Evaluation of Dynamic Traffic Assignment: Demand Estimation and Impacts of Traveler Information

Mark Chang

B.S. in Civil Engineering (1997)
University of California at Berkeley

Submitted to the Department of Civil and Environmental Engineering
in partial fulfillment of the requirements for the degree of

Master of Science in Transportation

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 1999

Author …………………………………………………………………………………..
Department of Civil and Environmental Engineering
May 21, 1999

Certified by ……………………………………………………………………………..
Moshe Ben-Akiva
Professor of Civil and Environmental Engineering
Thesis Supervisor

Certified by ……………………………………………………………………………..
Michel Bierlaire
Maitre D'enseignement et de Recherche, Ecole Polytechnique Federale de Lausanne
Thesis Supervisor

Accepted by ……………………………………………………………………………..
Andrew J. Whittle
Chairman, Departmental Committee on Graduate Studies

Evaluation of Dynamic Traffic Assignment: Demand Estimation and Impact of Traveler Information

by
Mark Chang

Submitted to the Department of Civil and Environmental Engineering
on May 7, 1999 in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Transportation

Abstract

Case studies are conducted to evaluate DynaMIT, a dynamic traffic assignment system developed at MIT. Two main areas are examined. Demand estimation accuracy is judged by observing how closely estimated origin-destination (O-D) flows match actual O-D flows. The impact of traveler information is assessed by looking at DynaMIT's ability to accurately predict traffic conditions, then observing the effect that information distributed to travelers has on user travel times.

Demand estimation in DynaMIT is conducted by a Kalman Filter algorithm, which uses transition and measurement equations based on the concept of estimating deviations from historical values. Results indicate that the algorithm is an extremely effective method of estimating O-D flows when inputs are of high to moderate quality. Estimation errors in percentage terms are generally kept within a range smaller than the percent error contained within the input data.

Operation of the DynaMIT system in a simulation environment was shown to improve mean vehicle travel times in situations of non-recurrent congestion. DynaMIT predicted travel conditions to a reasonable degree of accuracy, and provided travelers with a beneficial information strategy that was unbiased with respect to its predictions. The supply simulator had slow queue dissipation and difficulties with complex weaving sections. The user optimality objective was affected by behavior model parameters regarding the treatment of descriptive information.

The rolling step size, rolling length, and number of system iterations all impacted DynaMIT system performance in an intuitive fashion. As the number of informed and compliant drivers increased, system performance improved while the marginal benefit of information for such informed travelers diminished in some cases. Prescriptive, as opposed to descriptive, information had some advantages. The results overall are promising from both a performance and a research standpoint.

Thesis Jointly Supervised by:
Moshe Ben-Akiva Professor, Department of Civil and Environmental Engineering
Michel Bierlaire Maitre D'enseignement et de Recherche, Ecole Polytechnique Federale de Lausanne

Acknowledgments

I thank my advisors, Moshe Ben-Akiva and Michel Bierlaire, for their great support. Their knowledge and encouragement have been invaluable in guiding this thesis. I have benefited in numerous ways from having the opportunity to work with them.

I am thankful to Oak Ridge National Laboratory and the Federal Highway Administration for sponsoring the DynaMIT project and advancing the field of dynamic traffic assignment.

I thank Didier Burton, Ismail Chabini, Mithilesh Jha, Haris Koutsopoulos, and Qi Yang for their insight and excellent research. I thank Cheryl Gillespie for keeping the lab functioning smoothly.

I also thank my fellow students at MIT for providing an exciting and enjoyable environment where learning is so highly valued: Kazi Ahmed, Hernan Alperin, Owen Chen, Dave Cuneo, Atul Dalmia, Bruno Fernandez-Ruiz, Sridevi Ganugapati, Masroor Hasan, Sreeram Thirukkonda, and Tomer Toledo, among others. Thanks also to Constantinos Antoniou, Kalidas Ashok, and Jon Bottom for their many contributions to the project.

Good luck to all of you, and hopefully we'll cross paths in the future.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Traffic congestion is faced by millions of travelers each day, resulting in lost time and added stress among other negative impacts. As auto ownership levels are rising, land use patterns are decentralizing, and the population is growing throughout the world, the problem of traffic congestion will continue to get worse unless effective solutions can be developed and implemented. Market measures, improved transit, and roadway expansion are all possibilities that have been used previously and will remain as options. However, the reality of political, financial, and environmental concerns requires that serious attention must be given to other strategies.

Interest in the broadcasting of accurate real-time network information to travelers is building rapidly among transportation professionals. Locations and severity of congestion within a transportation network change continuously, and the travel decisions that users of a network habitually make may not be ideal with respect to travel times. By having accurate real-time information, some travelers may choose to switch mode, cancel their trip, or begin their trip at another time. Others may be able to choose a different route within the network to reach their particular destination.

A major benefit of providing accurate information to travelers is faster travel times in the network. Improved safety, lower fuel consumption, and better air quality are other potential effects stemming directly from reduced congestion. In addition, travelers will be more comfortable with their own travel decisions. DynaMIT (Dynamic Network Assignment for the Management of Information to Travelers) is a real time dynamic traffic assignment system developed at MIT specifically to attain such benefits. DynaMIT is also designed to be a powerful tool for transportation research.

This thesis will evaluate the DynaMIT system in a systematic and rigorous fashion. The demand estimation component will first be evaluated on the basis of quality and robustness. The existing DynaMIT system in its entirety, in operation within a simulation environment, will then be evaluated. Criteria for evaluation will be the consistency of predicted link travel times and impacts of the distributed travel information on both a user and system level.

1.2 Overview of DynaMIT

1.2.1 DynaMIT Objectives

The eventual role of the DynaMIT system is to serve as an advanced traveler information system, or *ATIS*, to improve the travel decisions that users of a transportation network make. DynaMIT would reside in a transportation management center and generate traffic information to be distributed to travelers who are in or plan to enter the network. This travel information is developed and distributed according to two main objectives: *unbiasedness* and *consistency*.

Unbiasedness means that the system information provided is based on the best knowledge of future network conditions that are available, rather than desired conditions according to some system objective. All travelers who are in or plan to use the network and are able to receive information must receive information that is unbiased, rather than just some travelers. Consistency means that the network conditions that travelers experience coincide with the predicted conditions on which the information was based.

Input errors to DynaMIT can exist, and the models used by DynaMIT are not a perfect reflection of reality. Within these limitations, if the properties of unbiasedness and consistency hold, then no other information about anticipated travel conditions could be provided to users that would enable them to make better travel decisions. This principle is called *user optimal information*. It takes into account two user criteria: *travel time* in the network and *schedule delay*, or the acceptable absolute value of the difference between the traveler's desired and actual arrival time at the destination of interest.

Another concept that exists is *system optimal information*. This is based on some global criteria such as minimizing the total travel time experienced or fuel consumed in the network. While DynaMIT is anticipated to assist in achieving such objectives, they are not the primary purposes on which the system was developed. Information distributed to satisfy system-level objectives may result in some travelers being sent to paths that are not optimal from their individual point of view. In the long-term, travelers will ignore such information and system performance will deteriorate.

1.2.2 Inputs

The overall structure of DynaMIT is illustrated in Figure 1. The first box contains the inputs that DynaMIT requires. A *database* has historical information with traveler soceioeconomic characteristics (age, gender, income, auto ownership, trip purpose) by zone obtained from census data and surveys. The database also contains the network description: node and segment locations, segment capacities, and free-flow segment travel times. Time-dependent origin-destination (O-D) matrix flows obtained from external surveys and off-line estimation are another part of the database. A richer historical database leads to more accurate results. However, DynaMIT can begin operation with a limited database and build it up over time.

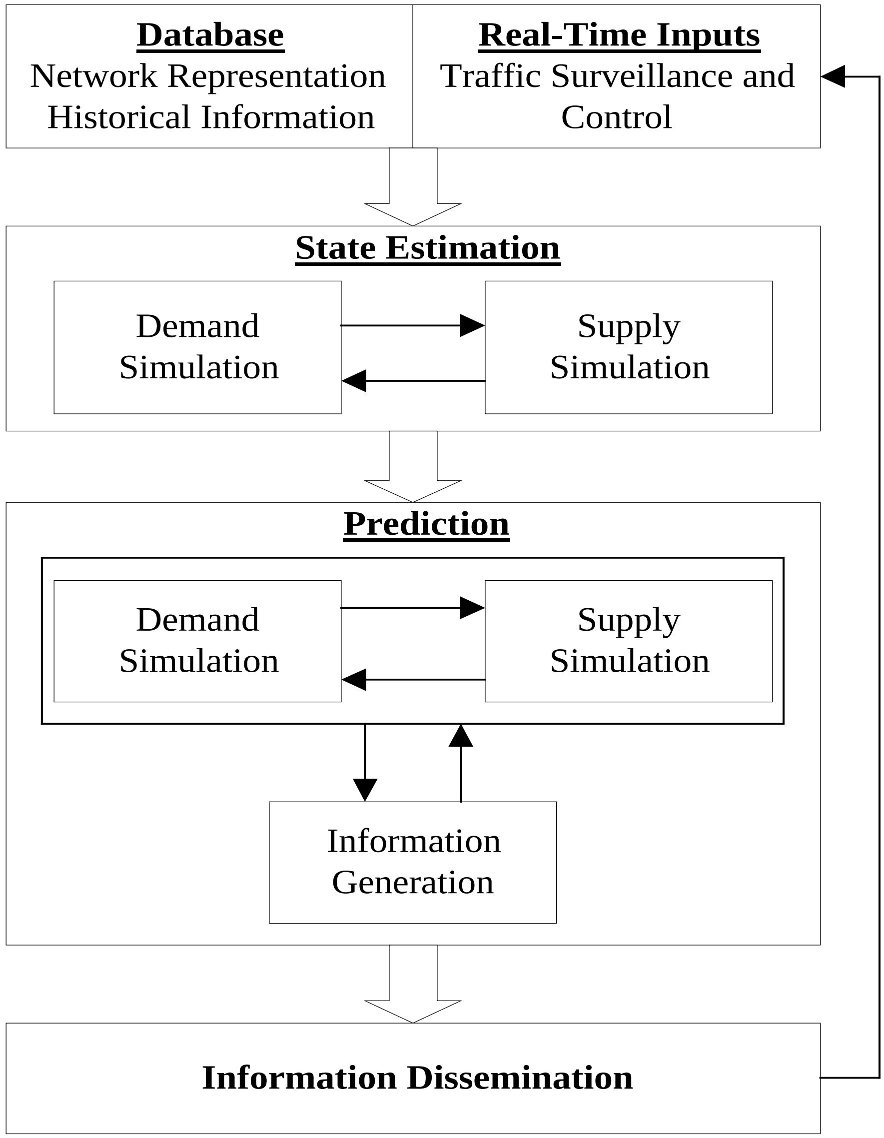

Figure 1: Structure of DynaMIT

Segment-level traffic counts from a surveillance system and logic of the traffic control system (traffic lights, ramp meters, toll booths) are the source of *real-time inputs* to DynaMIT. These inputs help describe the current conditions in the network. Traffic counts serve as partial measurements of the actual unknown origin-destination (O-D) flows. The surveillance system data is combined with historical O-D flows updated by traveler behavior models to obtain the O-D flow estimate.

1.2.3 State Estimation

The purpose of the *state estimation* process is to estimate demand levels and traffic conditions in the network given the set of inputs. Two separate but interacting parts are used here: the demand simulator and the supply simulator. The *demand simulator*, shown in Figure 2, estimates O-D flows and traveler behavior decisions based on historical O-D flows and surveillance system information. Each network trip is individually represented so that this can be translated into detailed vehicle movements on the network.

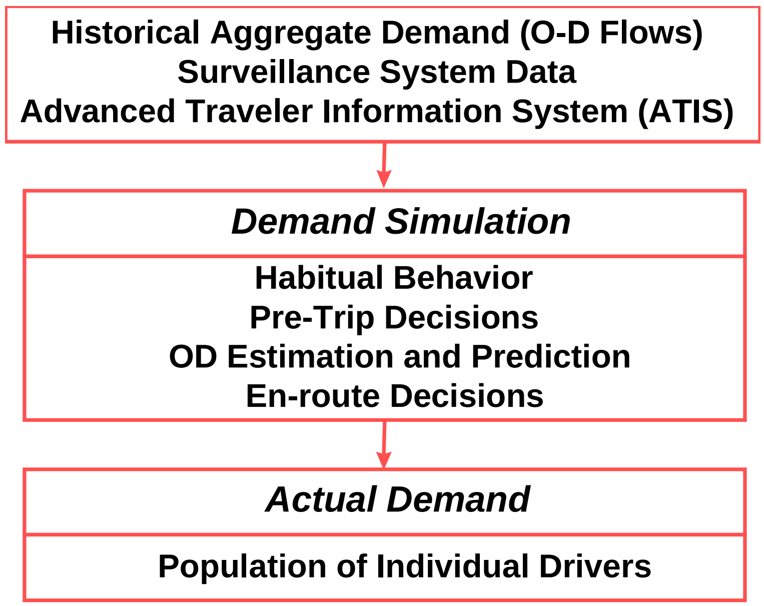

Figure 2: Demand Simulator

The O-D estimation process is based on a Kalman Filter algorithm formulated by Ashok and Ben-Akiva (1996), and is described in section 1.3. The behavior model developed by Antoniou, Ben-Akiva, Bierlaire, and Mishalani (1997) estimates traveler decisions, including departure time, mode, and route choices, for each trip in order to complete the trip characteristics for drivers that are currently in the network. An important part of this model is how real-time information distributed to travelers affects their travel decisions. This model is summarized in section 1.4.

The *supply simulator*, given in Figure 3, was developed by Heiler and Koutsopoulos (1997). Its role is to simulate the movement of vehicles in the network. Inputs include a list of drivers produced by the demand simulator, control strategies for traffic lights and ramp meters, and knowledge of any incidents. An *incident* is a temporary reduction of capacity at some network location. Incidents can occur due to an auto breakdown, a traffic accident, weather, objects in the roadway, or some other random event.

Output from the supply simulator contains a wide range of network performance indicators including travel time, flows, and densities. The supply simulator combines a microscopic representation of traffic with macroscopic models capturing the traffic dynamics. The decision of using macroscopic traffic dynamics models is mainly based on the real-time operational requirement.

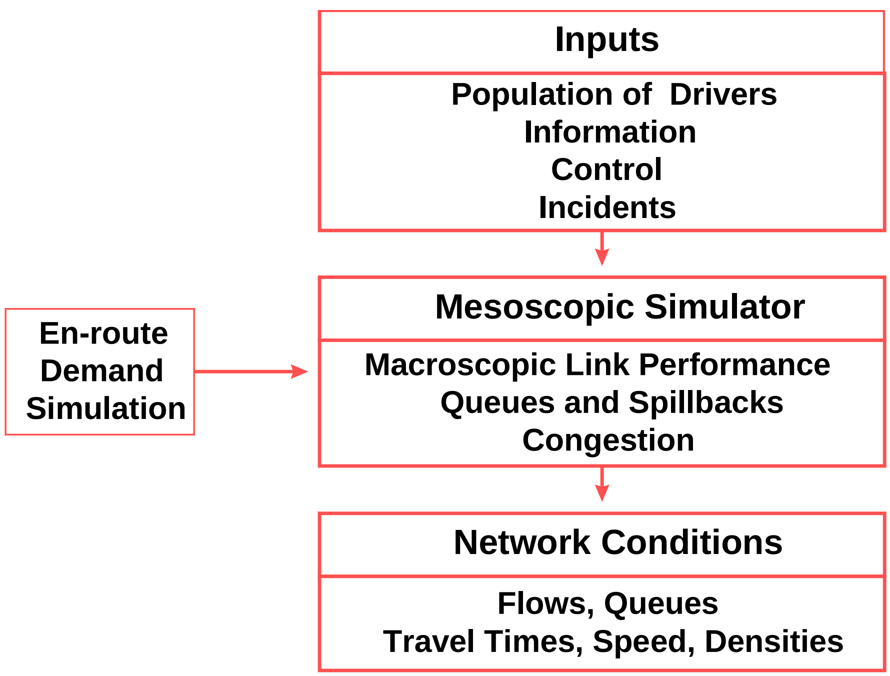

Figure 3: Supply Simulator

The network representation consists of a set of links, nodes, and loading elements. The nodes correspond to intersections of the actual network, while links represent unidirectional pathways between them. The loading elements represent locations where traffic is generated or attracted. Each link is divided into segments that each have a capacity constraint at its downstream end. Each segment has a moving part and a queuing part. The moving part represents the portion of the segment where vehicles can move with some speed. The queuing part represents vehicles that are queued up.

Traffic dynamics are captured by two major models: a deterministic queuing model and a speed model. Each specific queue status (formation, dissipation, blockage, etc.) is captured by a different model. As an example, the position $q(t)$ of a given vehicle joining a dissipating queue at time t is given by

$$q(t) = q(0) + l(ct-m)$$

where $q(0)$ is the position of the end of the queue at time 0, l is the average length of vehicles, c is the output capacity (i.e. the dissipation rate) and m is the number of moving vehicles between the considered vehicle and the end of the queue at time 0.

The speed model is based on the following assumptions. For a given moving part of a segment, two speeds are computed. The speed at the upstream end of a segment is a function of the average density on the moving part of the segment. The speed at the downstream end is the speed at the upstream end of the next segment. An acceleration/deceleration zone is defined at the end of the moving part. Before that zone, each vehicle is moving at a constant speed. Within the zone, the speed of vehicles varies linearly as a function of the position.

Several iterations may be needed between demand and supply in order to converge towards a state estimation. This is because feedback exists between demand and supply. Most notably, the fraction of traffic from each O-D pair and departure time interval that passes over a particular sequence of network links during the estimation interval depends on supply parameters. In other words, driver route choices and travel times must be approximated in order to estimate time-dependent O-D flows, and such factors depend on prevailing traffic conditions.

1.2.4 Prediction

The role of the *prediction* process is to predict the traffic conditions in the network for some future time period ahead of the current time. For prediction, the demand and supply components described in the previous section are used in much the same way as they were for estimation. The demand simulator predicts future O-D flows and future traveler decisions. The supply simulator predicts the movements of vehicles in the network in the future time period of interest.

An iterative process between demand and supply is needed for prediction as well. However, in prediction there is one additional component that must be included in the iterative process. This is the *information generation* function, whose role is to generate unbiased and consistent network information for distribution to travelers. Basing the information on predicted network conditions, which is anticipatory, is likely to be more effective than information based only on current traffic conditions because it accounts for the evolution of traffic conditions over time.

Anticipatory information is derived from predictions of future conditions, but these conditions will themselves be affected by travelers' reactions to the information. An iterative process that involves demand, supply, and information generation has to take place in order to identify an information strategy that will lead to a fixed point of predicted network conditions and experienced network conditions. One iteration consists of a trial information strategy, the state prediction (supply and demand) under the trial strategy, and an evaluation of the predicted state.

A time smoothing algorithm, developed by Ben-Akiva and Bottom (1997), based on a method of successive averages is used for information generation. The progress of the computation is measured in terms of the "inconsistency norm": $\| c - S*D*G(c) \|$, where c is the vector of time-dependent link times, G is the guidance mapping, D is the demand model, and S is the network loading model. Because of the time-dependent nature of real-time information computation, the least inconsistent solution encountered during the iterations is kept track of and used as the information strategy if time runs out.

1.2.5 Rolling Horizon Implementation

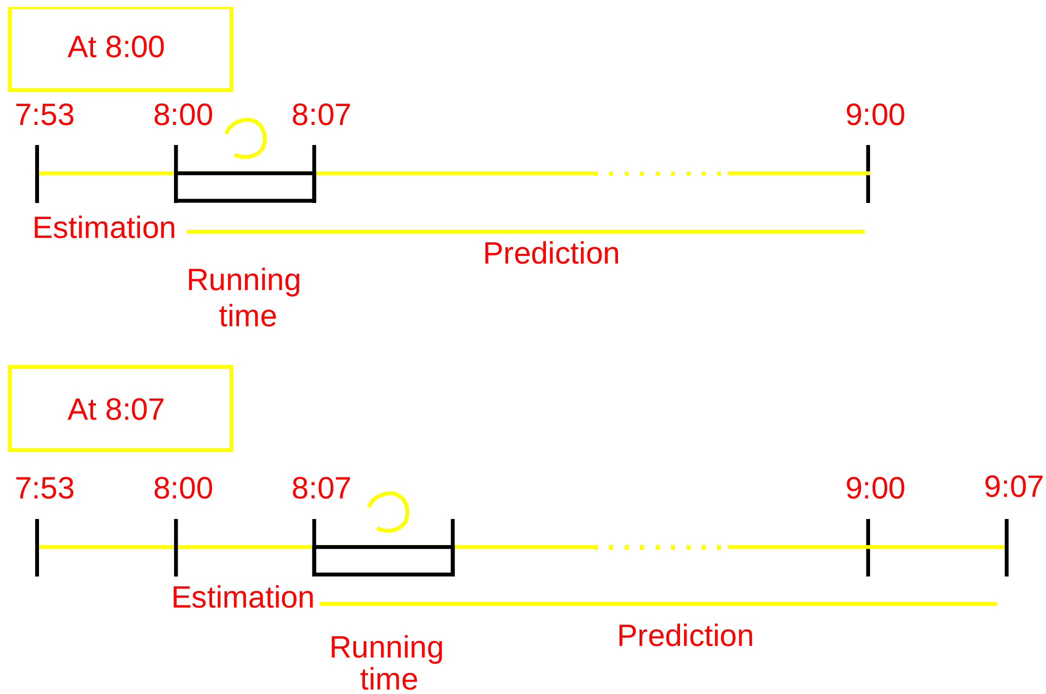

Figure 4: Rolling Horizon Implementation

DynaMIT operates continuously in real-time via a rolling horizon implementation, shown in Figure 4. In the top half of the figure, the current time is 8:00. DynaMIT estimates the current conditions in the network based on a historical database and surveillance system data collected in some recent time period. This previous time is called the *estimation period*, shown from 7:53 to 8:00. Based on a historical database, the probable evolution of network flows, and the anticipated response of travelers to information, DynaMIT then predicts network conditions for some future period of time. This future time is referred to as the *prediction period* or *rolling horizon*, shown from 8:00 to 9:00.

In this example, DynaMIT takes seven minutes to conduct its iterative estimation and prediction processes. The information strategy that DynaMIT generated is available for distribution to travelers in the network. DynaMIT is now ready to begin the iterative processes again, as shown in the bottom half of the figure. The time is 8:07, and actual traveler demand and traffic conditions in the network have changed. DynaMIT must be aware of changes that actually took place in the network so that its prediction process can be using the most current information available. Therefore, the estimation period is now set to 8:00-8:07, while the prediction period is set to 8:07-9:07.

