes 3 and 4) between Locations C and D, with the travel times as shown in the following figure:

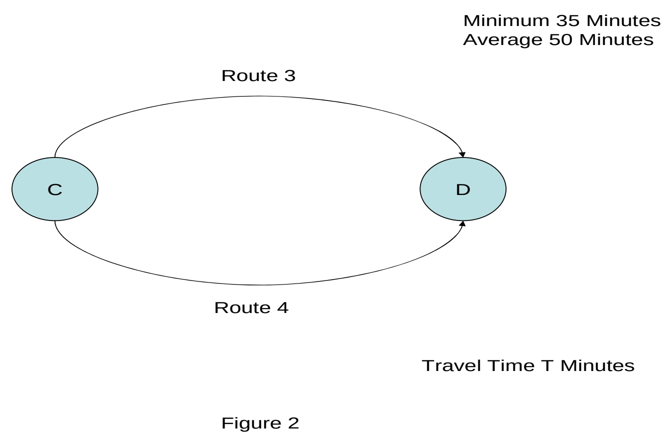

Figure A2: Network for survey question 2

The travel time on Route 3 is unreliable has a *minimum* travel time of 35 minutes on a good day, but on the *average*, the travel time is 50 minutes.

The travel time on Route 4 is very reliable and is *constant* at *T* minutes.

What is the value of *T* so that you would consider both routes having the same quality? That is, what is the value of *T* so that you do not have any preference of one route over the other?

Answer (please circle one): *T* = 50, 55, 60, 65, 70, 75, 80 minutes

SURVEY RESULTS

Surveyee No.	Question # 1 T (minutes)	Question # 2 T (minutes)	Question # 1 a1	Question # 2 a1
1	30	50	1.000	1.000
2	35	55	1.500	1.333
3	30	50	1.000	1.000
4	30	50	1.000	1.000
5	30	50	1.000	1.000
6	35	60	1.500	1.667
7	40	60	2.000	1.667
8	30	50	1.000	1.000
9	40	55	2.000	1.333
10	40	55	2.000	1.333
11	35	55	1.500	1.333
12	30	50	1.000	1.000
13	30	50	1.000	1.000
14	35	60	1.500	1.667
15	30	50	1.000	1.000
16	30	50	1.000	1.000
17	35	55	1.500	1.333
18	40	55	2.000	1.333
19	30	50	1.000	1.000
20	35	55	1.500	1.333
21	35	60	1.500	1.667
22	35	60	1.500	1.667
23	30	50	1.000	1.000
24	30	50	1.000	1.000
25	45	75	2.500	2.667
26	30	50	1.000	1.000
27	35	55	1.500	1.333
28	30	55	1.000	1.333
29	35	50	1.500	1.000
30	45	70	2.500	2.333
31	35	65	1.500	2.000
32	45	60	2.500	1.667
33	30	50	1.000	1.000
34	30	50	1.000	1.000
35	35	55	1.500	1.333
36	30	50	1.000	1.000
37	35	55	1.500	1.333
38	30	50	1.000	1.000
39	30	50	1.000	1.000
40	30	50	1.000	1.000
41	35	55	1.500	1.333
42	30	50	1.000	1.000
43	30	60	1.000	1.667
44	35	60	1.500	1.667
45	30	50	1.000	1.000
46	30	50	1.000	1.000
47	40	60	2.000	1.667
48	30	50	1.000	1.000
49	40	60	2.000	1.667

Surveyee No.	Question # 1	Question # 2	Question # 1	Question # 2
	T (minutes)	T (minutes)	a1	a1
50	30	50	1.000	1.000
51	35	55	1.500	1.333
52	30	50	1.000	1.000
53	45	55	2.500	1.333
54	30	50	1.000	1.000
55	35	55	1.500	1.333
56	45	75	2.500	2.667
57	50	60	3.000	1.667
58	35	50	1.500	1.000
59	30	50	1.000	1.000
60	40	60	2.000	1.667
61	30	50	1.000	1.000
62	50	70	3.000	2.333
63	30	50	1.000	1.000
64	30	50	1.000	1.000
65	30	50	1.000	1.000
66	30	50	1.000	1.000
67	30	50	1.000	1.000
68	30	50	1.000	1.000
69	30	50	1.000	1.000
70	30	50	1.000	1.000
71	30	50	1.000	1.000
72	35	55	1.500	1.333
73	30	50	1.000	1.000
74	30	50	1.000	1.000
75	30	50	1.000	1.000
76	40	65	2.000	2.000
77	30	50	1.000	1.000
78	45	65	2.500	2.000
79	30	60	1.000	1.667
80	40	65	2.000	2.000
81	35	60	1.500	1.667
82	30	50	1.000	1.000
83	40	60	2.000	1.667
84	30	50	1.000	1.000
85	40	50	2.000	1.000
86	35	55	1.500	1.333
87	35	55	1.500	1.333
88	30	50	1.000	1.000
89	30	50	1.000	1.000
90	30	50	1.000	1.000
91	30	50	1.000	1.000
92	35	55	1.500	1.333
93	50	70	3.000	2.333
94	30	50	1.000	1.000
95	30	50	1.000	1.000
96	40	65	2.000	2.000
97	40	65	2.000	2.000
98	40	65	2.000	2.000
99	40	55	2.000	1.333
100	35	55	1.500	1.333
101	35	55	1.500	1.333
104	40	60	2.000	1.667

Surveyee No.	Question # 1	Question # 2	Question # 1	Question # 2
	T (minutes)	T (minutes)	a1	a1
105	30	50	1.000	1.000
106	40	55	2.000	1.333
107	45	50	2.500	1.000
108	30	50	1.000	1.000
109	35	60	1.500	1.667
110	40	55	2.000	1.333
111	40	60	2.000	1.667
112	30	50	1.000	1.000
113	40	60	2.000	1.667
114	35	55	1.500	1.333
115	30	50	1.000	1.000
116	45	50	2.500	1.000
117	30	50	1.000	1.000
118	30	55	1.000	1.333
119	30	55	1.000	1.333
120	40	55	2.000	1.333
121	30	50	1.000	1.000
122	30	50	1.000	1.000
123	30	50	1.000	1.000
124	40	65	2.000	2.000
125	35	55	1.500	1.333
126	30	50	1.000	1.000
127	30	50	1.000	1.000
128	30	50	1.000	1.000
129	30	60	1.000	1.667
130	40	65	2.000	2.000
131	45	60	2.500	1.667
132	40	55	2.000	1.333
133	40	60	2.000	1.667
134	35	50	1.500	1.000
135	35	50	1.500	1.000
136	40	60	2.000	1.667
137	40	55	2.000	1.333
138	45	60	2.500	1.667
139	30	50	1.000	1.000
140	40	70	2.000	2.333
141	35	55	1.500	1.333
142	30	50	1.000	1.000
143	30	50	1.000	1.000
144	30	55	1.000	1.333
145	30	50	1.000	1.000
146	35	60	1.500	1.667
147	30	50	1.000	1.000
148	60	60	4.000	1.667
149	30	50	1.000	1.000
150	40	60	2.000	1.667
151	40	60	2.000	1.667
152	35	55	1.500	1.333
153	30	50	1.000	1.000
154	30	50	1.000	1.000
155	45	60	2.500	1.667
156	40	60	2.000	1.667
157	30	50	1.000	1.000