1.2.6 Real-Time System Requirement

Network conditions can change rapidly, and information can quickly become outdated. Therefore, DynaMIT must generate information for distribution to travelers on a fairly regular basis. It is important for DynaMIT to keep up fairly closely with the actual network time rather than spending too long on one calculation cycle. This is known as the *real-time system requirement*. To accomplish this, available computational power must be sufficient for the specific network size and traveler demand pattern. In addition, two DynaMIT system parameters can be calibrated in advance for optimal system performance: the rolling horizon and the number of iterations.

The *rolling horizon*, or prediction period, is the amount of time in the future for which DynaMIT predicts traffic conditions. A long rolling horizon is generally viewed as desirable for improving DynaMIT's information strategy. However, as the rolling horizon is extended, there is likely to be a higher level of uncertainty associated with the prediction accuracy at the most distant end of the period. This is illustrated in Figure 5. Moreover, predictions made well into the future may not be particularly relevant to travelers who are in or are planning to enter the network at the present time. Identifying the ideal rolling horizon for a given scenario is an interesting issue.

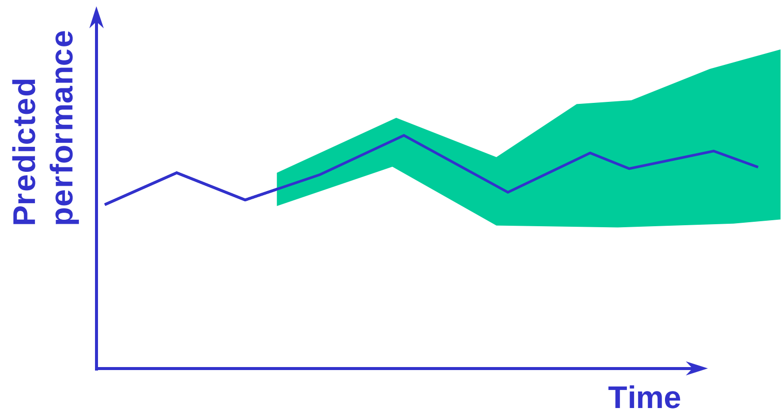

Figure 5: Prediction Quality

The *number of iterations* is the maximum number of system iterations that are allowed in either the estimation or the prediction process. If the number of iterations is too small, DynaMIT may have difficulties estimating and/or predicting network conditions. If the number of iterations is too large, the real-time system requirement may be violated. Note that it is possible for DynaMIT to stop either its estimation or prediction process before the maximum number of iterations allowable is reached. This is more likely when traffic conditions have been fairly stable over time, as opposed to rapidly changing conditions.

Sections 1.3 and 1.4 describe in greater detail the most relevant aspects of DynaMIT, in the context of the evaluation conducted in this thesis.

1.3 Behavior Models

1.3.1 Role of Models

Behavior models are used in DynaMIT to predict the impacts that travel information will have on traveler behavior. This is critical for an accurate estimation and prediction process, and therefore plays an important role in generating an unbiased and consistent information strategy. A number of different model structures have been developed in DynaMIT to enhance flexibility with respect to data requirements and the type of information distributed within the network of interest.

Travel information can be provided in various ways, including the radio, in-vehicle equipment, and variable message signs (VMS). When information is given to travelers who have not yet entered the network, this is referred to as *pre-trip information*. Such information may cause some travelers to cancel their trip or select another mode, which removes them from the driver population. Pre-trip information may also lead to traveler departure time changes or route changes. When information is made available to travelers who are already in the network, this is referred to as *en-route information*. Such information can only change route decisions.

The following sections focus specifically on what was used for the evaluation conducted in this thesis. The evaluation used en-route traveler information provided by VMS. If desired, drivers can change routes from their habitual pattern in response to the messages. The VMS were placed near entrance points to the network so that drivers are able to adjust their behavior before they must commit to a particular route. Note that the terms *route* and *path* are used interchangeably here.

1.3.2 Habitual Path Assignment

A historical database of O-D flows is disaggregated by DynaMIT into individual travelers. Habitual paths are then assigned to each traveler. This is done through Monte Carlo simulation based on the following equation:

$$\mathbf{P(p)} = \mathbf{e}^{\mathbf{V(p)}} \,/\, \sum_{i=1}^{n} \mathbf{e}^{\mathbf{V(p(i))}}$$

where:

P(p) = the probability that a traveler will choose path **p** as the habitual path from the set of available paths connecting a particular origin and destination.

e = the number 2.71828…

V(p) = the systematic utility of path **p**.

n = the total number of available paths in the network for the O-D pair of interest.

This is the multinomial logit model formulation. **V(p)** is calculated as follows:

$$\mathbf{V(p) = (\beta 1)*tt^{H}_{p} + (\beta 2)*CF_{p} + \beta 3}$$

H refers to historical path-level travel times.

p refers to some particular path among the set of paths connecting the origin and desired destination for a certain driver.

$\mathbf{tt^{H}_{p}}$ = historical travel time for path **p** in minutes.

$\mathbf{CF_p} = \ln \sum_j \omega_{jp} N_j$, the commonality factor for path **p**.

j is a link contained in the path **p**. The summation is done for all links that make up the path **p**. ω_{jp} is the fraction of the path **p** total length attributed to link ***j***. N_j is the number of paths between the same O-D pair that share link ***j***. This factor is described in more detail by Cascetta (1996). Its role in the route choice process is to deal with the well-known independence for irrelevant alternatives (IIA) property.

β1, **β2**, and **β3** are coefficients that can be calibrated by maximum likelihood estimation from an off-line dataset of travelers. Such a dataset would contain the $\mathbf{tt^{H}_{p}}$ and $\mathbf{CF_p}$ values for each available path, as well as the actual path selection that was made, for every traveler with their respective O-D pair. **β3** is an alternative specific constant associated with a particular path. **β3** can appear in the utility of no more than ***n-1*** paths.

For this evaluation, **β1** is set to -5.0 and **β2** is set to -1.0. These are arbitrary values, assigned as negative numbers since a route with high travel time and greater commonality should be less likely to be selected by a particular driver. The value of **β3** is set to 0 for all paths, indicating an assumption that there is no a priori preference for a particular path outside of the historical travel times and commonality factor.

1.3.3 Structure of Models

In this evaluation, distinctions are made among drivers with respect to their information access and compliance. Drivers who cannot read the VMS are called *uninformed*. Drivers who do read the VMS are called *informed*, and are divided into two groups. Those who use the information for their route decision are called *guided*. Those who disregard the information are combined with uninformed drivers and together are referred to as *unguided*. Such unguided drivers are assumed to follow habitual travel choices. Note that since each driver views the VMS only once, it is not possible for an unguided driver to become guided later in the trip.

Two separate en-route models were used for the behavior of guided drivers: *descriptive* and *prescriptive*. With descriptive information, a full description of predicted travel time conditions is provided. Guided drivers then decide which route to select. With prescriptive information, only the final recommendation from DynaMIT is provided. Guided drivers comply with this recommendation.

The descriptive model is shown in Figure 6. Uninformed drivers disregard the information and do not change from their habitual path, shown in the left branch. Guided drivers use the information to choose which path to select from the set of available paths, shown in the right branch.

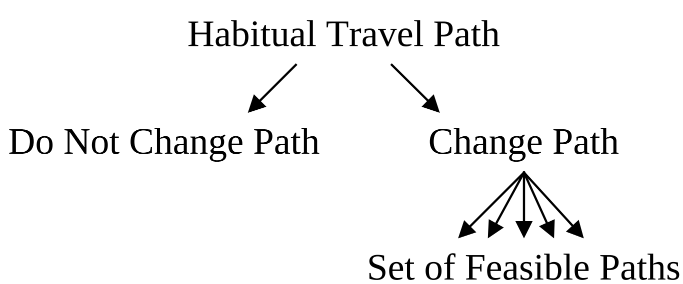

Figure 6: En-route Descriptive Choice Tree

The path chosen by guided drivers is modeled by the following equation.

$$\mathbf{P(p) = e^{V(p)} / \sum_{i=1}^{n} e^{V(p(i))}}$$

where:

$$\mathbf{V(p) = (\beta 1)*tt^{I}_{p} + (\beta 2)*CF_{p} + \beta 3}$$

The notation used is the same as for the habitual path section, with one addition:

$\mathbf{tt^{I}_{p}}$ = travel time provided by the information system for path **p** in minutes. The superscript **I** refers to the information strategy as generated by the DynaMIT system.

The DynaMIT prescriptive en-route behavior model is shown in Figure 7. Unguided drivers do not change from their habitual path, shown in the left branch. Guided drivers select the path recommended by DynaMIT.

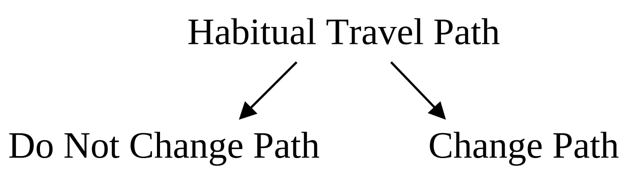

Figure 7: En-route Prescriptive Choice Tree

Note that for simplicity, socioeconomic and other path-level characteristics are not included in this evaluation. However, such characteristics can be important with respect to how travelers interpret information, as discussed in Chapter 2, and could be an area of future research.

1.4 Kalman Filter Algorithm

1.4.1 Inputs to Estimation Process

Figure 8 is a simplified diagram of how the O-D flow estimation and prediction processes in DynaMIT works, as developed by Ashok (1996) and Antoniou (1997). The estimation process, which will be discussed first, is based on a Kalman Filter algorithm. The approach is based on estimating a vector of deviations between the true O-D flows in real-time and historical estimates. This is done primarily in order to use the wealth of information gained over previous estimations regarding relationships of travel demand and their variations over time.

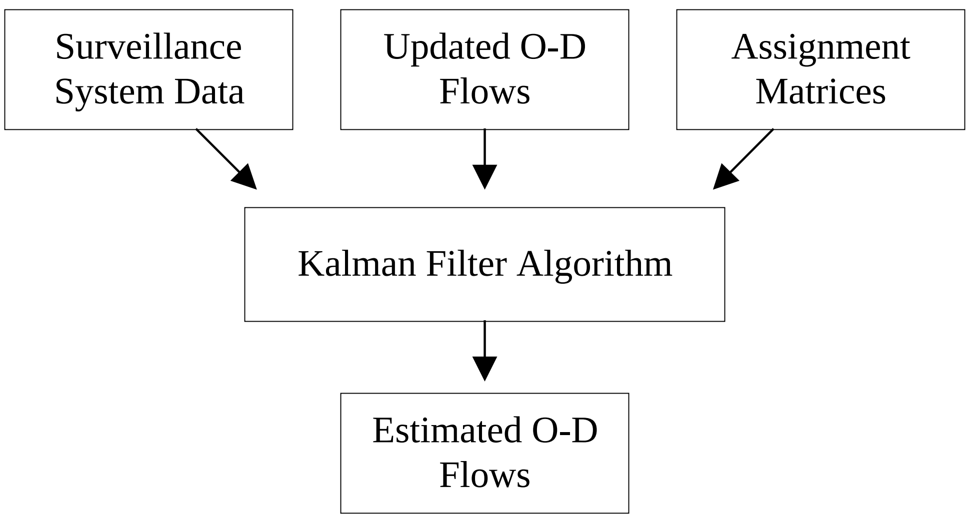

Figure 8: O-D Flow Estimation

Surveillance system data consists of real-time traffic counts from sensors placed in the network. Improving the quantity and/or quality of this data will improve the estimation process. This could be done by adding more sensors in the network or by using sensors with a lower malfunction rate.

The pre-trip behavioral model, described in section 1.3, is applied to each historical traveler disaggregated from flows contained in the historical database. This is done to explicitly incorporate the impact of real-time information that has been generated thus far.

Updated travel decisions for each traveler are then aggregated into *updated O-D flows*, which serve as an input to the Kalman Filter algorithm. The translated of historical flows to updated flows was evaluated by Antoniou (1997).

An *assignment matrix* gives the fraction of traffic from each O-D pair and departure time interval that passes over each sensor in the network during some time period of interest. For example, one line in an assignment matrix might look like this:

7:30-7:45 H #10003 0.5 7:15-7:30

This means that 0.5, or 50%, of the vehicles from the O-D pair #10003 during the 7:15-7:30 departure time interval passed over sensor H from 7:30-7:45. Multiple assignment matrices are needed as inputs to the Kalman Filter algorithm. This is because some travelers who entered the network in earlier time intervals are still in the network during the estimation interval and continue to cross sensors.

In the future, vehicle transponders may be able to track the movements and intended destinations of individual vehicles. This would allow for true assignment matrices to be computed from real-time surveillance system data. However, sensor counts that are typically available now do not allow for such direct computation. Therefore, an a priori set of assignment matrices must be generated using the traffic simulator and appropriate historical demand by tracking the movement of vehicles in the network.

The traffic simulator keeps track of the departure time, origin, and destination of each vehicle that crosses each sensor in the network. In other words, the assignment matrices generated through scenario simulation are assumed to represent the true assignment matrices in reality. As an iterative process between demand and supply occurs within DynaMIT, the assignment matrices are adjusted at each iteration to better represent an estimate of what the true O-D flows are. This is done as knowledge of network conditions and the impact of real-time information on traveler behavior improves.

1.4.2 Algorithm Components

A brief description of the Kalman Filter algorithm used in DynaMIT is provided in this section. Note that this description does not fully represent how the algorithm has actually been implemented in DynaMIT; it serves only to explain the basic concepts. A more complete discussion of the algorithm and implementation is provided by Ashok (1996) and Antoniou (1997). The algorithm has three interacting components: the measurement equation, the transition equation, and the state vector. The purpose of each is summarized here.

The current time interval for which an O-D flow estimate is desired is taken into account for all components. Note also that some components must take into account some set of time intervals previous to the current estimation interval. This again relates to the fact that some travelers who entered the network in earlier time intervals are still in the network during the estimation interval and continue to cross sensors. Some notation is presented here to assist in explanation of the algorithm.

h = the current time interval for which an O-D flow estimate is desired.

q = the maximum number of time intervals needed to travel in the network for vehicles from any O-D pair.

p **=** the earliest previous time interval that must be considered. This is calculated back from the time interval ***h*** by subtracting **q**.

h-1 = the time interval that immediately precedes the time interval ***h***.

c = the number of sensors placed in the network.

n = the number of O-D pairs to be estimated.

1 = the number one.

The *measurement equation* relates actual observed indicators to the unknown network state. The assignment matrices and link counts, as the sources of real-time network information, serve as inputs. The basic idea is that:

$$\sum_{p}^{h} \mathbf{A} \sum_{p}^{h} \mathbf{F} = \mathbf{L}$$

where: **A** = a **c** by **n** assignment matrix.

F = an **n** by **1** vector of O-D flows.

L = a **c** by **1** vector of observed sensor counts, corresponding to the interval ***h***. It is the summation of **A*F** for all time intervals considered.

The set of current and previous time intervals from ***p*** to ***h*** takes into account the entire period of time that needs to be considered by the algorithm.

Because of network topology and driver path choices, it is extremely rare for a unique value of **F** to be identified from the measurement equation for the time interval ***h***. Also, because of possible errors in either **A** or **L**, the equation will typically not be exact. This is exactly why additional components of the Kalman Filter must be used to obtain a good estimate of O-D flows.

The *measurement equation error covariance matrix* gives the level of reliability that the sensor measurements are believed to have. This is a **c** by **c** matrix. Each diagonal term is the variance associated with a link count. The off-diagonal terms are the covariances between two link counts.

The *transition equation* relates to the evolution of the network state over time. This equation can be thought of as:

$$\sum_{p}^{h-1} \mathbf{F} \sum_{p}^{h-1} \mathbf{X} = \mathbf{V}$$

where: **F** = an **n** by **n** matrix that captures the temporal relationship between the vector **X** and the vector **V**. Diagonal terms relate one O-D pair to itself over time, while off-diagonal terms relate one O-D pair to another over time.

X = an **n** by **1** vector of deviations between the historical O-D flows and the estimated O-D flows for a previous time interval.

V = an **n** by **1** vector of deviations between the historical O-D flows and the estimated O-D flows for the time interval ***h***. It is the summation of **F*X** for all time intervals considered.

The *transition equation error covariance matrix* is an **n** by **n** matrix that gives the reliability that the transition inputs are believed to have. There is one such matrix corresponding to each time interval from ***p*** to ***h-1***. The diagonal terms are variances that relate O-D pair to itself over time. The off-diagonal terms are covariances between two different O-D pairs over time.

The *state vector* is the size **n** by **1**, and represents the updated O-D flows input. The *state variance matrix* gives the reliability that the state vector input is believed to have. This is an **n** by **n** matrix. The diagonal terms are variances for the same O-D pair. The off-diagonal terms are covariances between two O-D pairs.

Note that values for the measurement equation error covariance matrix, the transition equation error covariance matrix, and the state variance matrix can be assumed or can be calibrated by observing the empirical relationships in such deviations over some historical time period. The same is true for values in each matrix **F**. The three components work together through an autoregressive process described by Antoniou (1997).

1.4.3 O-D Flow Prediction

An autoregressive process is also used by the Kalman Filter algorithm for O-D flow prediction. Deviations between historical O-D flows and predicted O-D flows are modeled. This is done for each future time interval that a prediction is desired, using the transition equation formulation described in the previous section. The notation changes as follows.

$\boldsymbol{h}$ = the future time interval for which an O-D flow prediction is desired.

Similar to estimation, values for each matrix **F** and the error covariance matrices can be assumed or calibrated off-line. A historical database must be available for future time periods. One additional feature of the prediction process is the effect of the anticipated distribution of real-time traveler information on future O-D flows. This is done, similar to estimation, by using behavior models to update historical flows for future time intervals. Updated flows are subsequently used as an algorithm input.

1.5 Thesis Contribution

A literature review is provided in Chapter 2 that reviews some of the previous research work related to dynamic traffic assignment. Chapter 3 provides a detailed methodology for how the evaluation will be conducted. This also serves as a useful framework for future evaluation work.

Chapter 4 identifies how successful the Kalman Filter algorithm used in DynaMIT can estimate unknown origin-destination pair demands given some set of inputs. The algorithm is first applied to estimate the unknown O-D pairs assuming no errors in the inputs were present. This is set as the base, a scenario that has the most ideal conditions possible. Successful results from this test would demonstrate that the algorithm is a capable method for conducting an O-D flow estimation.

It is unlikely in reality that Kalman Filter algorithm inputs will not contain any errors. Therefore, the algorithm is reapplied for different scenarios, assuming that one or more input errors are present. This is done as a check for robustness, or to observe how close the estimated O-D flows are to the true O-D flows despite the presence of the input errors. Results here will indicate if the algorithm is working as it intuitively should, and if the algorithm is able to yield useful results under different types of input conditions.

Chapters 5, 6, 7, and 8 demonstrates the capabilities of the DynaMIT system in improving network performance for a wide range of scenarios. While an extensive amount of previous evaluation work of DynaMIT has been accomplished, including the material presented in Chapter 4 of this thesis, much of it dealt with testing individual components as opposed to the entire system operation. The following objectives of this work have been identified and are discussed based on an examination of the evaluation results.

1) Determine the level of system accuracy. DynaMIT should be able to accurately estimate and predict actual traffic conditions.

2) Evaluate improvements in network performance achieved by distributing DynaMIT information to travelers. The travel times that travelers experience should be reduced by providing them with unbiased and consistent information.

3) Demonstrate the applicability of DynaMIT, as demonstrated by low stochasticity levels in DynaMIT's predictions.

4) Identify the refinements necessary to improve system performance.

A summary of evaluation results, proposed refinements to the DynaMIT system, and areas for future research are presented in Chapter 9, the conclusion.

Chapter 2

Literature Review

2.1 Demand Estimation

Most work in origin-destination (O-D) flow estimation has dealt with the static case. For real-time applications, dynamic O-D estimation that takes the time-dependent nature of traffic flow into account is necessary. Ashok and Ben-Akiva (1993) developed a dynamic Kalman Filter algorithm that estimates and predicts the deviations of real-time O-D flows from a historical database. This algorithm is structured to explicitly take into account all the experience gained from prior estimations through the use of this database. Another key advantage is that this algorithm does not need all the entry and exit counts within the network for an estimate to be obtained.

The demand estimation algorithm evaluated in this thesis was developed by Antoniou, Ben-Akiva, Bierlaire, and Mishalani (1997). Antoniou *et. al* developed a Kalman Filter algorithm that has predictive capabilities but is less computationally intensive than Ashok and Ben-Akiva's work. Antoniou ran an evaluation of this Kalman Filter algorithm using a simulation laboratory. What is needed for an extension of this evaluation is additional sensitivity analysis with respect to various algorithm inputs and scenarios.

2.2 Benefits of Information

Several papers have been written regarding the benefits of traveler information over the past few years. Results from these studies vary because of differences in the type of network, demand levels, and assumptions made regarding the information system. A simulation-based study by Mahmassani (1991) stated that system-wide benefits of 5% or less are possible when using ATIS in situations of recurrent congestion. ATIS reassures travelers of their projected travel times, but does not actually affect travel times significantly. Many of the studies done therefore have focused on the application of ATIS under situations of non-recurrent congestion, or incident conditions.

A simulation of the Santa Monica, CA freeway corridor (1989) found that a 25% system-wide travel time benefit is possible when incidents are present. Koutsopoulos and Xu (1993) found that ATIS travel time benefits of about 8% under incident conditions were obtained using simulation on a fictitious network. Al-Deck and Kanafani (1993) studied the impacts of ATIS analytically using one origin-destination (O-D) pair and two route choices. They found an upper bound of time savings to travelers to be about 40% under incident conditions. The magnitude of this benefit depends greatly on the capacity of alternative routes that are not typically used.

Emmerick, Axhausen, Nijkamp, and Rietveld (1995) conducted a simulation-based study using one O-D pair, 25 possible routes, and nine decision points. Under incident conditions on a particular link, the highest possible system-wide travel time benefits was about 25%. This maximum is reached at a market penetration rate (MPR), or percent of informed drivers, of roughly 75%. At a lower MPR such as 20%, informed drivers can benefit by more than 25% but the benefits to uninformed drivers are less than 10%.

While a low MPR in this study makes the information system more beneficial for its users, a high MPR may be better for all travelers in the system as a whole. An MPR of greater than 75% presumably led to some over-reaction, or a shifting of congestion. This is a distinct possibility with ATIS when a very high MPR is present unless the system is capable of giving different information to drivers with the same O-D pair and departure time. Such an action though would be active manipulation by the system that goes against the principles of consistency described in Chapter 1.

2.3 Traveler Response to Information

An important consideration of ATIS is how travelers perceive and respond to the information that is provided. Bovy (1996) discusses the fact that drivers have different perceptions and preferences with respect to route characteristics that leads to different route choices, all of which may be optimal from the perspective of the driver. Ben-Akiva and Bierlaire (1998) state that value of time, access to traffic information, and trip purpose could be significant influences in route choice and departure time behavior.

Polydoropoulou (1993) analyzed survey data for 898 commuters to the Massachusetts Institute of Technology who made a total of 3,218 commute trips in a five-day period. She determined that 37% of the respondents often listened to radio traffic reports. Women, those who travel longer distances, and those with less arrival time flexibility were more likely to listen. 25% of the total respondents considered traffic reports to be reliable. 36% of respondents trust their own judgement more than traffic reports, while 22% trust traffic reports more. Those who considered traffic reports to be reliable were generally more likely to listen to and respond to the information.

81% of the respondents are very familiar with two or more alternative routes. Over the five-day period, 5% of the total trips involved a route switching. Of those who switched, 12% did so because of radio reports while 62% switched because of their own visual observation. For 41% of the trips involving a switch, the respondents were confident in their decision on the basis of saving travel time. 38%, however, were not confident. These results illustrate that a reliable information system is likely to have considerably more impact, effectiveness, and positive perception than a system that is not reliable.

Many travelers are restricted in terms of their departure time choice based on time restrictions in their activities. Mahmassani and Liu (1997) collected diary data from forty-five workers. They found that for the morning commute, 13.7 minutes before the scheduled work starting time was the average preferred arrival time for the travelers. Travelers were significantly more likely to switch routes, as opposed to switch departure time, in response to improved traveler information.

Barfield, Haselkorn, Spyridakis, and Conquest (1991) conducted a survey of 3,893 motorists in the Seattle, WA area. They found that travelers who made pre-trip route choice adjustments occasionally were more common than those who occasionally made departure time adjustments (50% to 44%). For departure time switching, commuters had more flexibility leaving work than when leaving home. Males and those with higher incomes were generally less likely to switch departure time or mode. Females were more likely to make pre-trip travel changes but less likely to make en-route changes.

91% of travelers in the Barfield *et al.* study found information from commercial radio to be somewhat or very helpful. 36% found variable message signs to be helpful, and 18% found TV information to be helpful. 55% prefer to receive traffic information pre-trip, while 44% prefer to receive traffic information en-route. Most travelers (90%) had access to a radio in their homes and cars, and 45% had access to a radio in their office. 92% stated they would use a radio station dedicated to traffic information, while 34% stated they would use a phone hotline.

Wardman, Bonsall, and Shires (1997) found that variable message signs vary widely in terms of effectiveness. Providing the magnitude and cause of the traffic delay was found to be helpful for travelers. Compliance to VMS was significantly lower if no cause was provided. Lotan (1997) conducted a hypothetical case study for the MIT area, and found that travelers who were unfamiliar with a particular area were more likely to depend on information for route choices.

Abdel-Aty, Kitamura, and Jovanis (1997) conducted a stated preference survey of morning commuters in the Los Angeles, CA area. The survey contained questions with a fictitious route choice set and travel times. They found that females and the elderly were less likely to switch to a route that they are personally unfamiliar with. Travelers based their route decisions more heavily on travel time variability than on mean travel time alone. However, an actual application of ATIS would likely have difficulties stating its predicted route travel times in the form of a confidence interval. Travelers may also have problems interpreting such an interval.

While findings from the studies differ, one overall point is the importance of behavioral considerations with respect to travel choice. DynaMIT can take into account the heterogenous response of travelers to information in its prediction and information generation processes. This is done through the use of behavior-based models that could include socioeconomic characteristics such as schedule delay, value of time, trip purpose, and access to ATIS. Route level features such as signalized intersections and the number of left turns can also be included. This thesis does not examine behavior aspects in detail due to the unavailability of actual travel data. This is an area of ongoing research.

Chapter 3

Evaluation Methodology

3.1 Simulation Laboratory

The evaluation in this thesis will be carried out using the MITSIM Simulation Laboratory, as has been used successfully for previous work. MITSIM is a microscopic traffic simulator developed at MIT. A complete description is provided by Yang (1997); a brief overview is provided here. MITSIM moves individual vehicles in a traffic network based on desired speed, car-following, and lane changing models. The structure of the network is known for each lane on every segment. Specialized network features such as traffic signals, ramp meters, and toll booths can be represented. MITSIM also explicitly simulates drivers' response to real-time information.

The MITSIM laboratory has been specifically designed for the evaluation of Dynamic Traffic Management Systems, and is an excellent way to evaluate the capabilities of DynaMIT. The laboratory is a convenient and flexible alternative as compared to obtaining traffic data from the field. Numerous scenarios can be tested rapidly, and output such as sensor counts, vehicle travel times, and points of congestion can be generated and stored.

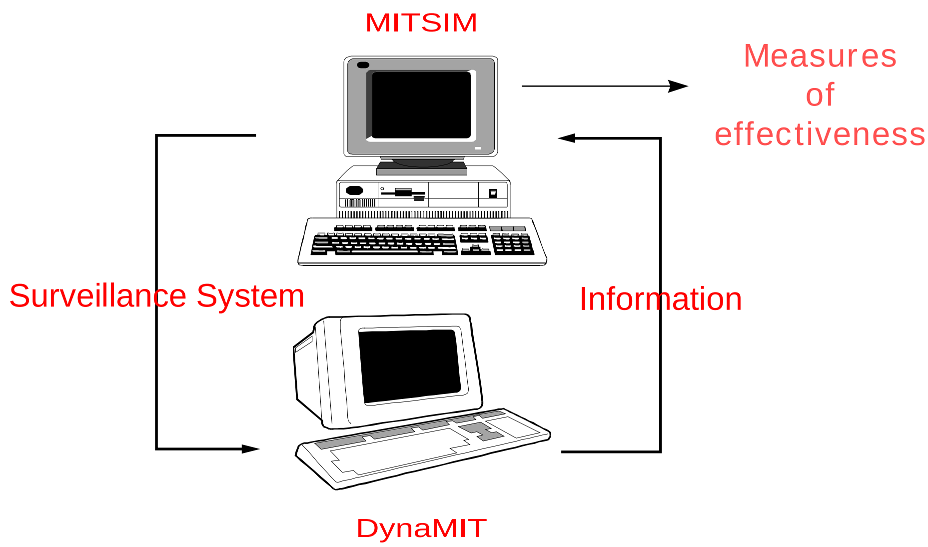

Figure 9: Simulation Laboratory

DynaMIT is assumed to be residing in a traffic management center (TMC), while MITSIM represents the real world. The interactions between the two are shown in Figure 9. MITSIM provides various types of sensor data to DynaMIT similar to how a TMC would receive data from the real world. Meanwhile, DynaMIT provides information to travelers in MITSIM in the same way that a TMC would communicate with travelers in reality. This sensor data comprises one of the inputs to the DynaMIT components.

3.2 Behavior of Drivers in MITSIM

MITSIM maintains two sets of travel time information: historical and real-time. Historical travel times remain static during the simulation and do not take into account incident impacts. Unguided drivers select routes based only on historical travel times. Real-time travel times are updated periodically by DynaMIT at each rolling step size or update interval. Guided drivers in MITSIM make route decisions based on the real-time travel times in the case of descriptive information. With prescriptive information, guided drivers in MITSIM follow the recommendation from DynaMIT.

The DynaMIT system evaluation is affected by the treatment of driver behavior in the MITSIM representation of reality. For this evaluation, the behavioral model structure and parameters used in DynaMIT and MITSIM are identical. Therefore, the results provided are not affected by differences in traveler behavior representation. This is done to allow for greater control with respect to identifying the performance of the various components and making sense of the results.

It would be an interesting exercise to make the behavioral models in the MITSIM reality more complicated and assume that DynaMIT operates with a more limited model. This is left for future research.

3.3 Scenarios

Each scenario considered in the evaluation is a combination of several dimensions. Dimensions are referred to by a capital letter, while the specific dimension value that a particular scenario uses is referenced by an index number.

For the demand estimation analysis provided in Chapter 4, the following dimensions are relevant: **A-B-C-D-E-F-G-H-I**

For the impact of information analysis provided in Chapters 5, 6, and 7, the following dimensions are relevant: **A-B-D-J-K-L-M-N**

3.3.1 Network (A-1)

The network used for evaluation is the Central Artery/Tunnel (CA/T) Network in Boston, as it will appear in 2004. The CA/T network, shown in Figure 10, has 185 nodes and 214 links. The network connects Route 1A and Logan Airport in the east with I-93, Storrow Drive, Route 1, and the Massachusetts Turnpike in the west. This is done by two underwater tunnels, the Sumner/Callahan Tunnel in the north and the Third Harbor

Tunnel in the south. This network is realistic and is sufficiently complex to address the multiple evaluation criteria that were described in Section 1.5.

This evaluation process involved using a slightly modified Central Artery network. Some links and nodes were added in the network to provide for greater route choice flexibility in the network. More specifically, the additions make it possible for drivers to turn freely from/to the Third Harbor Tunnel, the Sumner/Callahan Tunnel, and I-93 at interchange points in any direction except for a U-turn. In some cases, these additional links allow for a representation of drivers who leave the freeway network, use local streets, and return to the network shortly thereafter.

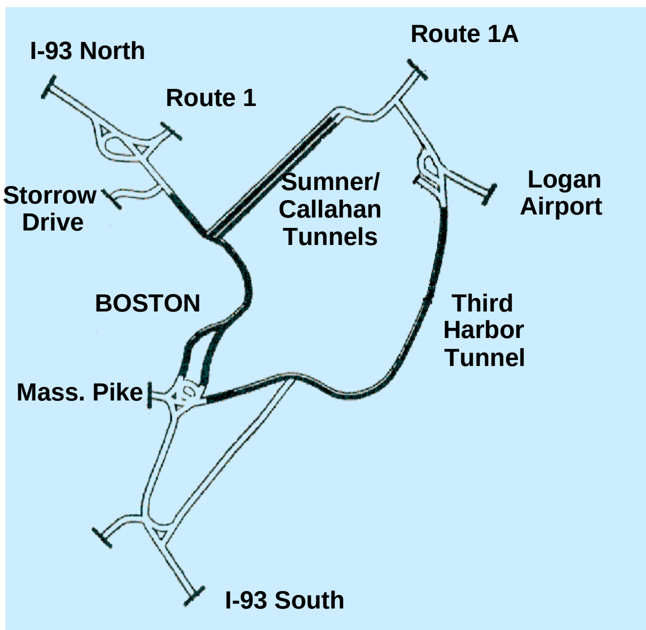

Figure 10: Central Artery Network

3.3.2 Actual Demand (B)

- B-1: Ten origin-destination pairs.

For the demand estimation evaluation, there are five origins and two destinations for a total of ten origin-destination pairs. The locations are shown in Figure 11.

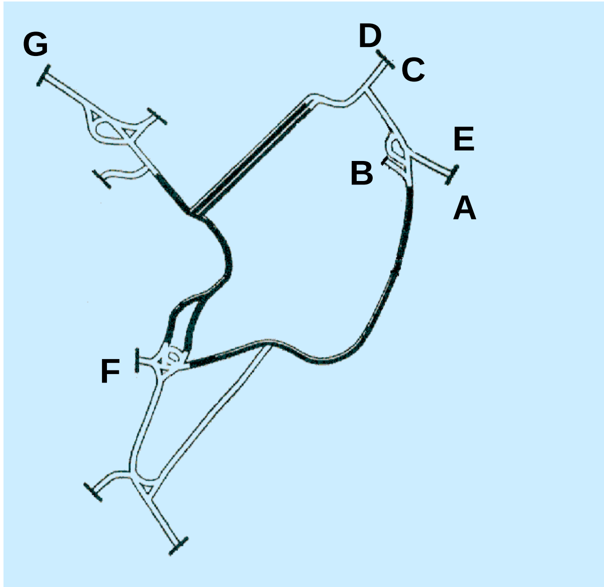

Figure 11: Origin and Destination Locations

The demand pattern to be simulated goes from 7:00 am to 7:45 am. The simulation period is divided into three fifteen-minute time intervals. The demand for each interval, listed by OD pair, is shown in Table 1. This evaluation uses the Kalman Filter algorithm off-line for estimation of O-D demand levels in the third time interval of the simulation (7:30-7:45), based on sensor counts from the simulation and a historical database.

OD pair #	*7:00 - 7:15*	*7:15 - 7:30*	*7:30 - 7:45*
1 (A-F)	240	270	300
2 (A-G)	240	270	300
3 (B-F)	120	135	150
4 (B-G)	120	135	150
5 (C-F)	180	202.5	225
6 (C-G)	180	202.5	225
7 (D-F)	60	67.5	75
8 (D-G)	60	67.5	75
9 (E-F)	120	135	150
10 (E-G)	120	135	150

Table 1: Actual O-D Pair Demand

- B-2: Fifty-six origin-destination pairs.

For the DynaMIT system evaluation, there are eight origin and destination locations as shown in Figure 12. No vehicles are assumed to have a destination at the same place as the origin, but vehicles move between any two different locations. As such, there are a total of fifty-six O-D pairs (8*8 - 8). This demand pattern is representative of actual peak hour conditions.

The case study is interested in travelers that enter the network during some typical weekday between 7:00 AM and 8:30 AM. It is necessary to run the simulation for longer than this, such that all the drivers that enter the network at 8:30 AM are able to exit the network during the simulation period. Therefore, the simulation begins at 7:00 AM and ends at 9:30 AM. The analysis to be described does not consider vehicles that entered the network after 8:30 AM, particularly because many of these vehicles were not able to complete their trip when the simulated ended.

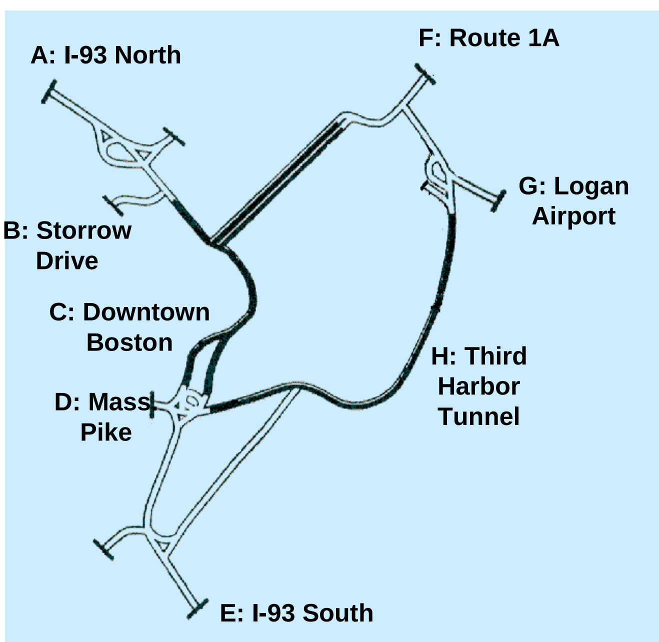

Figure 12: Origin-Destination Pairs

The base demand level for each of the fifty-six O-D pairs is 400 vehicles per hour. This base demand is scaled, as given in Table 2. This is done to provide for some natural peaking within the morning period, centered from 7:30 AM to 8:00 AM.

Time Period	**7:00-7:15**	**7:15-7:30**	**7:30-7:45**	**7:45-8:00**	**8:00-8:15**	**8:15-8:30**
Demand at each O-D Pair in vehicles/hr	**320**	**360**	**400**	**400**	**360**	**320**

Table 2: Demand Peaking

For purposes of analyzing stochasticity, an additional scenario is used that reduces the demand levels shown in Table 2 by 30%.

- B-3: Fifty-six origin-destination pairs, reduced demand.

3.3.3 Historical Demand (C)

For the base scenario, the historical demand used as input to the Kalman Filter is exactly equal to the true demand. In reality, since historical demand may not reflect traffic conditions in real-time, other values are tested as well. The set of values are given here:

- C-1: Historical demand equals true demand.
- C-2: Historical demand is 5% higher than true demand.
- C-3: Historical demand is 5% lower than true demand.
- C-4: Historical demand is 10% higher than true demand.
- C-5: Historical demand is 10% lower than true demand.
- C-6: Historical demand is 20% higher than true demand.
- C-7: Historical demand is 20% lower than true demand.
- C-8: Historical demand is unknown and is arbitrarily set to zero.

The C-8 value assumes that the Kalman Filter algorithm operates without the assistance of any historical information. This is a rather extreme case, used to test the limits of the algorithm performance.

3.3.4 Incident Conditions (D)

- D-1: No incident.
- D-2: Fifteen-minute incident in Third Harbor Tunnel.
- D-3: Thirty-minute incident in Sumner/Callahan Tunnel.
- D-4: Thirty-minute incident in Third Harbor Tunnel.

In D-2, the incident affects two lanes in the Third Harbor Tunnel from 7:15 to 7:30, closing off one lane completely and restricting vehicle movement in the other lane to 15 miles an hour. This incident condition is used for the demand estimation analysis. Note that values for the dimensions E and F to follow vary depending on which incident condition was simulated. The E and F values used in the evaluation process pertain specifically to the value of the D dimension that was simulated.

D-3 and D-4 are used for the impact of information analysis. The incident reduces vehicle speeds for all lanes in both directions to 10 mph from 7:15 to 7:45. In D-3, the incident occurs in the Sumner/Callahan Tunnel. In D-4, the location is the Third Harbor Tunnel. DynaMIT is assumed to be aware of an incident one minute after its occurrence, and the system has good knowledge with respect to the severity and duration.

3.3.5 Sensor Counts (E)

Consistent with the concept of the simulated laboratory, the surveillance system data needed for the O-D estimation process in DynaMIT are made available from the MITSIM traffic simulator. MITSIM provides link counts for each network traffic sensor, where link counts refer to the cumulative number of vehicles that traversed a link during a given time interval. In this laboratory, one sensor can count multiple lanes of traffic but only in one direction of movement.

For this evaluation, a total of thirty-five sensors were spaced fairly evenly throughout the network. The simulation was conducted in MITSIM and sensor counts were obtained. The set of sensor count values used in this evaluation are as follows:

- E-1: Actual sensor counts.
- E-2: Sensor counts have systematically high errors of 5%.
- E-3: Sensor counts have systematically low errors of 5%.
- E-4: Sensor counts have systematically high errors of 10%.
- E-5: Sensor counts have systematically low errors of 10%.
- E-6: Sensor counts have systematically high errors of 20%.
- E-7: Sensor counts have systematically low errors of 20%.
- E-8: Counts for four sensors omitted.
- E-9: Systematically high 10% errors, counts for four sensors omitted.
- E-10: Systematically low 10% errors, counts for four sensors omitted.

In reality, sensor counts may have errors associated with them. It is important to observe how well the Kalman Filter algorithm can estimate demand despite the presence of sensor count errors. Dimensions E-8, E-9, and E-10 are used for further investigation of estimation quality with respect to incident conditions. Information from four sensors located just upstream of the incident were not taken into account for these dimensions.

3.3.6 Assignment Matrices (F)

DynaMIT will ultimately compute its own estimate of assignment matrices in real-time by matching estimated O-D flows with updated O-D flows, as described in section 1.4.1. For this evaluation, actual assignment matrices are computed using the MITSIM traffic simulator and are used as inputs to the Kalman Filter algorithm. One assignment matrix relates to the estimation interval of interest (7:30-7:45). Another corresponds to the previous time interval (7:15-7:30), while a third corresponds to the pre-previous time interval (7:00-7:15).

The set of assignment matrix values used are as follows:

- F-1: True assignment matrices used.
- F-2: Assignment matrices randomly perturbed to a maximum error of 5%.
- F-3: Assignment matrices randomly perturbed to a maximum error of 10%.
- F-4: Assignment matrices randomly perturbed to a maximum error of 20%.

The random perturbations are linearly distributed. For example, in F-2, every matrix value between -5% of the true value and +5% of the true value is equally likely to be selected during the perturbation process. These perturbations are introduced to evaluate how the Kalman Filter algorithm performs when assignment matrix errors are present.

3.3.7 Flow Estimates for Earlier Intervals (G)

The Kalman Filter algorithm uses O-D flow estimates from the previous and pre-previous time intervals as an input for the current time interval estimation. This is done through the transition equation, as described in section 1.4. The set of values used here are:

- G-1: Estimated demand for previous and pre-previous intervals are equal to the true demand for those intervals.
- G-2: Estimated demand for previous interval has a 10% error (too high).
- G-3: Estimated demand for previous interval has a 10% error (too low).
- G-4: Estimated demand for pre-previous interval has a 10% error (too high).
- G-5: Estimated demand for pre-previous interval has a 10% error (too low).
- G-6: Estimated demand for previous interval has a 20% error (too high).
- G-7: Estimated demand for previous interval has a 20% error (too low).

The values G-2 through G-7 are used in order to determine how the performance of the Kalman Filter algorithm is affected by errors in earlier estimates.

3.3.8 Transition Matrices (H)

Two transition matrices are used. One relates the temporal deviations between the historical and updated flows between the estimation time interval and the previous time interval, and another does the same for the estimation interval and the pre-previous time interval. The following transition matrix values are evaluated:

- H-1: Transition matrices have diagonal values equal to one, and off-diagonal values equal to zero.
- H-2: All matrix values are equal to zero.

The value H-1 assumes that deviations between historical and estimated O-D flows for the two previous time intervals are expected to carry over to the current estimation interval in exactly the same magnitude with respect to the same O-D pair value. The value H-2 assumes that deviations for previous time intervals have no relationship with the current time. No deviation between historical and estimated O-D flows is expected for the current time interval, regardless of what happened in the past.

3.3.9 Error Covariance Matrices (I)

As mentioned in Section 1.4, three error covariance matrices are used by the Kalman Filter algorithm. One is for the transition equation, one is for the measurement equation, and one is for the state matrix. Recall that the role of these matrices is to account for the fact that errors in algorithm inputs may be present, and that relationships between the inputs and the state variables to be estimated are not perfectly deterministic.

- I-1: Error covariance matrices as specified below.

For I-1, the values for these error covariance matrices were selected as follows. No covariance is assumed between the values for any matrix; the off-diagonal terms all have values of zero. This is done for simplicity. For the measurement equation error covariance matrix, the variance of each link count is assumed to be equal to the value of the count itself times 1. This is a Poisson distribution assumption, that the variance associated with each sensor value over some period of time is equal to the mean.

There are two transition error covariance matrices needed, one for each transition matrix. For these matrices, the variance associated with flow relationships over time may be expected to be roughly proportional to the historical O-D pair values. These historical values were multiplied by a factor of 1.5, which is larger than the factor of 1 used for the measurement equation variances. This takes into account that current information is generally assumed to be of greater relevance and accuracy to real-time flow estimation than information that reflects only a historical average.