Surveyee No.	Question # 1	Question # 2	Question # 1	Question # 2
	T (minutes)	T (minutes)	a1	a1
158	35	50	1.500	1.000
159	35	55	1.500	1.333
160	30	50	1.000	1.000
161	30	50	1.000	1.000
162	30	50	1.000	1.000
163	30	50	1.000	1.000
164	35	50	1.500	1.000
165	40	55	2.000	1.333
166	30	50	1.000	1.000
167	55	55	3.500	1.333
168	30	50	1.000	1.000
169	40	60	2.000	1.667
170	30	50	1.000	1.000
171	30	50	1.000	1.000
172	35	60	1.500	1.667
173	30	50	1.000	1.000
174	35	55	1.500	1.333
175	40	60	2.000	1.667
176	45	60	2.500	1.667
177	40	65	2.000	2.000
178	45	60	2.500	1.667
179	40	50	2.000	1.000
180	40	55	2.000	1.333
181	30	50	1.000	1.000
182	40	50	2.000	1.000
183	35	60	1.500	1.667
184	35	55	1.500	1.333
185	35	50	1.500	1.000
186	55	50	3.500	1.000
187	50	60	3.000	1.667
188	30	55	1.000	1.333
189	40	65	2.000	2.000
190	30	50	1.000	1.000
191	40	50	2.000	1.000
192	30	50	1.000	1.000
193	45	50	2.500	1.000
194	30	60	1.000	1.667
195	45	65	2.500	2.000
196	50	65	3.000	2.000
197	40	60	2.000	1.667
198	55	75	3.500	2.667
199	30	50	1.000	1.000
200	45	60	2.500	1.667
201	45	75	2.500	2.667
202	45	75	2.500	2.667
AVERAGE a1			**1.456**	

APPENDIX B

NOTES FROM TRAVEL TIME RELIABILITY WORKSHOP

A workshop was held by the research team on 28 August 2007 at the University of Texas at El Paso campus for staff from TxDOT and El Paso MPO. In the workshop, the research team presented the concept of *traffic assignment with a fixed O-D* and *traffic assignment with departure time choice*, and demonstrated the use of the Travel Time Reliability Program Suite. This Appendix documents the self-assessment conducted by the research team after the workshop. It is hope that the experience shared by the research team here would help TxDOT in conducting future workshops during project implementation.

- <u>Pre-Workshop</u>. It is recommended that each participant familiar him/herself with the fundamentals of GISDK, matrix operations and basic traffic assignment procedure in TransCAD. It is also preferable that each participant bring his/her own laptop computer pre-installed with TransCAD Version 4.8. Some of the functions in the Travel Time Reliability Program Suite may not work earlier version of TransCAD. The laptop computer must have a DVD drive. Otherwise, the training/workshop classroom must have computer with enough TransCAD Version 4.8 licenses installed. Each participant should be provided with a hard copy of the User's Guide which can also be used as class notes.

- <u>Installation DVD</u>. The research team has prepared DVDs to be distributed to all workshop participants. The DVD contains the source file of Travel Time Reliability Program Suite, the User Guide, and sample data sets for each of the programs. As some of the participants may not have sufficient background in GISDK, the trainer/instructor should go through the installation procedure step-by-step (although the procedure has already been explained clearly in the User's Guide). The installation of Travel Time Reliability Program Suite and copying of data file may take up to 20 minutes.

- <u>Review of Traffic Assignment Approaches</u>. Before going into the details of the Travel Time Reliability Program Suite, it is recommended that the trainer/instructor review the two traffic assignment approaches with the participants. The slides used for the Closeout Meeting are excellent materials for a 20-minute review.

- <u>Sequence of Programs</u>. The trainer/instructor should go through the following four programs in sequence, to demonstrate the steps in performing *traffic assignment with a fixed O-D matrix*, since the concepts and procedure are easier to understand:

  Adjust O-D Matrix
  Adjust Capacity
  Traffic Assignment with Fixed O-D
  Capacity Reliability

  After taking a short break, the trainer/instructor should go through the remaining programs for *traffic assignment with departure time choice*:

  Set Variance of O-D Travel Time

Traffic Assignment with Departure Time Choice
Plot VMT & VHT
Plot Hotspots

While going through the following steps, the participants should follow the trainer/ instructor step-by-step, using the sample data set as an exercise. After this the trainer/instructor should allocate time for personal instructions or for participants to clarify certain points or steps in the programs.

- Duration. The first half of the workshop which included software installation, review of traffic assignment approaches and going through the four programs that relate to *traffic assignment with a fixed O-D matrix* took approximately 2 hours. After break, the four programs that concern with *traffic assignment with departure time choice* took approximately 1.5 hours. A good workshop schedule is to start at 10:00 a.m., with a one-hour lunch break after conducting the first half, from 12 p.m. to 1:00 p.m. The second half should end at 2:30 p.m. The remaining time can be allocated to further discussions and hands-on practice if a participant has brought along his/her own data.