For the variance of the state vector, the diagonal terms are set equal to the value of the historical flows for the time interval of interest, times a factor of 1.5. This factor was selected for the same reason as described for the transition variances.

- I-2: Error covariance matrices with values close to zero.

An additional scenario was evaluated that involved setting all the diagonal values for the error covariance matrices close to zero. The algorithm will not operate if matrix values are all zero, so diagonal values of one were used. This is not a realistic assumption, and is done solely in order to verify that the Kalman Filter algorithm is able to attain a perfect estimate when given perfect inputs. In other words, if the algorithm inputs are known to have no errors, then setting the error covariance matrices close to zero should eliminate the possibility that noise could be added during the estimation process.

For reasons to be described in Chapter 4, it became valuable to test additional variance values for the state vector. For the scenarios I-3 through I-7 below, the measurement and transition variance matrices are kept the same as in I-1. The state vector variance is set to the following values.

- I-3: Variance of state vector set to twice the historical flows.
- I-4: Variance of state vector set to three times the historical flows.
- I-5: Variance of state vector set to values of 1,000.
- I-6: Variance of state vector set to values of 5,000.
- I-7: Variance of state vector set to values of 10,000.

3.3.10 Percent of Informed and Compliant Travelers (J)

The percent of travelers using the network who comply with information provided by DynaMIT is likely to be an important consideration with respect to network performance. The following values of this parameter are evaluated. J-3, J-5, and J-7 are used for descriptive information. J-1, J-2, J-4, J-6, and J-8 are used for prescriptive information.

- J-1: 10% of travelers informed and compliant.
- J-2: 20% of travelers informed and compliant.
- J-3: 25% of travelers informed and compliant.
- J-4: 40% of travelers informed and compliant.
- J-5: 50% of travelers informed and compliant.
- J-6: 70% of travelers informed and compliant.
- J-7: 75% of travelers informed and compliant.
- J-8: 95% of travelers informed and compliant.

3.3.11 Type of Information Provided (K)

As described in section 1.3, there are two types of information that can be provided to drivers. With descriptive information, drivers are provided with travel times for a set of alternative routes. With prescriptive information, drivers are provided with a single route recommendation.

Prescriptive information can in turn be divided into two groups. The first is called *naive*, which simply directs all informed travelers to choose the route that does not contain the incident. This means the VMS displays the same message to all travelers who view it, regardless of their eventual network destination. The second type is termed *specific*. This type recognizes that for travelers from certain O-D pairs, it makes sense to choose the Sumner/Callahan Tunnel regardless of the incident occurrence. Therefore, the messages displayed on the VMS are destination-specific. This is described in greater detail in Chapter 8.

- K-1: En-route descriptive information is provided.
- K-2: En-route specific prescriptive information is provided.
- K-3: En-route naïve prescriptive information is provided.

3.3.12 Rolling Step Size (L)

The actual DynaMIT information operates continuously, as described in Chapter 1. Information is not necessarily generated and released to travelers at set times, but is done intermittently whenever the information is ready. However, for the purposes of this evaluation, a parameter referred to as the *rolling step size*, or the update interval, can be set. At frequencies equal to the rolling step size, DynaMIT releases the latest information that is available to travelers. A more frequent rolling step size is assumed to be preferable assuming that the real-time system requirement is not violated.

- L-1: Ten minute rolling step size.
- L-2: Twenty minute rolling step size.
- L-3: Thirty minute rolling step size.
- L-4: Sixty minute rolling step size.

3.3.13 Rolling Horizon (M)

As described in Section 1.2.5, the rolling horizon refers to how far into the future DynaMIT predicts beyond the current estimation time. The following values are evaluated.

- M-1: Fifteen minute rolling horizon.
- M-2: Thirty minute rolling horizon.
- M-3: Forty-five minute rolling horizon.
- M-4: Sixty minute rolling horizon.

3.3.14 Number of Iterations (N)

As mentioned in Section 1.2.5, the number of iterations represents the maximum number of times that DynaMIT will iterate between demand, supply, and information generation in its prediction process before the information strategy is distributed. The following values are evaluated.

- N-1: One iteration.
- N-2: Three iterations.
- N-3: Five iterations.

Note that at the time this evaluation work was conducted, the Kalman Filter algorithm had not yet been integrated with the rest of the DynaMIT system. It is assumed in this evaluation process that DynaMIT knows what the actual demand levels are.

3.4 Performance Measures

3.4.1 System Accuracy

This involves determining how closely the link travel times that are estimated and predicted by DynaMIT match the true conditions that actually take place as the simulation proceeds. Travelers in the network who comply with the information provided by DynaMIT should encounter traffic conditions as predicted by DynaMIT.

3.4.2 Network Performance

A comparison of travelers' route choices with and without DynaMIT in operation is provided. The information provided by DynaMIT in general should influence travelers to stay away from incident locations in the network. However, the information should not influence so many travelers to change travel patterns such that the travel times they experience are worse than if they would have passed through the incident locations. In other words, DynaMIT should be able to avoid *over-reaction*.

Another important measure is to determine the travel times that travelers experienced in the network for each test. Travelers who comply with DynaMIT information should not have been able to select a faster route than the one recommended by the system. The total system travel time with and without DynaMIT will also be compared.

3.4.3 System Applicability

There is expected to be some variance in the results between multiple replications of the same scenario. An actual traffic management center does not have the luxury of running multiple replications of a particular traffic condition. Therefore, it is ideal for the stochasticity of DynaMIT to be kept low. The operation of DynaMIT should improve traffic conditions for each replication in a similar, effective fashion.

Chapter 4

Evaluation of O-D Flow Estimation

4.1 Set-Up

The results from the analysis are provided in the following set of figures. Note that each figure has a different scale on the vertical axis, so they are not directly comparable visually. One number provided for each scenario is the maximum percent error associated with the Kalman Filter estimate from any one of the ten O-D flows. The second number given for each scenario is the average percent error associated with the Kalman Filter estimate from all ten O-D flows. The scenarios are listed first, followed by the corresponding figure with the estimation results for each scenario. The same base scenario is listed in multiple figures for comparison purposes.

4.2 No Incident Results

<u>For Figure 13</u>

Base: Base conditions, perfect inputs.

(A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1)

Cou+10: Sensor counts have systematically high errors of 10%.

(A-1, B-1, C-1, D-1, **E-2**, F-1, G-1, H-1, I-1)

Cou-10: Sensor counts have systematically low errors of 10%.

(A-1, B-1, C-1, D-1, **E-3**, F-1, G-1, H-1, I-1)

Hist+10: Historical demand is higher than the true demand by 10%.

(A-1, B-1, **C-2**, D-1, E-1, F-1, G-1, H-1, I-1)

Hist-10: Historical demand is lower than the true demand by 10%.

(A-1, B-1, **C-3**, D-1, E-1, F-1, G-1, H-1, I-1)

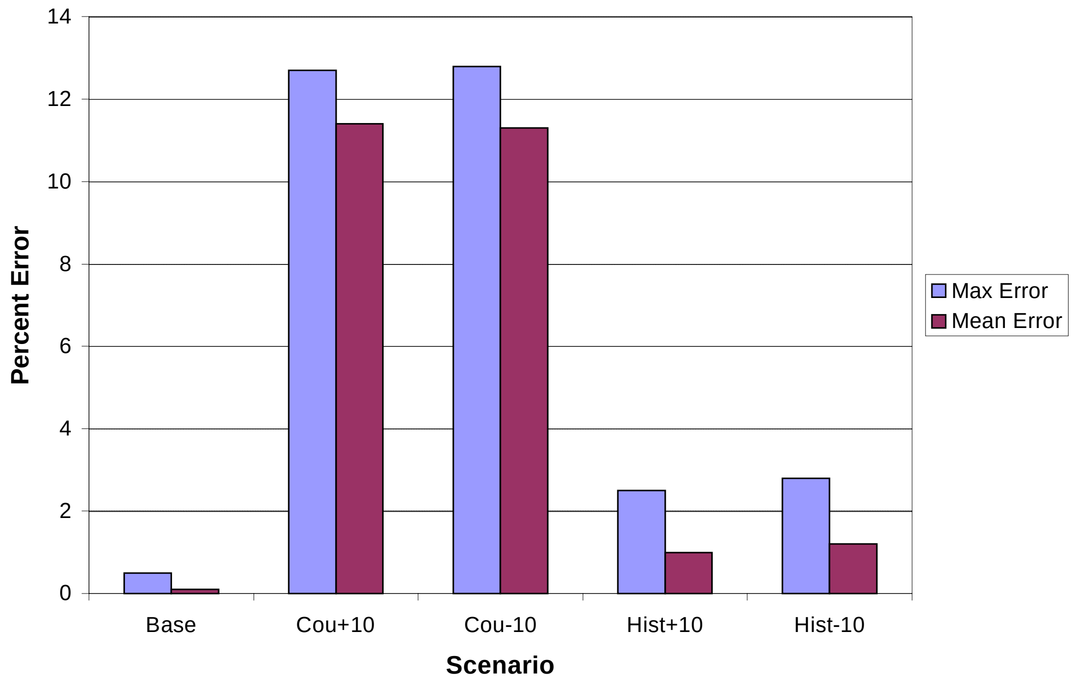

Figure 13: Estimation Results #1

- The results from the base scenario (Base) are good. No estimate varies from the actual O-D flow loaded on the network by more than 0.6%. The noise that is added to the estimate results from the error-covariance matrices. When these error-covariance matrix values are all set to values near zero, estimate errors are reduced to zero (not shown in the figure).

- A 10% systematic error in sensor counts (Cou+10, Cou-10) resulted in about an 11% error in each O-D flow estimate. The magnitude of the estimate error is thus roughly proportional to errors in the sensor counts. This makes sense, given that the measurement equation error covariance matrix values assumes that the real-time link counts are highly reliable.

- Changing the historical counts from the true O-D flows by 10% (Hist+10, Hist-10) resulted in an average O-D flow estimate error of 1%. This shows that with the error covariance matrices that were specified, the historical counts do not have much influence on the results relative to other factors. This is good, assuming that this is believed to be true. However, if actual day-to-day flows are believed to not vary much from historical levels, then the variance of the state matrix should be reduced.

<u>For Figure 14</u>

Base: Base conditions, perfect inputs.

(A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1)

Prev+10: Estimated demand for previous interval has a 10% error (too high).

(A-1, B-1, C-1, D-1, E-1, F-1, **G-2**, H-1, I-1)

Prev-10: Estimated demand for previous interval has a 10% error (too low).

(A-1, B-1, C-1, D-1, E-1, F-1, **G-3**, H-1, I-1)

Zer+10: Transition matrices of zero, systematically high sensor count errors by 10%.

(A-1, B-1, C-1, D-1, **E-2**, F-1, G-1, **H-2**, I-1)

Zer-10: Transition matrices of zero, systematically low sensor count errors by 10%.

(A-1, B-1, C-1, D-1, **E-3**, F-1, G-1, **H-2**, I-1)

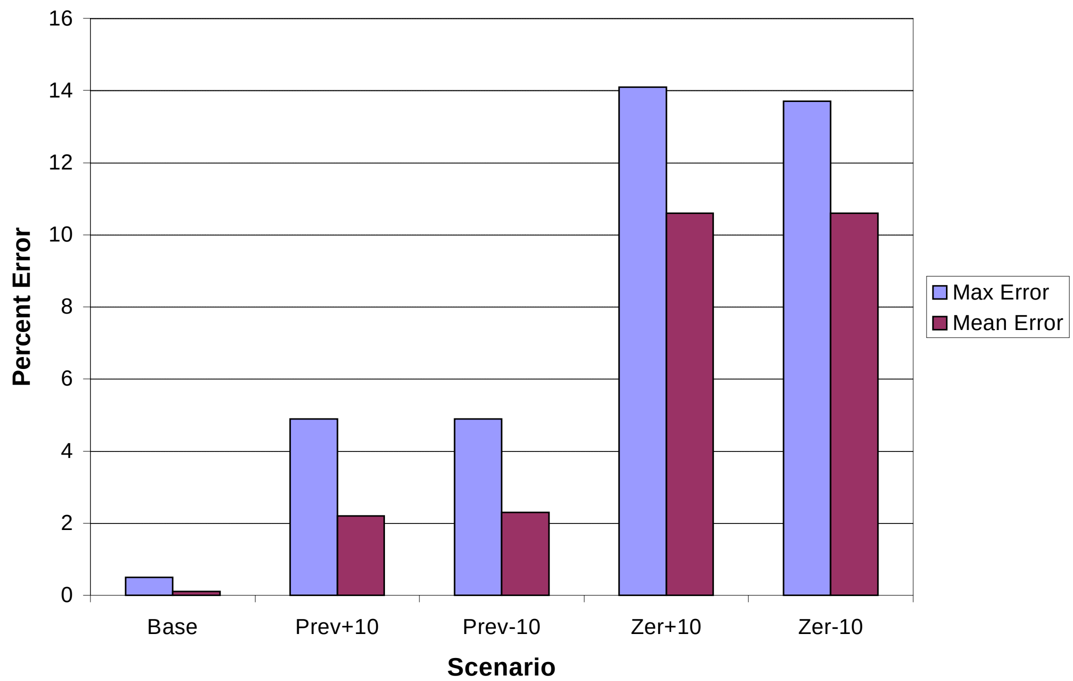

Figure 14: Estimation Results #2

- Increasing the estimated O-D flows for the previous interval by 10% as compared to the true O-D flows for that interval (Prev+10, Prev-10) resulted in O-D flow estimates for the current interval that were all somewhat low. The converse also holds. The reason for this is as follows.

The Kalman Filter algorithm comes up with its estimate by adding up the products of each assignment matrix with the estimated O-D flows from each interval. As the estimated flows for the previous interval increase, the assignment matrix is allocating greater emphasis of its estimate on that previous interval, rather than on the current interval. The algorithm wants to keep its estimate close to the obtained link counts, which have remained constant. In order to do this, the estimated O-D flows for the current interval must decrease.

Note that this outweighs a competing effect, which should be caused since in these scenarios the transition matrices are equal to one. The algorithm should be expecting that the deviation of the estimated O-D flows from the historical O-D flows for the previous interval will remain constant for the current time interval.

- Introducing a 10% error in the estimated O-D flows for the pre-previous time interval had virtually no effect on the O-D pair flow estimates for the current interval (this is not shown in the figure). This is reasonable since the Kalman Filter does not use this information heavily. Most vehicles that entered the network during the pre-previous time interval have left the network before the current interval begins, and the assignment matrix reflects this.

- Setting the transition matrices equal to zero in addition to having sensor count errors (Zer+10, Zer-10) yielded O-D flow estimation errors that were somewhat greater than what occurred when sensor count errors were present with transition matrices equal to one. This is expected, given that having transition matrices equal to one should have a stabilizing effect on the amount of error.

  This stabilizing effect occurs because demand estimates for the previous and pre-previous time intervals are equal to the historical O-D flow values for those intervals. There is no deviation between historical flows and estimated flows for previous time intervals. Transition matrix values of one thus pulls the estimated O-D flows for the current interval closer to its historical values.

For Figure 15

Base: Base conditions, perfect inputs.

(A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1)

HistZer: Historical demand unknown; historical matrix set to zero.

(A-1, B-1, **C-4**, D-1, E-1, F-1, G-1, H-1, I-1)

HZC+10: Historical matrix of zero, systematically high sensor count errors by 10%.

(A-1, B-1, **C-4**, D-1, **E-2**, F-1, G-1, H-1, I-1)

HZC-10: Historical matrix of zero, systematically low sensor count errors by 10%.

(A-1, B-1, **C-4**, D-1, **E-3**, F-1, G-1, H-1, I-1)

HZZer: Historical matrix of zero, transition matrices set equal to zero.

(A-1, B-1, **C-4**, D-1, E-1, F-1, G-1, **H-2**, I-1)

- Setting the historical matrices equal to zero for the current interval (HistZer), a significant input error, weakened the estimate quality as expected. The estimate is low since the historical flow values are much lower than the true flow values. For the first two O-D pairs (from Logan Airport), there was about an 11% error between the estimate and the true demand. The next two OD pairs (from South Boston) had their estimates affected more substantially, with a reduction of about 24% from the true demand being observed. Effects on the other six OD pairs were not as great, with errors of about 10%.

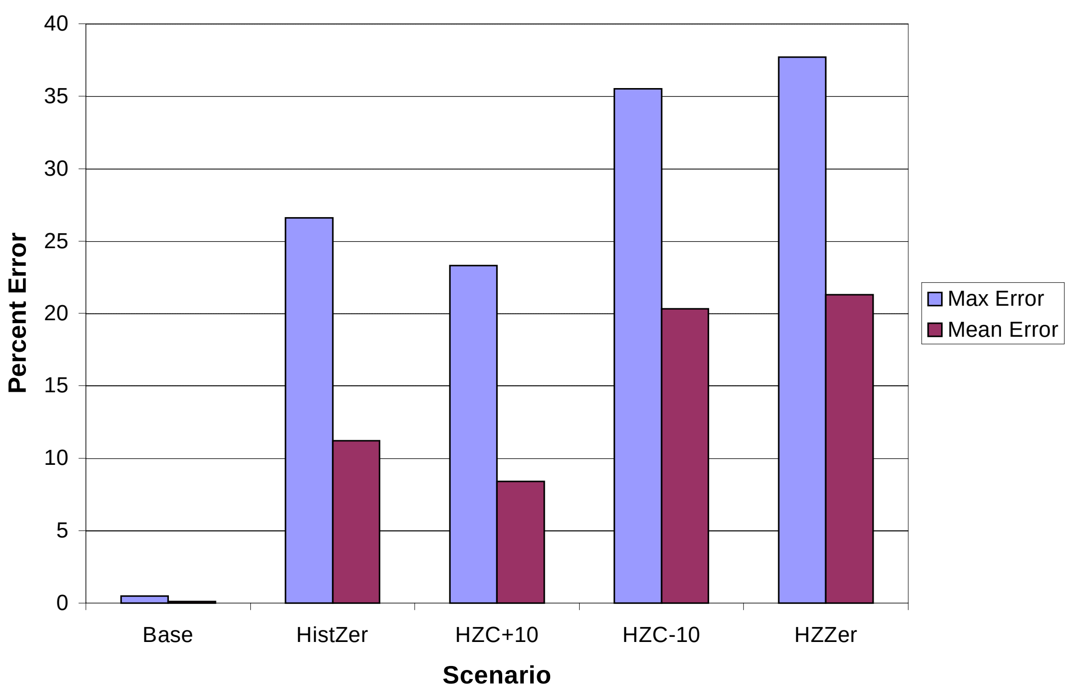

Figure 15: Estimation Results #3

The first four O-D pairs were affected downwards more heavily than the other pairs because the vehicles entered the network into a queue caused by toll booths. This reduces the number of link counts measurements that were available for these O-D pairs, and hence the stabilization role that is played by the historical matrix is more important for these estimates.

- Combining a poor historical matrix with sensor count errors (HZC+10, HZC-10) yielded intuitive results. When sensor count readings are erroneously low, estimation errors become worse since the historical matrix is erroneously low also. When the sensor count readings are erroneously high, this partially balances out the erroneously low historical matrix and errors are reduced as compared to the HistZer scenario.

- Combining a poor historical matrix with a transition matrix set to zero (HZZer) increased errors in the O-D flow estimates. This is because with the effects of the transition equations eliminated, the algorithm places greater emphasis on the measurement and state equations. While the measurement equation inputs have no errors in this scenario, the state equation inputs (the historical matrix) are poor.

<u>For Figure 16</u>

Base: Base conditions, perfect inputs.

(A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1)

AsP5: Assignment matrix randomly perturbed to a maximum error of 5%.

(A-1, B-1, C-1, D-1, E-1, **F-2**, G-1, H-1, I-1)

AsP10: Assignment matrix randomly perturbed to a maximum error of 10%.

(A-1, B-1, C-1, D-1, E-1, **F-3**, G-1, H-1, I-1)

AsP20: Assignment matrix randomly perturbed to a maximum error of 20%.

(A-1, B-1, C-1, D-1, E-1, **F-4**, G-1, H-1, I-1)

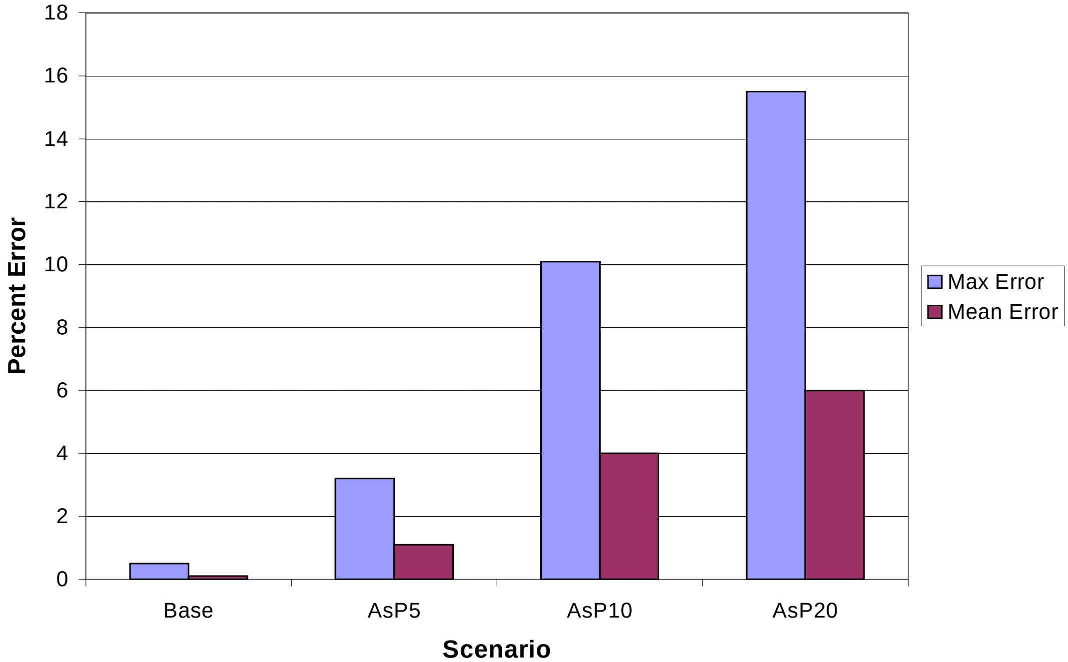

Figure 16: Estimation Results #4

- The mean O-D flow estimate errors obtained from introducing errors in the assignment matrix were rather moderate (1.1% for a 5% perturbation, 4.0% for a 10% perturbation, 6.0% for a 20% perturbation). This indicates that the algorithm is rather robust with respect to the assignment matrix input, which is promising given that in reality the true assignment matrix is likely to not be known perfectly in the absence of specialized in-vehicle tracking devices.

4.3 With Incident Results

<u>For Figure 17</u>

Incid: Fifteen-minute incident in Third Harbor Tunnel.

(A-1, B-1, C-1, **D-2**, E-1, F-1, G-1, H-1, I-1)

ICou+10: Incident with 10% high systematic sensor count errors.

(A-1, B-1, C-1, **D-2**, **E-2**, F-1, G-1, H-1, I-1)

ICou-10: Incident with 10% low systematic sensor count errors.

(A-1, B-1, C-1, **D-2**, **E-3**, F-1, G-1, H-1, I-1)

IHist+10: Incident with 10% high historical demand compared to true.

(A-1, B-1, **C-2**, **D-2**, E-1, F-1, G-1, H-1, I-1)

IHist-10: Incident with 10% low historical demand compared to true.

(A-1, B-1, **C-3**, **D-2**, E-1, F-1, G-1, H-1, I-1)

IPrev+10: Incident with 10% error in previous interval estimate (too high).

(A-1, B-1, C-1, **D-2**, E-1, F-1, **G-2**, H-1, I-1)

IPrev-10: Incident with 10% error in previous interval estimate (too low).

(A-1, B-1, C-1, **D-2**, E-1, F-1, **G-3**, H-1, I-1)

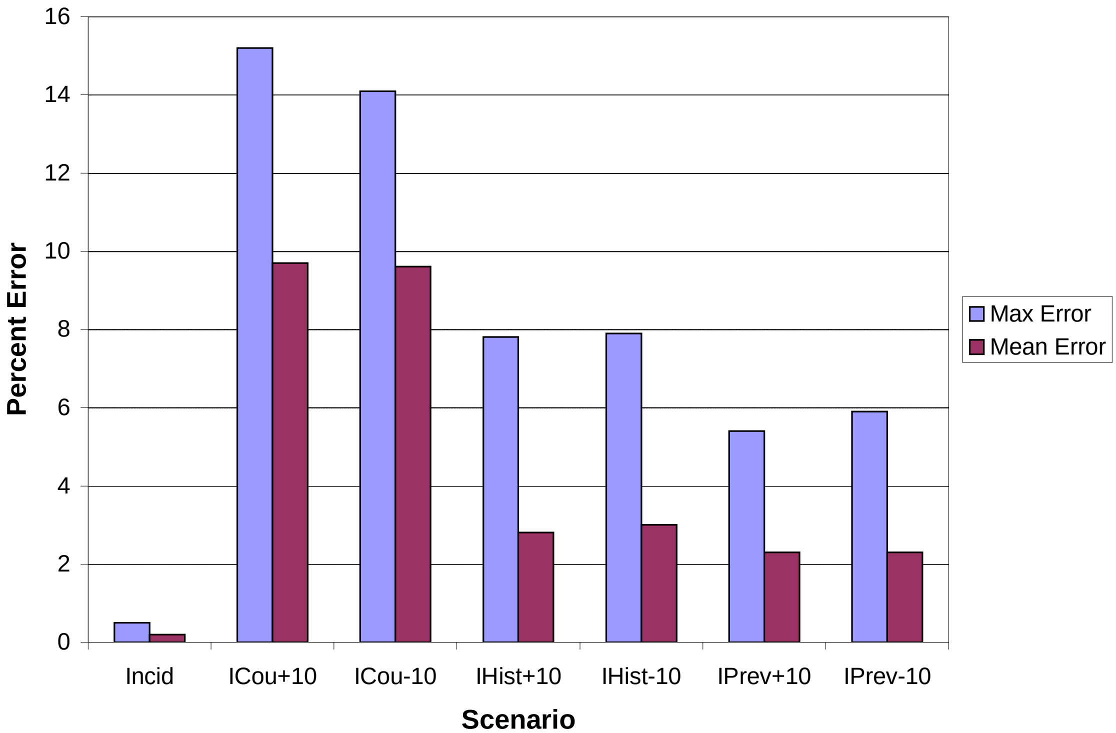

Figure 17: Estimation Results #5

- For the base incident scenario (Incid), the estimate is very good again with no O-D pair estimate off by more than 0.5%. This makes sense given the lack of input errors.

- Errors in the sensor counts by 10% in either direction (ICou+10, ICou-10) had a somewhat greater effect in the incident case (by about 2%) on errors present in the four O-D pair estimates from the Logan Airport / South Boston area. Errors in the estimates of the previous time interval also had a slightly greater impact (about 1%) on errors in the Logan Airport O-D pair estimates.

- A 10% difference between the historical and the true O-D flows (IHist+10, IHist-10) results in errors in the Airport O-D estimates that are about a factor of three greater than the no incident case. With a reduced number of inputs in the measurement equation, the historical matrix plays an important stabilizing role. Only a minor increase in estimation errors between the incident and the non-incident case were observed when previously estimated flows contained errors (IPrev+10, IPrev-10).

For Figure 18

Incid: Fifteen-minute incident in Third Harbor Tunnel.

(A-1, B-1, C-1, **D-2**, E-1, F-1, G-1, H-1, I-1)

IHistZer: Incident with historical matrix set to zero.

(A-1, B-1, **C-4**, **D-2**, E-1, F-1, G-1, H-1, I-1)

IHZC+10: Incident with historical matrix of zero, sensor count errors (high by 10%).

(A-1, B-1, **C-4**, **D-2**, **E-2**, F-1, G-1, H-1, I-1)

IHZC-10: Incident with historical matrix of zero, sensor count errors (low by 10%).

(A-1, B-1, **C-4**, **D-2**, **E-3**, F-1, G-1, H-1, I-1)

IHZZer: Incident with historical matrix of zero, transition matrices set to zero.

(A-1, B-1, **C-4**, **D-2**, E-1, F-1, G-1, **H-2**, I-1)

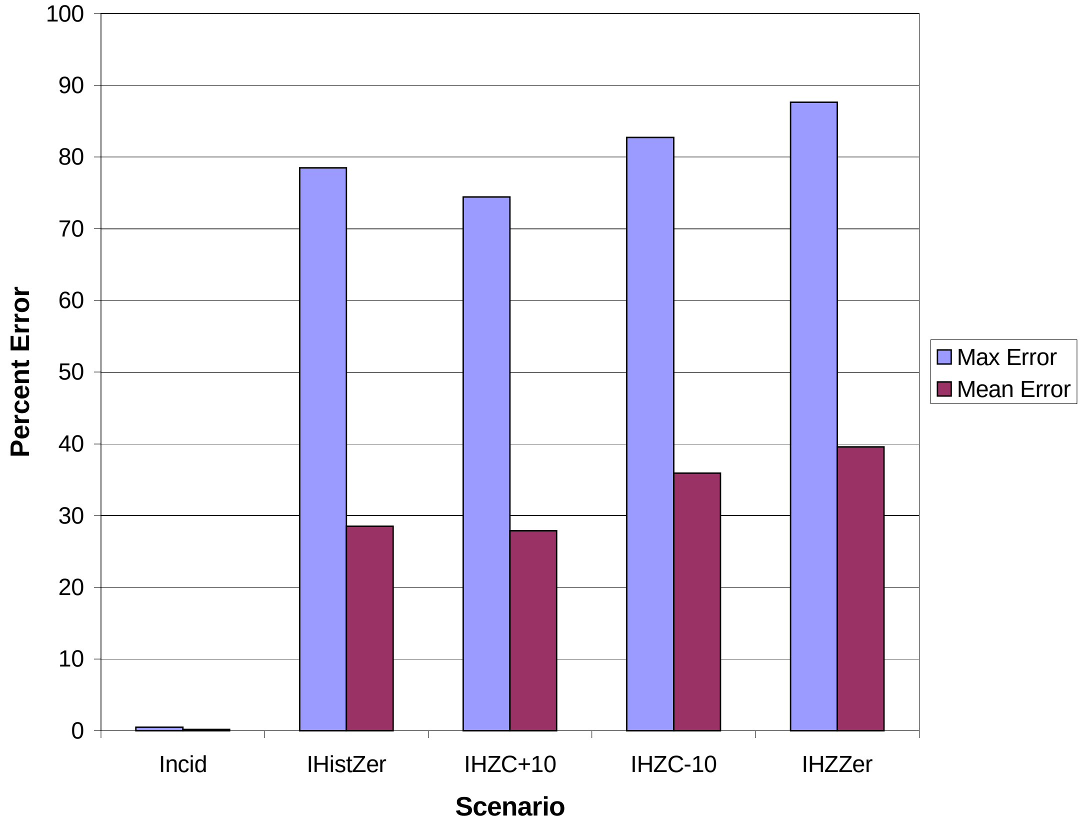

Figure 18: Estimation Results #6

- With historical matrices set to zero (IHistZer), the effect on errors for the four O-D pairs from Logan Airport was far more severe with the incident case than with the no incident case. The estimated O-D pair flows were brought down from the actual demand by as much as 78.5%. A historical matrix of zero in addition to sensor count errors or a transition matrix of zero (IHZC+10, IHZC-10, IHZZer) also yielded greater estimation errors in the incident case.

- Perturbations in the assignment matrix in addition to the incident occurrence (not shown in the figure) yielded results similar to the no incident case.

For this incident scenario, information contained in the measurement equation (sensor reading) inputs was reduced because vehicles for certain O-D pairs were not able to proceed particularly far within the network during the estimation time period. With the lack of input errors, the estimation quality for the incident scenario remained high. This gives an indication that if accurate real-time sensor counts and a historical database are used, the Kalman Filter algorithm will be effective during incident conditions.

However, the impacts of any input errors on the estimation accuracy of the algorithm are magnified in this incident case. This was particularly true when errors are present in the historical matrix. Given a reduction of real-time surveillance system information that can occur during incident situations, having a good historical matrix becomes more critical. The results also indicate that the allocation of sensors within the network could be an important issue.

Out of the thirty-five sensors placed throughout the network in this case study, four of them are located in the area just upstream of the incident. These four sensors are the only source of real-time information that is capable of detecting origin B vehicles from the current estimation interval when the incident has occurred (origin B location shown in Figure 11). Note that due to network geometry, vehicles that enter the network from origin B must use the Third Harbor Tunnel.

The Kalman Filter algorithm during incident conditions was applied assuming that these four upstream sensors do not exist. Surveillance system data therefore is used from only thirty-one sensors. Results are highlighted in Figure 19.

<u>For Figure 19</u>

IncidRev: Fifteen-minute incident, fewer sensors.

(A-1, B-1, C-1, **D-2**, **E-4**, F-1, G-1, H-1, I-1)

IRCou+10: Incident, fewer sensors, sensor count errors (high by 10%).

(A-1, B-1, C-1, **D-2**, **E-5**, F-1, G-1, H-1, I-1)

IRCou-10: Incident, fewer sensors, sensor count errors (high by 10%).

(A-1, B-1, C-1, **D-2**, **E-6**, F-1, G-1, H-1, I-1)

IRHist+10: Incident, fewer sensors, 10% high historical demand compared to true.

(A-1, B-1, **C-2**, **D-2**, **E-4**, F-1, G-1, H-1, I-1)

IRHist-10: Incident, fewer sensors, 10% low historical demand compared to true.

(A-1, B-1, **C-3**, **D-2**, **E-4**, F-1, G-1, H-1, I-1)

IRHistZer: Incident, fewer sensors, historical matrix of zero.

(A-1, B-1, **C-4**, **D-2**, **E-4**, F-1, G-1, H-1, I-1)

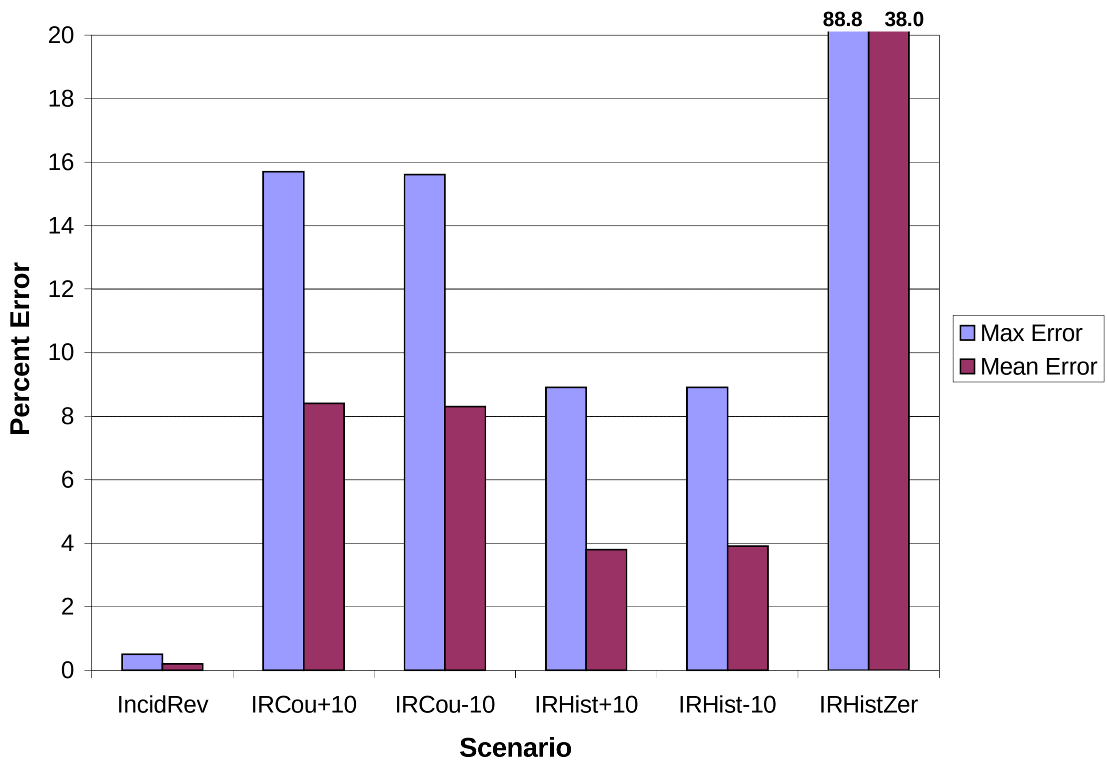

Figure 19: Estimation Results #7

When inputs are free from errors (IncidRev), the loss of sensor information has no measurable impact on the estimation quality. When the loss of sensor information is combined with errors in the sensor counts (IRCou+10, IRCou-10), the estimate quality actually improves slightly as compared to the full sensor information case.

However, when input errors in the historical matrix are combined with a loss of sensor information (IRHist+10, IRHist-10, IRHistZer), estimation errors increase as compared to full surveillance data. This increase was most notable for O-D pairs from origin B. Because no real-time information at all is available for such O-D pairs without these four sensors, the algorithm sets the demand estimate close to historical matrix values. Therefore, when the historical values are set to zero, the estimated demand for these O-D pairs are fairly close to zero. The effect of the transition equation, using O-D pair estimates from previous intervals, is most likely what keeps the estimates above zero.

4.4 Prediction Results

As described in Chapter 1, the full O-D demand prediction process requires interaction between the demand, supply, and information generation components of DynaMIT. This is because the anticipatory information produced by DynaMIT for distribution to travelers will change network demand patterns. These tests deal only with an examination of the Kalman Filter algorithm in isolation from the other components, so a complete investigation of O-D prediction is not contained here. This section therefore describes some small tests run for off-line prediction.

Continuing with the scenario description given for estimation, described in the earlier sections of this chapter, a follow-up exercise is to determine what the algorithm predicts for O-D demand levels of the next fifteen-minute interval. The historical demand levels of the ten O-D pairs for this future interval were set to be 300-300-150-150-225-225-75-75-150-150, which are reasonable values for this study. Off-line prediction was then run for the following scenarios:

PBase: Base conditions, perfect inputs.

(A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1)

PEst+10: Current interval estimate 10% higher than historical demand.

(A-1, B-1, C-1, D-1, E-1, F-1, **G-2**, H-1, I-1)

PEst-10: Current interval estimate 10% lower than historical demand.

(A-1, B-1, C-1, D-1, E-1, F-1, **G-3**, H-1, I-1)

PEst+20: Current interval estimate 20% higher than historical demand.

(A-1, B-1, C-1, D-1, E-1, F-1, **G-6**, H-1, I-1)

PEst-20: Current interval estimate 20% lower than historical demand.

(A-1, B-1, C-1, D-1, E-1, F-1, **G-7**, H-1, I-1)

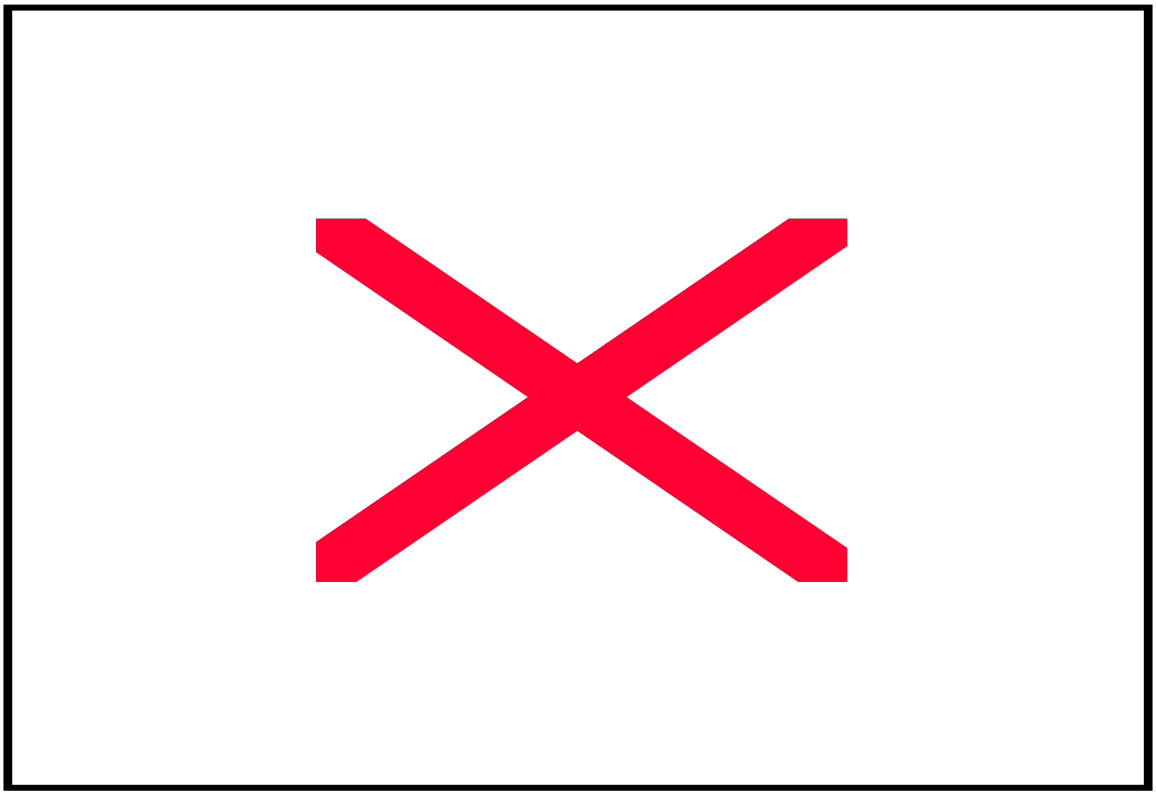

Figure 20: Prediction Results

The column Max Diff gives the maximum difference, in percent, between the historical demand and the predicted demand for any O-D pair. The column Mean Diff gives the mean difference across all ten O-D pairs.

Recall that the algorithm works with deviations; it predicts how deviations between the historical demand and the estimated demand will evolve over time. Under the base conditions (PBase), the predicted demand for the future interval was equal to the historical demand for that interval. This makes sense given that the deviation in the current interval between the historical and the estimated demand is close to zero.

However, when deviations between the two for the estimation interval are introduced (PEst+10, PEst-10, PEst+20, PEst-20), deviations also show up for the future time interval. These predicted deviations are of the same sign and roughly the same magnitude as for the estimation interval. The predicted deviations are not entirely consistent across the O-D pairs. In general though, such deviations were smaller than for the estimation interval, which indicates a tendency for the algorithm to slightly pull its predictions in towards historical levels.

Chapter 5

System Accuracy

This base scenario has the following set of values for the ten dimensions.

(J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, R-1, S-1)

5.1.1 Congestion Locations

As a result of the Sumner/Callahan Tunnel incident, congestion occurs on many links in the upper part of the network. Eight primary regions of congestion were defined. These regions are shown in Figure 21. E stands for East (right side of network), while W stands for West (left part of network). Congestion occurs within all four lanes of the Sumner/Callahan Tunnel since the incident affects both directions. Congestion also occurs on both the on-ramps and off-ramps leading to and from the tunnel in both directions, and adjacent freeway mainlines. A brief explanation for this is as follows.

Once capacity in the main tunnel starts to saturate due to the incident, queues push out onto the tunnel on-ramps. Off-ramp congestion begins to develop once the incident is cleared and the queue in the main tunnel starts to dissipate. When this occurs, the vehicles overflow the off-ramps as they exit the tunnel. Congestion near the off-ramps, or the weaving sections, is caused by the high level of lane changing that must occur for vehicles to make their exit from the tunnel successfully. Lane changing can cause huge delays in congested conditions as some vehicles must wait for a suitable gap. Most of these on- and off-ramps are a single lane with low capacities.

Figure 21: Regions of Congestion

If queues in the on-ramps are severe, they start to push back to the adjoining freeway mainlines. Off-ramp queues are less likely than on-ramp queues to result in mainline congestion on adjacent freeways, because in this situation a low capacity region of the network merges into a high capacity region. Mainline congestion slows down travel times for many drivers regardless of their route choice, whereas tunnel and on-/off-ramp congestion only affects drivers that actually select to use the Sumner/Callahan Tunnel.

5.1.2 Congestion Severity

When DynaMIT is not in operation, the congestion caused by the incident within the network is extreme. This is true both for severity and duration. Critical zones in the network are identified as follows.

Zone #1 - Sumner/Callahan Tunnel Westbound (East to West)
Zone #2 - Sumner/Callahan Tunnel Eastbound (West to East)
Zone #3 - On-ramps Westbound
Zone #4 - On-ramps Eastbound
Zone #5 - Off-ramps Eastbound
Zone #6 - Mainline, Interstate 93
Zone #7 - Mainline, Third Harbor Tunnel near Airport

Note that off-ramps Westbound are not included among the zones. In none of the scenarios were these off-ramps found to be significantly congested (more than 1.5 times greater than free-flow speed). This is because these westbound off-ramps lead directly into the high capacity I-93, so once queues begin to discharge from the Sumner/Callahan

Tunnel they can flow freely into the mainline. The off-ramps Eastbound do have congestion, since they lead into the relatively low capacity Third Harbor Tunnel area near the airport which cannot fully handle all of the traffic from the queue dissipation.

Figure 22 shows the congestion severity in the network that occurs without DynaMIT in operation, what occurs with DynaMIT in operation, and what is predicted to occur by DynaMIT. The horizontal axis refers to the zones listed previously, and the vertical axis gives the travel times through those zones as a multiple of the free-flow travel time. Travel times are time-dependent; the vertical axis value represents the maximum travel time encountered by drivers of any time interval. Note that zones #6 and #7 do not include the entire mainlines of I-93 and the Third Harbor Tunnel, but only the 1,000 feet that are closest to the on- and off-ramps to/from the Sumner/Callahan Tunnel. Note also that results represent an average of five replications.

Figure 22: Congestion Severity

Without DynaMIT in operation, all of the zones listed are affected by congestion. The most severe congestion during the simulation occurs in zones #5 and #6. The Eastbound off-ramps suffer due to low capacity, while the queue that backs up into the I-93 Mainline area, a major weaving section, has severe impacts on speeds. In both of these locations, any queues that begin to develop there grow extremely rapidly; these are high-risk zones. The DynaMIT system is effective in reducing congestion for most zones, particularly the high-risk locations.

Comparing the DynaMIT-Actual and DynaMIT-Predicted bars gives the quality of DynaMIT's prediction. For zones #1, #3, and #7, the predictions made by DynaMIT of the congestion severity is quite good. However, for zones #2, #4, and #5, DynaMIT's prediction of the congestion is low. All of these zones relate to the Eastbound direction.

Based at least partially on the inaccuracy of the Eastbound prediction, DynaMIT is not as effective in reducing congestion in this direction. The information provided by DynaMIT to Eastbound drivers underpredicts the amount of congestion that will develop. Therefore, a larger number of Eastbound drivers stay with their habitual route choice and end up being affected by the congestion that does occur.

DynaMIT has difficulty predicting congestion severity in Zone #6, the mainline I-93 area. The predicted congestion severity is consistent with the no DynaMIT case, but is not consistent with what happens when DynaMIT is in operation. This area is a major weaving section with many lane changes taking place. The prediction inaccuracy here probably stems from the complicated traffic patterns associated with the fairly special characteristics of this zone.

6.2.1 Predictive Quality

Predictive quality did not appear to be significantly affected by the rolling step size. Yet the rolling step size definitely had an effect on user and system performance, to be described in the following sections. The question arises then as to how this could be the case. Graphing a *congestion profile* for a particular zone will assist here. A congestion profile is a graph that shows the actual and predicted congestion levels over the course of the simulation.

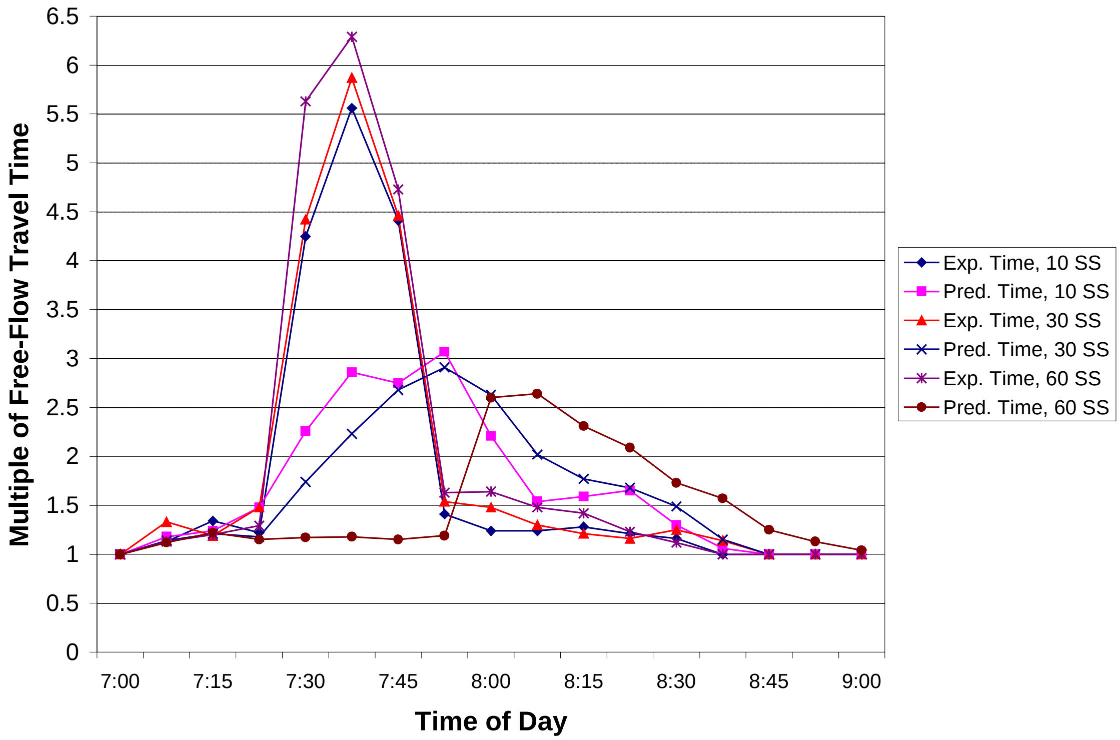

Figure 23: Zone #4 Congestion Profile

This is shown in Figure 23 for Zone #4, the Eastbound on-ramps. The figure indicates that in all scenarios, the actual congestion level spikes upwards at about 7:30, but comes back down again rapidly just past 7:45. Congestion does not build up until a few minutes after the incident has started, and ends quickly once the incident has ended (the incident lasts from 7:15 until 7:45).

For each of the three rolling step sizes, the predicted congestion lasts longer than the true congestion levels. For a 10 minute step size, the primary error is that the predicted severity peak at about 7:37 is 48.5% lower than the actual peak. The timing of queue formation and dissipation is quite good. For a 30 minute step size however, the timing of queue formation is not predicted until 7:30. For a 60 minute step size, the timing of queue formation is not predicted until 8:00 when a sharp spike occurs.

The danger of using a longer step size is that DynaMIT may not be able to adequately keep up with changing traffic conditions in the network. For a 30 minute step size, information is only generated and released to travelers every 30 minutes starting in this case at 7:30. By the time 7:30 comes around, network conditions have already changed substantially from 7:00.

6.3.1 Predictive Quality

A lower quality of congestion prediction was found when a shorter rolling length was used. Once again, plotting a congestion profile will be useful to identify what is taking place. This is shown in Figure 24 for zone #1, the Westbound Sumner/Callahan tunnel.

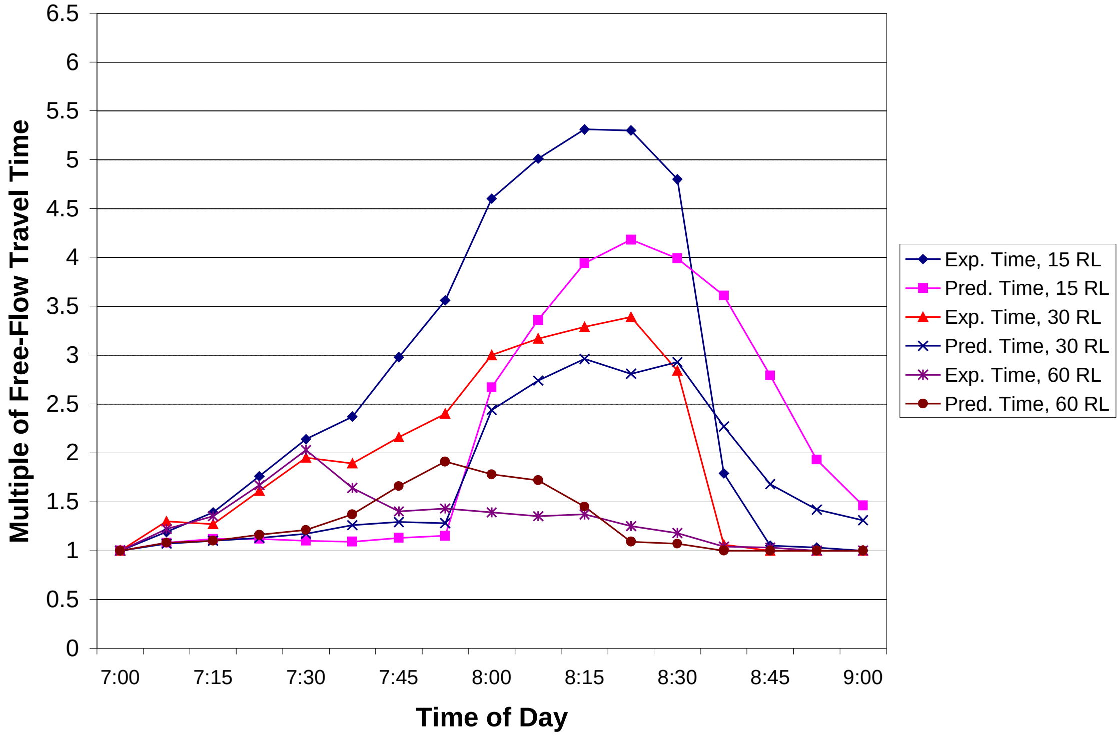

Figure 24: Zone #1 Congestion Profile

From 7:00 to 7:30, actual congestion levels in each scenario gradually build up in the tunnel faster than what is predicted by DynaMIT. Beyond 7:30, the rolling length scenarios of 15 and 30 minutes begin to underpredict the congestion levels to a greater extent than for the longer rolling length of 60 minutes. As DynaMIT information reaches the travelers, a greater number of travelers choose to use the Sumner/Callahan Tunnel for the shorter rolling length cases since less congestion is being reported. This in turn builds up congestion in the tunnel further, which widens the disparity in predicted and actual congestion up until 8:00.

During the incident periods, congestion severity is underpredicted in all cases. However, the magnitude of underprediction appears to be greater for shorter rolling lengths. Why this occurs is not certain and requires further investigation, but this may have something to do with the treatment of unfinished trips in the supply simulator. In DynaMIT, no output is recorded for such unfinished trips. Thus, travel time data related to these unfinished trips are not included in the information generation process.

For example, for vehicles from certain O-D pairs, the travel times in the network during incident conditions in reality can exceed fifteen minutes. If a rolling length of only fifteen minutes is used, many vehicles (particularly those which enter the network near the end of the simulation period) fail to complete their trip by the end of the rolling length. There are certainly going to be uncompleted trips at the end of the rolling length period regardless of what duration is simulated. However, as the rolling length period is reduced, the ratio of unfinished trips to finished trips goes up.

To maintain good network performance during incident conditions, prevention of queue buildup is crucial. Thus, in this case study, the time period from 7:15 to 7:45 when vehicle queues begin to develop is when accurate information provision to travelers regarding network congestion is most critical. During this time, unfinished trips on average are likely to have longer travel times than finished trips for two reasons. One is that trips that take a long time by definition are more likely to not be completed at the end of the simulation period. The other is that travel times in the network as a whole are getting longer due to queue buildup. It is hypothesized that these reasons are the source of greater congestion underprediction for shorter rolling lengths early in the simulation.

6.4.1 Predictive Quality

The predictive quality of DynaMIT when only one iteration was used instead of three was worse. Congestion severity was underpredicted for all zones, particularly #3 (on-ramps westbound) and #5 (off-ramps eastbound). The duration results indicated that when only one iteration was used, a time lag between the actual congestion and when DynaMIT predicted congestion occurred. DynaMIT with one iteration generally did not predict congestion until at least 15 minutes after it had already started. These are the results of poorer identification of a fixed point between demand, supply, and information.

The difference in predictive quality between three iterations and five iterations was extremely minimal.

7.2.2 Predictive Quality

No clear predictive quality patterns as a function of the number of guided travelers were found. This is a surprise, as predictions would be expected to improve if the percent of guided travelers that DynaMIT assumes is equal to the percent of guided travelers in the MITSIM reality. This result is probably more a by-product of the particular scenario being investigated as opposed to a general finding. The fact that, for this scenario, the actual percent of guided travelers has such a substantial impact on experienced congestion levels complicates the relationships and makes them harder to discern.

5.1.3 Congestion Duration

Figure 25 provides similar information for congestion duration, where the vertical axis indicates the number of minutes during the simulation that zonal travel times are predicted to be more than 1.5 times greater than the free-flow travel time. DynaMIT is successful in reducing the duration of congestion for all zones except #2. Congestion is virtually eliminated for zones #3 and #7; the Westbound on-ramps and Third Harbor Tunnel mainline respectively. DynaMIT also predicted that this elimination would occur.

DynaMIT tended to err on the side of slow queue dissipation. This is most evident for zones #4 and #5, the Eastbound on- and off-ramps. While the predicted severity of congestion in these zones was low, the predicted duration was high.

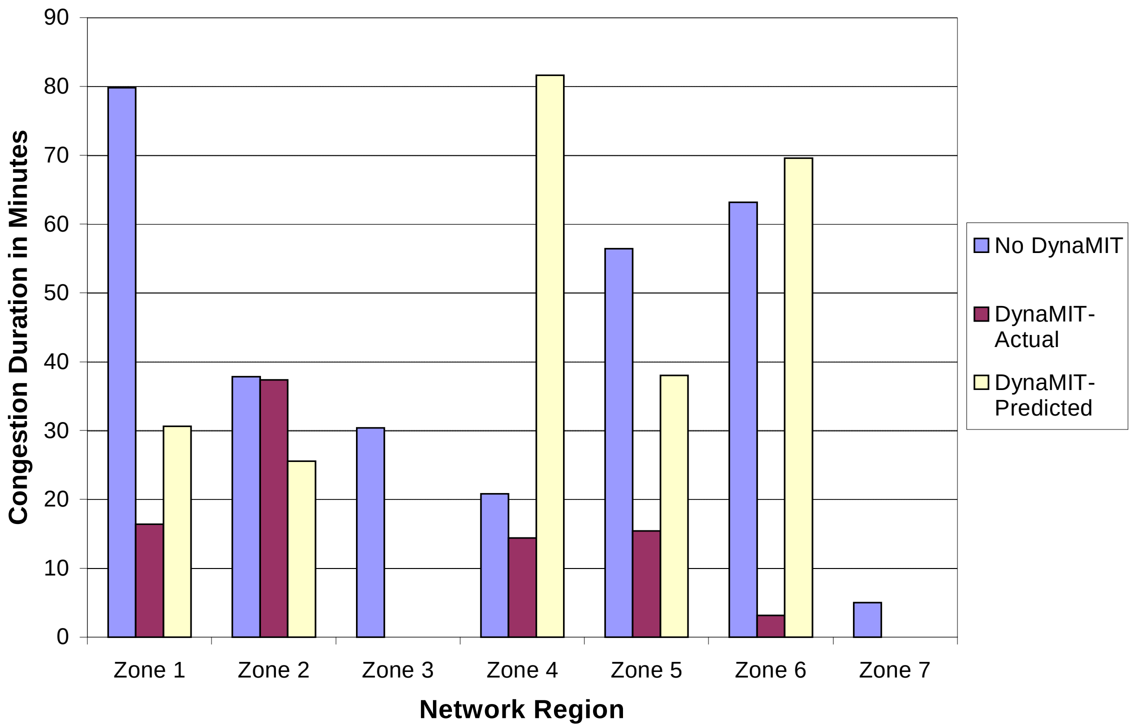

Figure 25: Congestion Duration

A topic related to duration is the predicted starting and ending time of the queues, shown in Table 3 averaged over five replications. The times listed are when the vehicle travel times through those zones exceed 1.5 times the free-flow speed. The Without DynaMIT-Actual row gives the congestion times without DynaMIT in operation. Soon after the incident begins, congestion starts to occur within the Sumner/ Callahan Tunnel. On-ramp congestion does not occur until some minutes after tunnel congestion has started, as the queue works its way back. Off-ramp Eastbound congestion does not occur until after the incident has cleared; the backlog of vehicles from the tunnel queue begins to advance.

A comparison of the first two rows of numbers gives the effects that DynaMIT has on changing the temporal patterns of congestion in reality. As mentioned previously, DynaMIT is more effective in reducing the Westbound congestion than the Eastbound congestion. The congestion start times generally do not change much when DynaMIT is in operation as compared to the congestion end times. This makes sense given that DynaMIT can take the incident into account only after it has already started.

A comparison of the With DynaMIT-Actual and With DynaMIT-Predicted rows gives the quality of the start and end time predictions. The bottom two rows of the table gives the error in minutes between the predicted start/end times and the actual start/end times of congestion in the with DynaMIT situation. A positive value indicates that DynaMIT predicted congestion before it actually happened, while a negative value indicates that DynaMIT predicted congestion after it actually happened.

	Zone #1: Tunnel Westbd	Zone #2: Tunnel Eastbd	Zone #3: On-ramps Westbd	Zone #4: On-ramps Eastbd	Zone #5: Offramps Eastbd	Zone #6: Mainline I-93	Zone #7: Mainline T Harbor
Without DynaMIT-Actual	**7:21-8:41**	**7:16-7:54**	**8:04-8:34**	**7:31-7:52**	**7:47-8:40**	**7:35-8:38**	**8:01-8:06**
With DynaMIT-Actual	**7:21-7:38**	**7:16-7:53**	**none**	**7:35-7:49**	**7:47-8:03**	**7:45-7:48**	**none**
Minutes Reduction	62	-1	30	6	37	58	10
With DynaMIT-Predicted	**7:43-8:16**	**8:02-8:28**	**none**	**7:19-8:41**	**7:41-8:19**	**7:29-8:39**	**none**
Start Time Error	-22	-46	0	+16	+6	+16	0
End Time Error	-38	-35	0	-52	-16	-49	0

Table 3: Congestion Start and End Times

For the Sumner/Callahan Tunnel itself, DynaMIT had negative start time errors. In contrast, DynaMIT had positive start time errors for the on- and off-ramps. Indeed, DynaMIT predicts that congestion occurs on these ramps before it occurs in the main tunnel. The end time errors are all negative, which is again indicating that queue dissipation in the DynaMIT supply simulator occurs at a slower rate than in reality. This is more notable for the low capacity ramps than the main tunnel.

5.1.4 Non-Incident Locations

The prediction quality results given in the previous sections are only for the areas at or near the occurrence of the incident. These are the areas where an accurate prediction process was expected to be more difficult. For the rest of the network, which covers about 70% of the total network links, DynaMIT travel time prediction had good accuracy and never differed from reality by more than 20%. Vehicle movements in these other links were predicted and actually were generally at or near free-flow speeds.

Chapter 6

Network Performance

6.2 Rolling Step Size

In this case study, three rolling step sizes were used and compared.

- Ten minute rolling step size (base).

  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, R-1, S-1)
- Thirty minute rolling step size.

  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, **Q-2**, R-1, S-1)
- Sixty minute rolling step size.

  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, **Q-3**, R-1, S-1)

6.3 Rolling Length

The scenarios of rolling length that were evaluated are:

- Sixty minute rolling length (base).

  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, R-1, S-1)
- Fifteen minute rolling length.

  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, **R-2**, S-1)
- Thirty minute rolling length.

(J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, **R-3**, S-1)

6.4 Number of Iterations

The scenarios investigated for the number of iterations were as follows.

- Three iterations (base).

  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, R-1, S-1)
- One iteration.

  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, R-1, **S-2**)
- Five iterations.

  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, R-1, **S-3**)

5.2 Network Performance

5.2.1 Traveler Behavior

The link travel time predictions made by the DynaMIT system are released to travelers in the network and affect their route choices accordingly. This section highlights these effects, which is useful for understanding the rest of the analysis.

It is most useful to focus on travelers from O-D pairs with high flexibility with respect to feasible route choices. Due to the network layout, certain origin and destination locations lie on either side of a freeway. Drivers with an origin and/or destination at these locations are committed to only one route choice because they must enter or exit the network on one particular side of the freeway. For other O-D pairs, one route choice is extremely circuitous and would only make sense in the case of an extremely severe incident or complete blockage. An example of this is from G: Logan Airport to F: Route 1A.

Figure 26 shows origins and destinations for two specific groups of travelers, A and B. Each group is made up of the O-D pairs listed here.

Group A	Group B
I-93 North to Route 1A	Mass Pike to Route 1A
Route 1A to I-93 North	Route 1A to Mass Pike
Storrow Drive to Route 1A	
Route 1A to Storrow Drive	

Most travelers in Group A habitually use the Sumner/Callahan Tunnel. The origins and destinations for travelers in Group A all are located in the upper portion of the network, and so the use of the Third Harbor Tunnel would be rather circuitous. In order for travelers in Group B to use the Sumner/Callahan Tunnel, they must exit the freeway portion of the Central Artery network and use local streets (added to the network for completeness) for part of the trip. Thus, the Third Harbor Tunnel is the logical habitual route choice for Group B travelers. Figure 27 shows the route choices made by travelers in the two groups during the simulation.

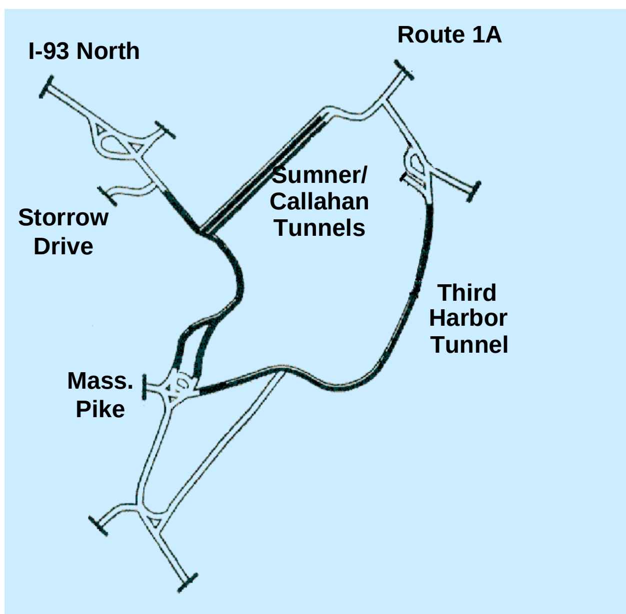

Figure 26: O-D Locations for Groups A and B

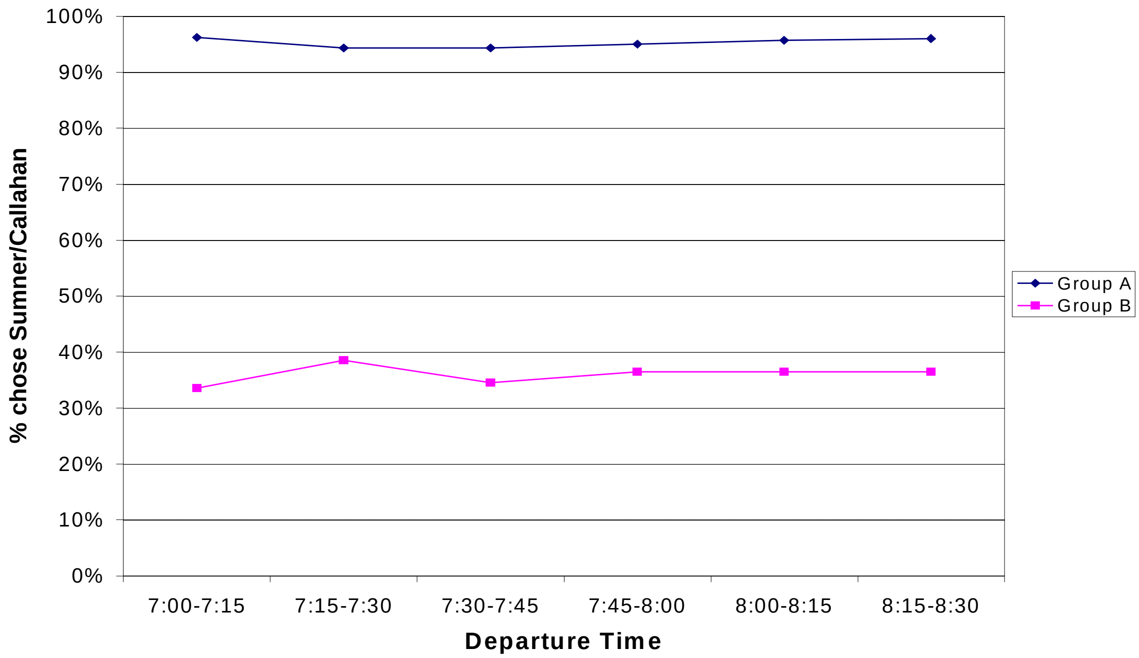

Figure 27: Route Choices With No DynaMIT

Figure 28 shows the travel time results from the simulation for the two groups. The vertical axis indicates the time savings experienced by drivers who chose the Sumner/Callahan tunnel as opposed to those who chose the other tunnel. A negative travel time savings indicates a travel time cost. Beyond 7:15, because of the incident, travelers who used the Sumner/Callahan Tunnel began to suffer.

Note that despite the presence of the incident, travelers in Group A who selected the Sumner/Callahan Tunnel still generally saved travel time as compared to those who used the other route. This is a critical point that will be highlighted later in this chapter.

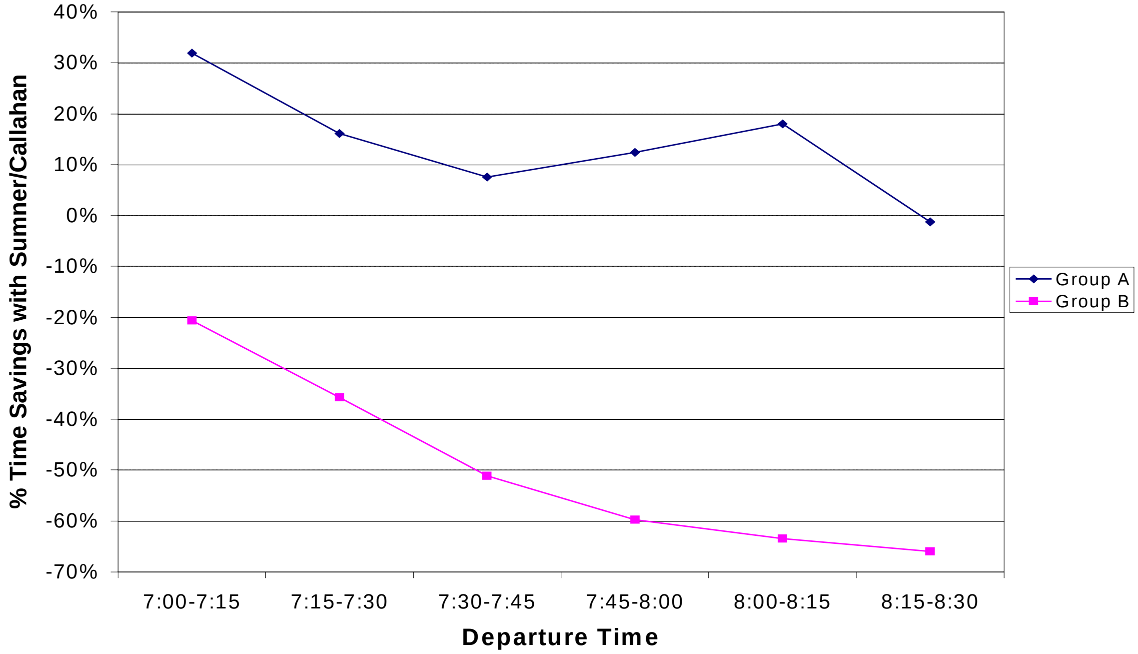

Figure 28: Travel Times With No DynaMIT

Traveler route choices made with DynaMIT in operation are shown in Figure 29. Many drivers avoid using the Sumner/Callahan Tunnel because of the information.

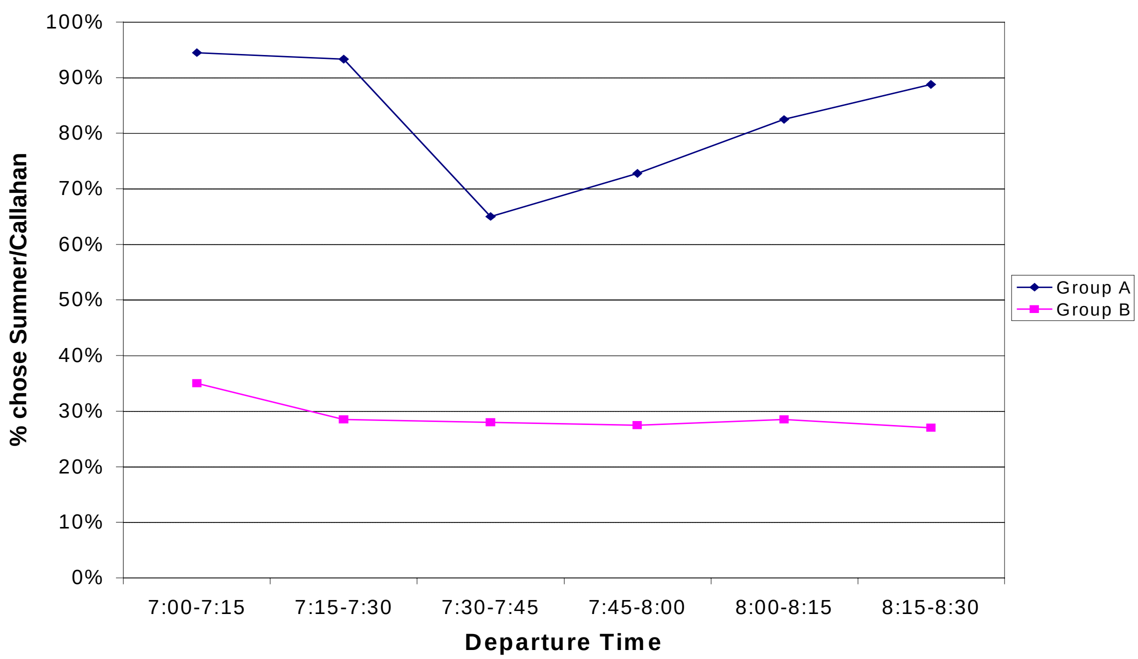

Figure 29: Route Choices With DynaMIT

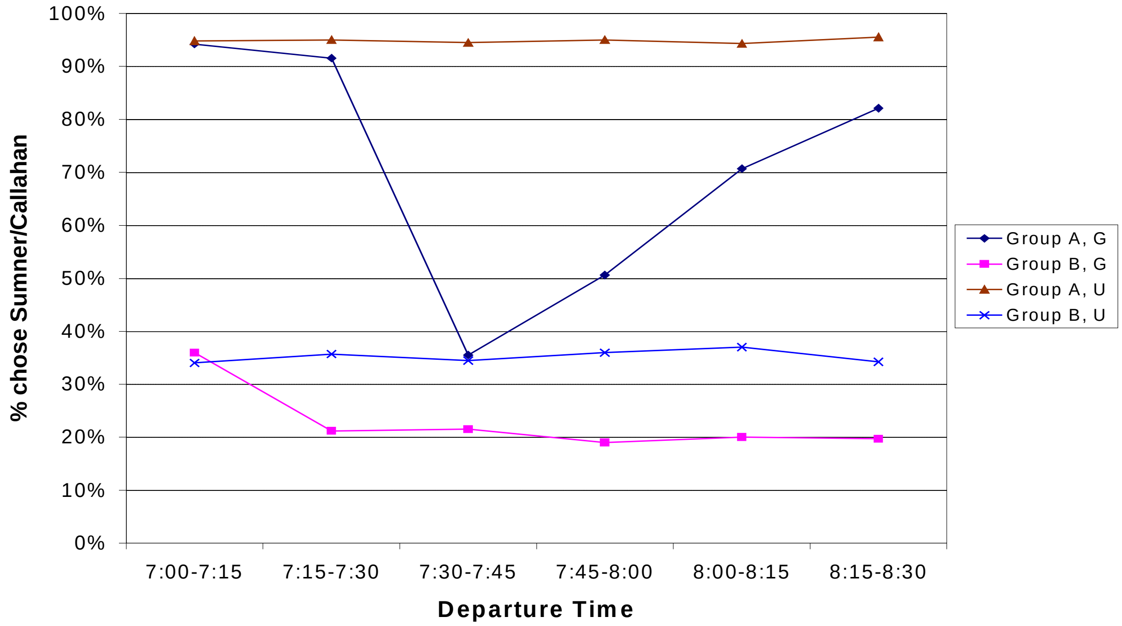

Figure 30: Route Choices, Guided and Unguided

Recall that in this scenario, half of the travelers (guided-G) are able to receive the information from DynaMIT while the other half (unguided-U) are not. Figure 30 shows the route choices for the two traveler groups, split into guided and unguided travelers. As expected, the route choices for unguided travelers remain at habitual levels while the route choices for guided travelers are greatly affected beyond 7:30.

The travel times of travelers in the two groups with the presence of DynaMIT under incident conditions are shown in Figure 31. The effects of the incident on travel times in the Sumner/Callahan Tunnel are greatly reduced in this case.

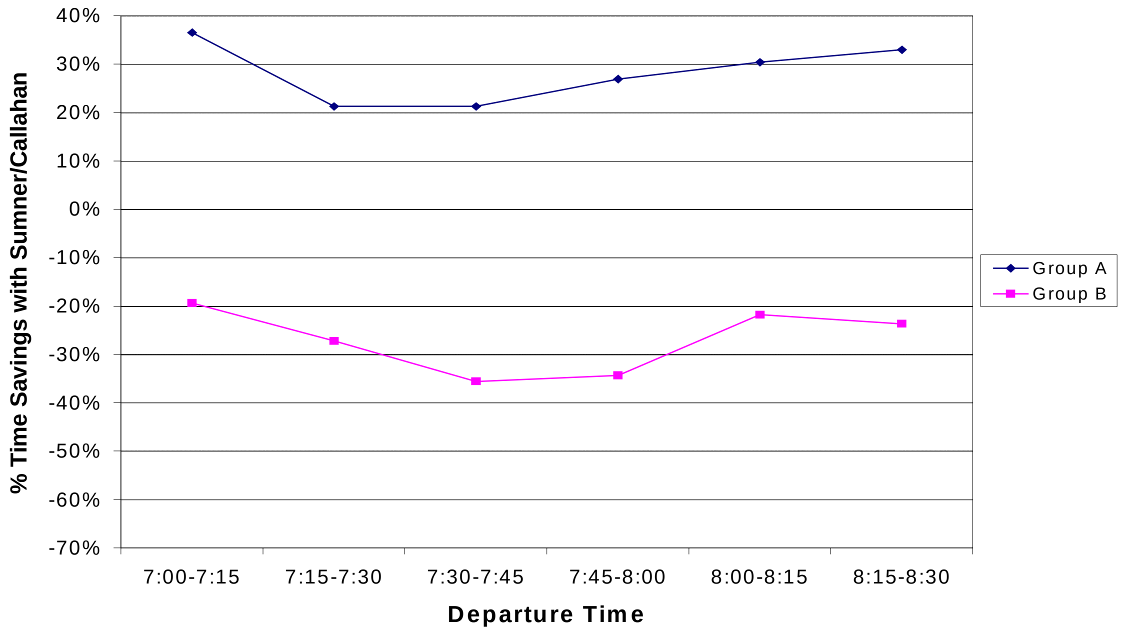

Figure 31: Travel Times With DynaMIT

5.2.2 User Optimality

Section 5.1 looked at the issue of accuracy with respect to the information generated by DynaMIT. The purpose of this section is to examine whether the release of this information led to an optimal outcome with respect to user travel times. Recall that a user-optimal outcome is when no traveler could have selected a better route on the basis of travel time than the one recommended by the DynaMIT system.

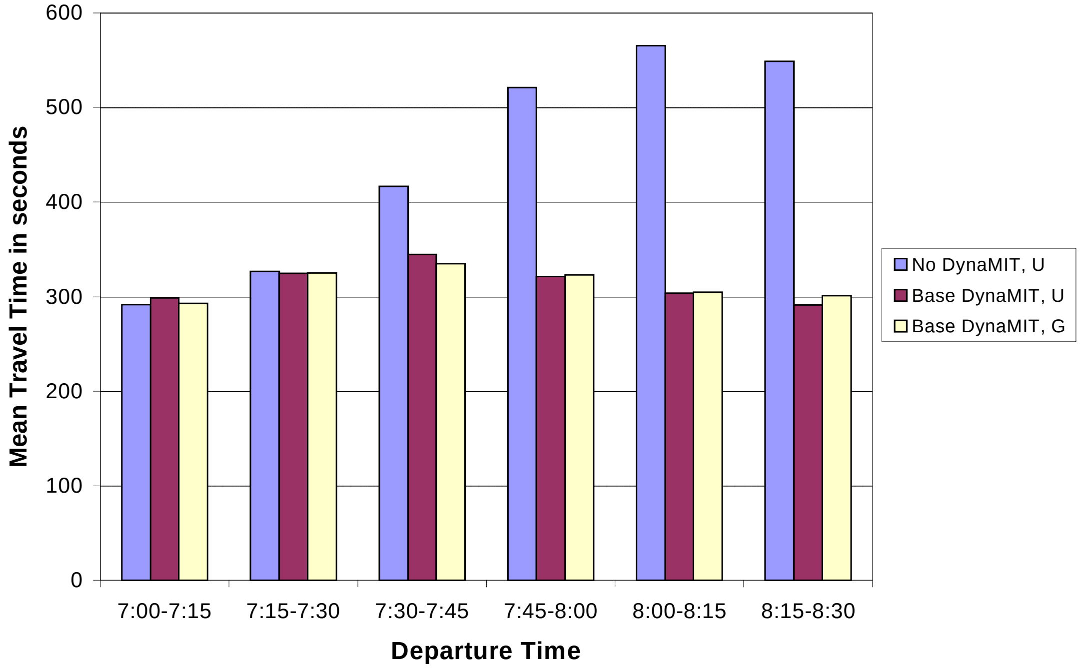

Figure 32: Mean Travel Times for all Travelers

Figure 32 shows the mean travel time in seconds for all travelers in the network under incident conditions, averaged over five replications. One bar series shows travel times when DynaMIT is not in operation (all travelers are unguided). The other bar series shows travel times for guided and unguided travelers separately when DynaMIT is in operation. It is clear from the figure that the information provided by DynaMIT helps all network travelers in terms of saving travel time. It is also evident that unguided and guided travelers do not differ much with respect to their mean travel times.

These results initially appear to be surprising. One would expect guided drivers to have lower average travel times than unguided drivers as a result of complying to information provided by DynaMIT. This calls into question whether the information provided by DynaMIT is informing drivers to select a user-optimal outcome. While inconsistency between DynaMIT's predicted link travel times and reality may contribute to this, there is another issue taking place. To determine what this is requires examining again the travel times for specific O-D pairs. This is shown in Figure 33 for the same two groups A and B used in the previous section.

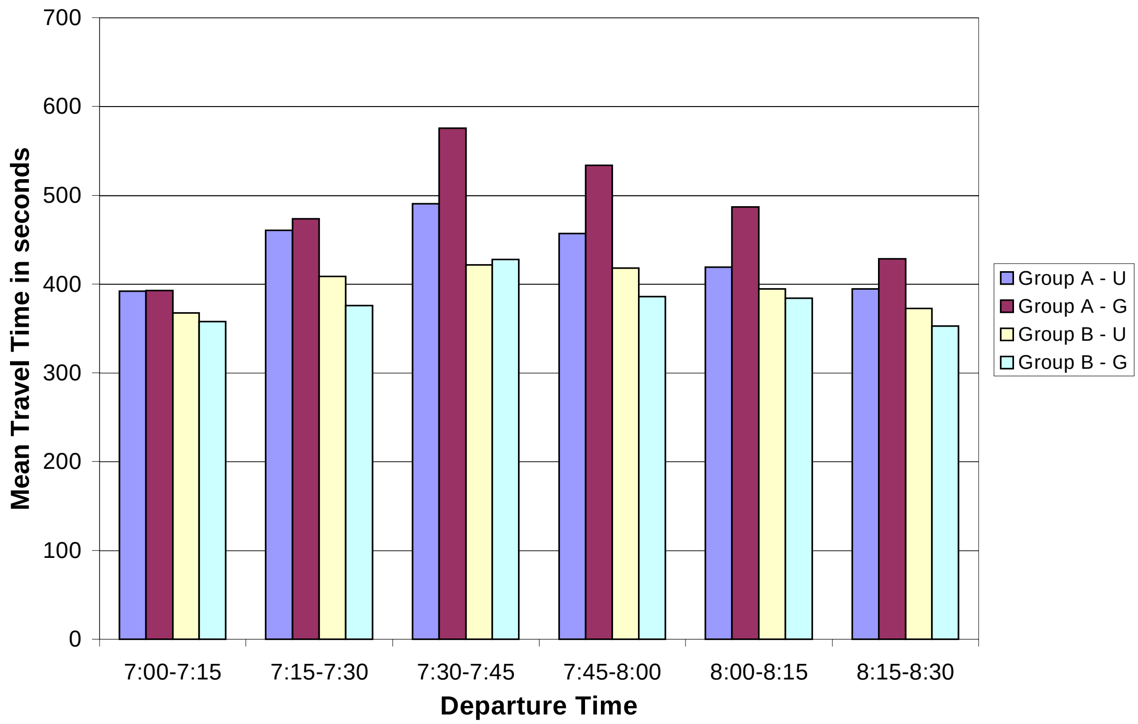

Figure 33: Mean Travel Times for Specific O-D Pairs

For travelers in Group B, guided travelers generally experience lower travel times than unguided drivers. However, for travelers in Group A, the reverse is true. Recall from Section 5.2 that guided travelers from both groups A and B were less likely to use the Sumner/ Callahan Tunnel as a result of DynaMIT information. Recall also that despite the presence of the incident, travel times via the Sumner/Callahan Tunnel remained lower than via the Third Harbor Tunnel for travelers in Group A.

5.2.3 Explanation of Findings

In the MITSIM reality, informed and compliant drivers make their route choice decisions using a logit model based on the updated travel times from the information system. Therefore, the provision of descriptive information regarding an incident affects the route choices of guided drivers in a similar fashion regardless of what O-D pair they belong to.

More specifically, if the updated link travel time tables indicate that travel times are longer in the Sumner/Callahan Tunnel, then more drivers from all O-D pairs will avoid using the tunnel. However, this occurs even if alternative routes still have longer travel times than the habitual route. This means that for certain O-D pairs, informed drivers end up making worse route decisions than uninformed drivers who stay on habitual paths.

For Group B, a greater percent of guided drivers are avoiding the Sumner/Callahan Tunnel than unguided drivers, and this avoidance makes sense from a travel time standpoint. For Group A, guided drivers are also avoiding the Sumner/Callahan Tunnel more than unguided drivers. However, guided drivers in Group A have longer travel times than unguided drivers since the Sumner/Callahan Tunnel remains faster than the other route despite the incident occurrence.

6.2.2 User Optimality

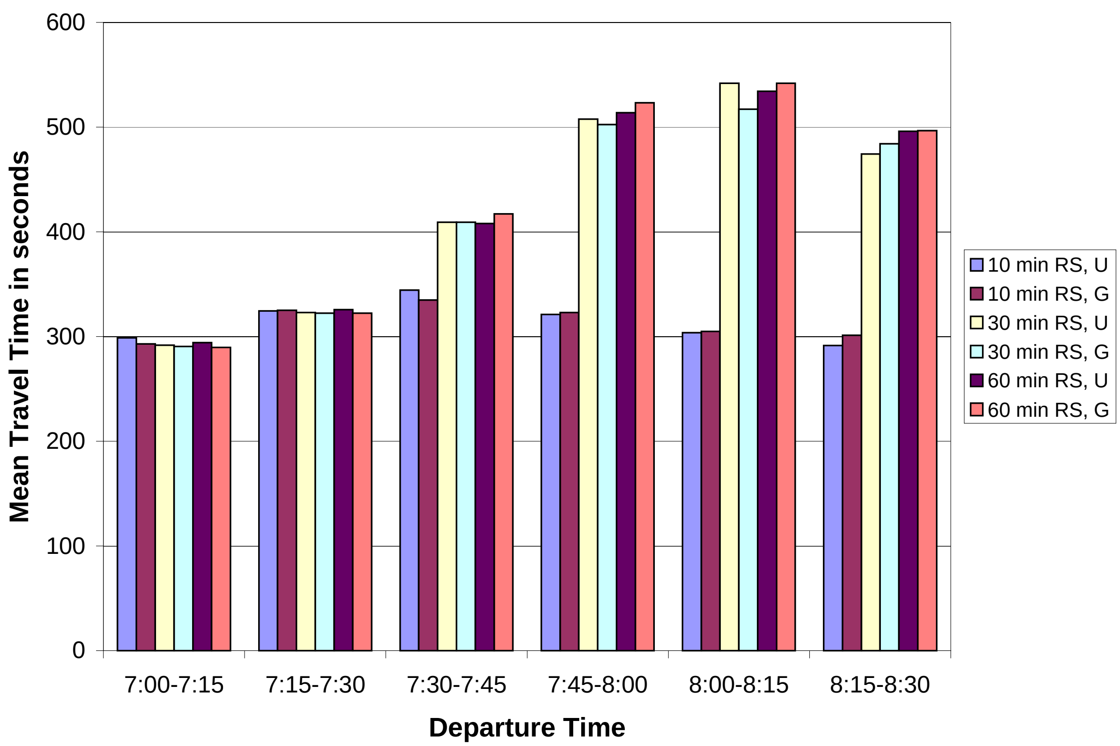

Figure 34: User Optimality, Rolling Step Size

Figure 34 shows the mean travel times experienced in the network for guided and unguided drivers during the course of the simulation for the three rolling step sizes. Results are averaged over five replications for each scenario. The overall benefits of the information are substantially greater when the 10 minute rolling step size is used. This becomes evident for travelers that enter the network beyond 7:30, when the effects of outdated network condition information on traveler behavior becomes more significant.

6.3.2 User Optimality

Because of differences in DynaMIT's predictions and information strategy, fewer travelers divert away from the incident when shorter rolling lengths are used. Figure 35 shows the mean travel times experienced in the network for guided and unguided drivers for the three rolling lengths, averaged over five replications. Benefits of information provision in these scenarios begin to differ beyond 7:30, and the gap closes somewhat only after 8:15.

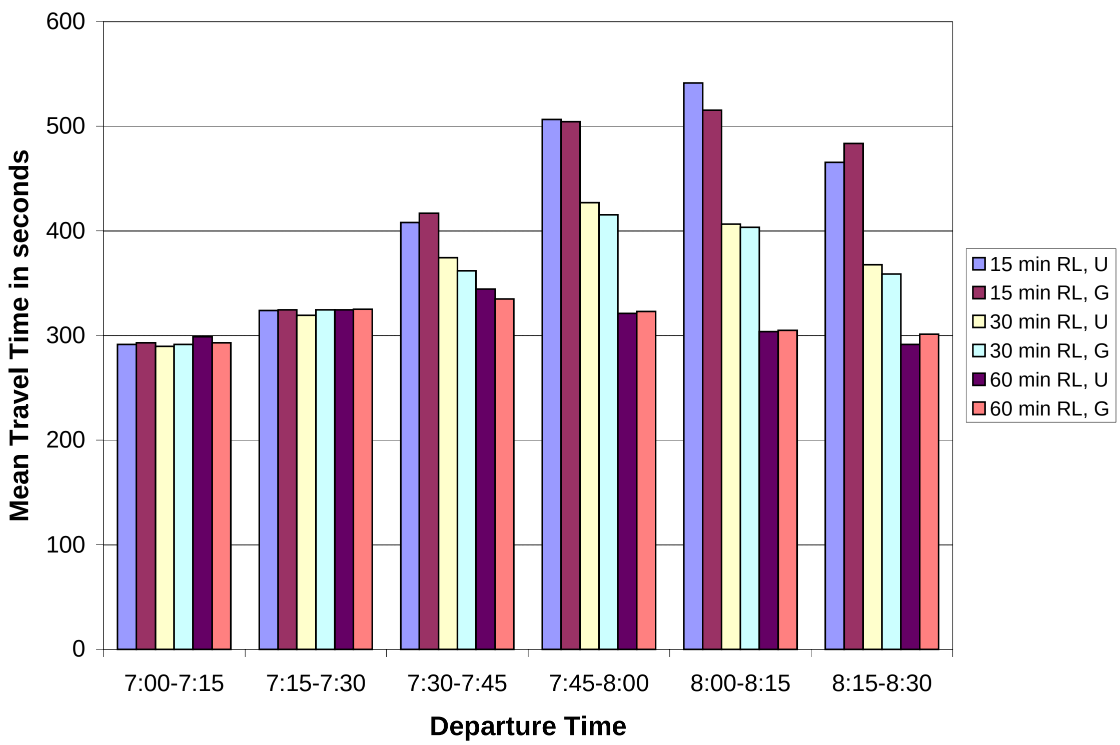

Figure 35: User Optimality, Rolling Length

6.4.2 User Optimality

Because of differences in DynaMIT's predictions and information strategy, fewer travelers divert away from the incident when a lower number of iterations is used. Figure 36 shows the mean travel times experienced in the network for guided and unguided drivers as a function of the number of iterations used. Performance between the three and five iterations scenarios remain about the same throughout. The benefits of information provision for the one iteration scenario become visibly worse beyond 7:30.

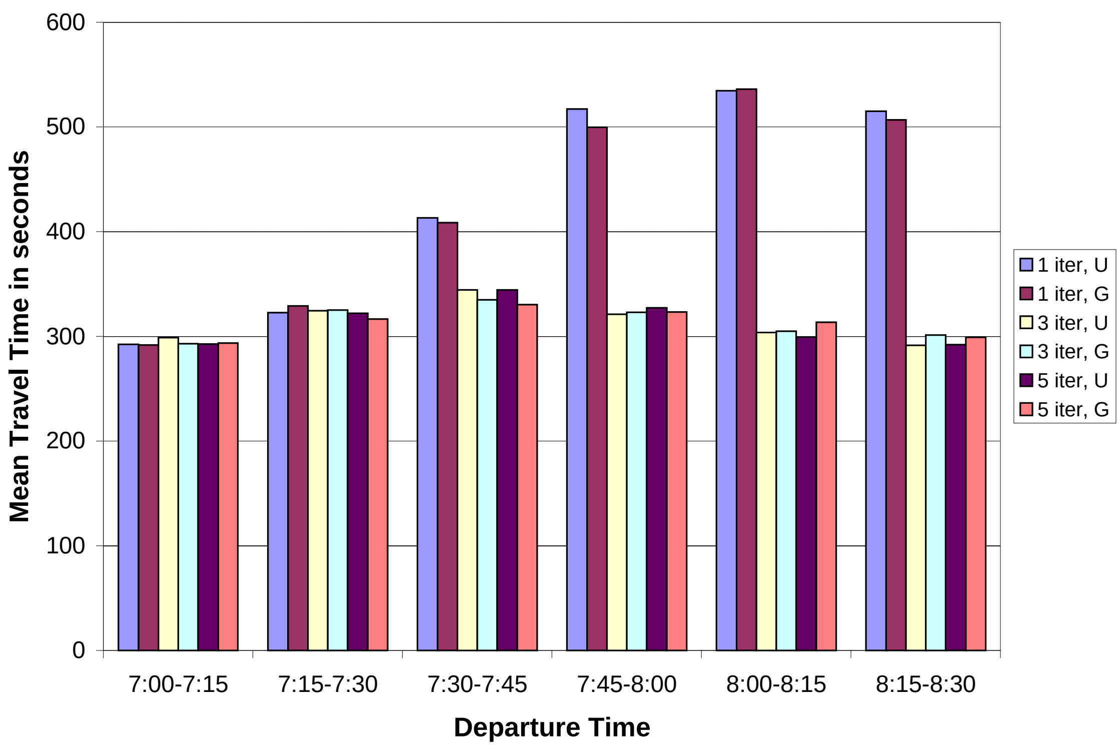

Figure 36: User Optimality, Number of Iterations

7.2.3 User Optimality

Fewer travelers divert away from the incident when the percent of guided travelers is smaller, as expected. The experienced travel times for the two groups A and B are shown in Figure 37 and Figure 38 for the 25% and 75% scenarios. In the 75% guided case, experienced travel times in the two tunnels stabilize much more rapidly to historical levels than in the 25% guided case.

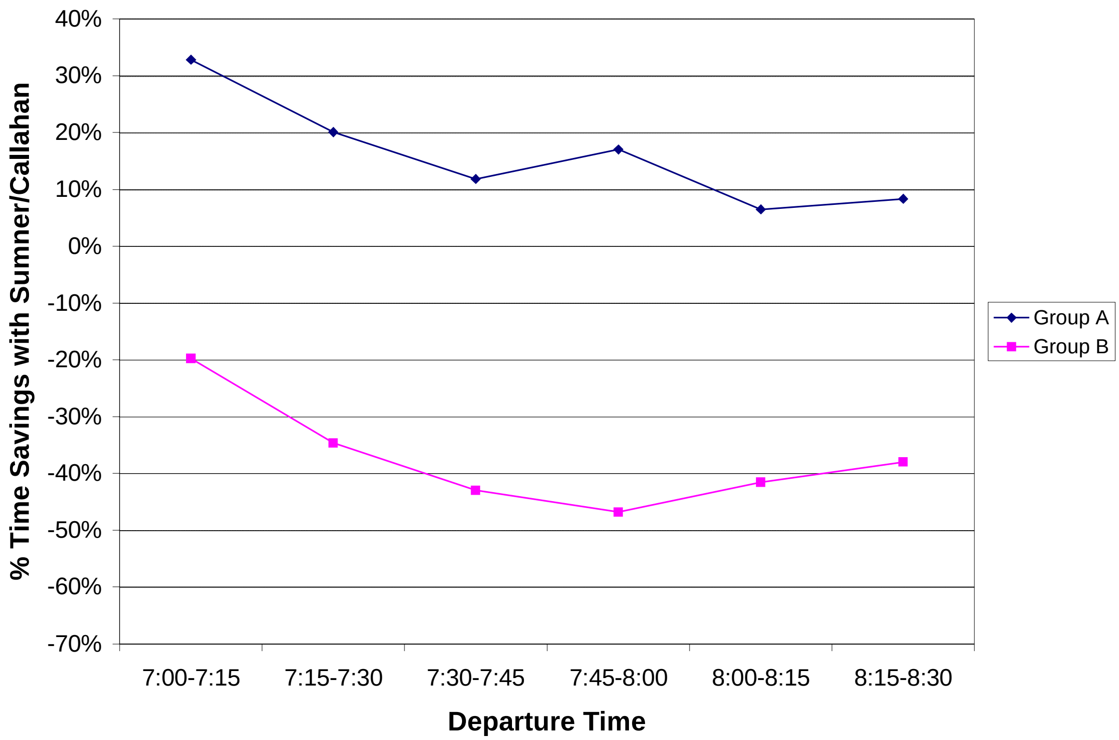

Figure 37: Travel Times, 25% Guided

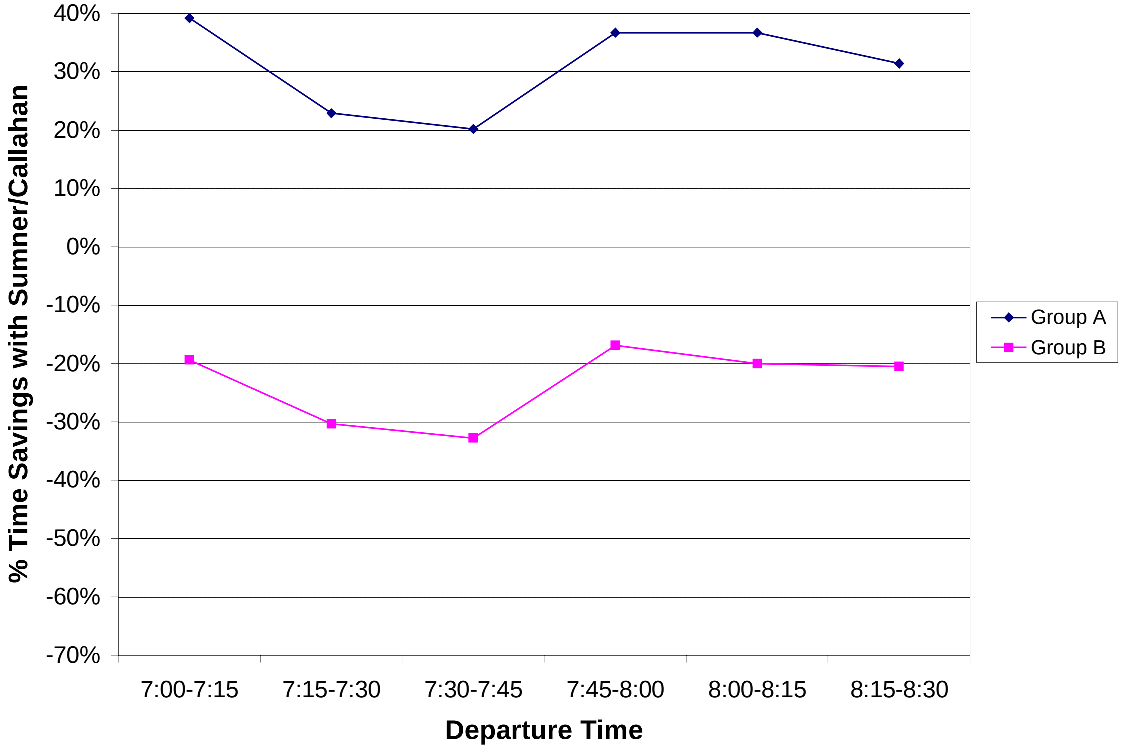

Figure 38: Travel Times, 75% Guided

Figure 39 and Figure 40 show how unguided, or uninformed, travelers compared to guided, or informed, travelers for the two O-D pair groups A and B during the simulation. Results are averaged over five replications for each. When 25% of travelers are guided, travelers in group A who are unguided experience lower travel times than guided travelers beyond 7:30. For group B, the opposite holds. This pattern is similar to what was determined in the Chapter 4 base scenario.

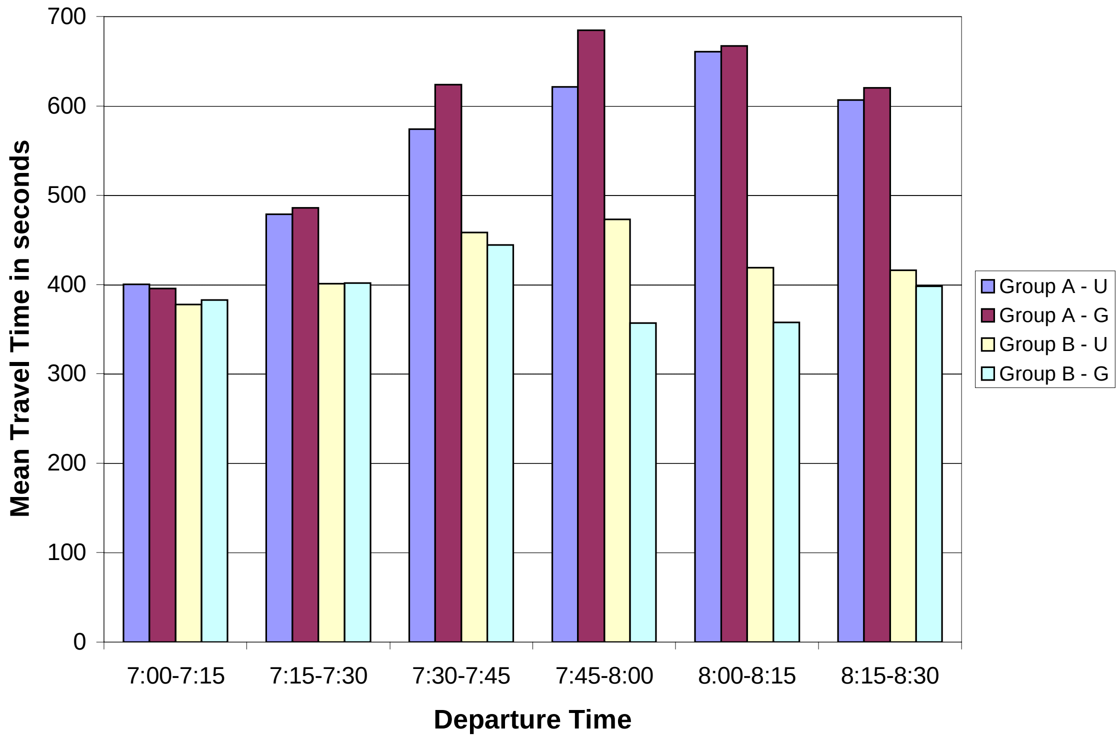

Figure 39: Unguided vs. Guided, 25% Guided

However, when 75% of travelers are guided, the pattern comes out somewhat differently. The difference in experienced travel times between unguided and guided travelers in Group A is quite large for those who enter the network between 7:45 and 8:15. For travelers in Group B, the time savings experienced by guided versus unguided travelers is virtually eliminated during the simulation period.

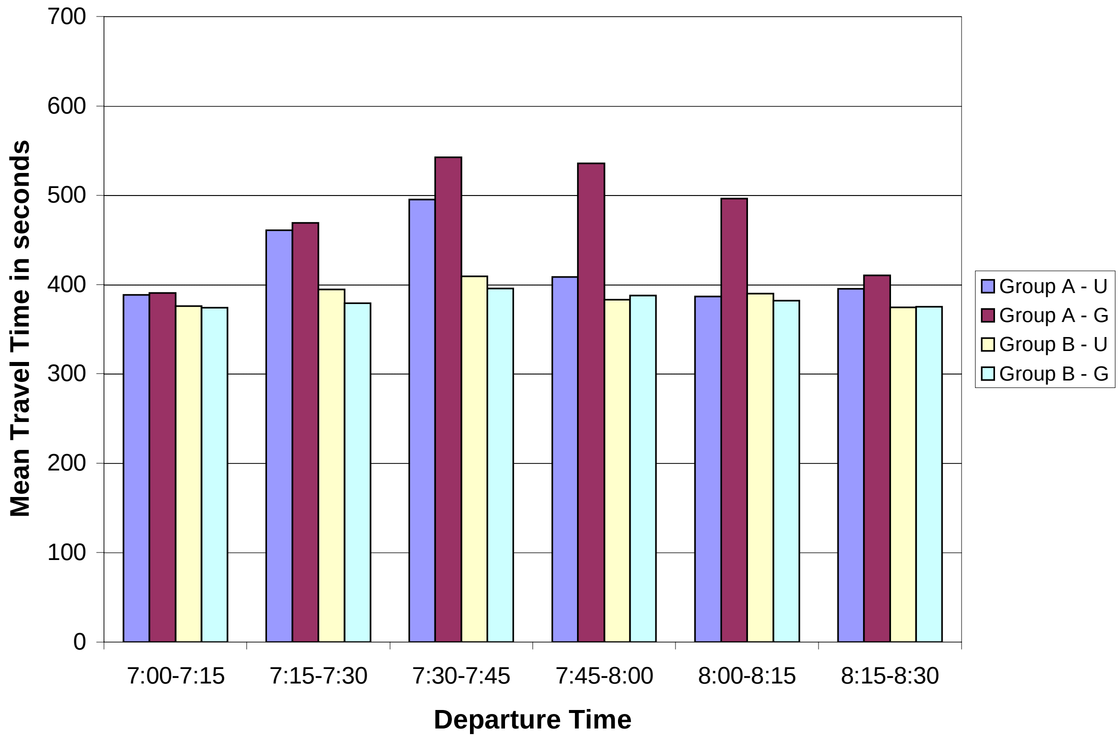

Figure 40: Unguided vs. Guided, 75% Guided

Figure 41 combines these findings for all travelers in the network during the simulation period. Beyond 7:15, all travelers in general experience shorter travel times when 75% of travelers are informed and compliant as compared to when 25% of travelers are informed / compliant. However, guided travelers in the 75% scenario have no time savings as compared to unguided travelers. In the 25% scenario, although overall travel time savings compared to the no DynaMIT case are small, guided travelers really benefit from the information in terms of travel time as compared to unguided travelers.

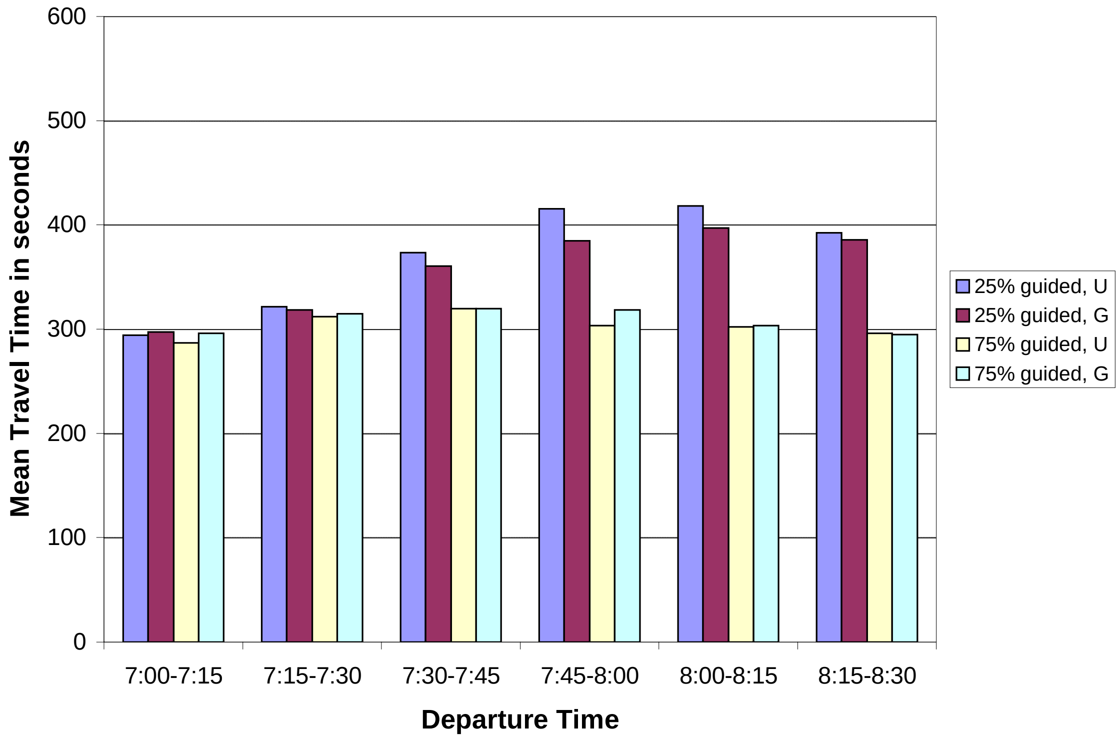

Figure 41: User Optimality, Information Levels

This discussion is important when thinking about user optimality vs. system optimality. When the percent of travelers provided with real-time information is fairly small and a severe incident occurs, informed travelers can benefit substantially in terms of travel time compared to uninformed travelers. Benefits to the system as a whole may be quite limited however since so few travelers are involved with respect to this information.

When the percent of travelers who are provided with real-time information is high, benefits to the system as a whole when a severe incident occurs can be quite large. This is assuming that information is consistent and that alternative routes exist with sufficient capacity to handle diverted traffic. However, the benefits of informed travelers relative to uninformed travelers will be reduced. If over-reaction occurs, informed travelers can face longer travel times than uninformed travelers even if system-wide benefits are impressive.

5.2.4 System Travel Times

The overall mean travel times and standard deviations across all fifty-six O-D pairs are provided in Table 4 and Table 5 as a measure of the system-level effectiveness of DynaMIT. The results reflect average values of five replications for the no DynaMIT and with DynaMIT cases.

The "standard deviation across vehicles" column applies to the travel times experienced by drivers from all O-D pairs within the indicated time period. The value is rather high since vehicles from different O-D pairs need to travel varying distances. The "standard deviation across replications" column applies to the mean travel time experienced by drivers for the indicated time period across the five replications that were run. The value is rather low since each replication simulates the same scenario. The standard deviation values in this column represents stochasticity of the MITSIM simulator.

	Mean (in seconds)	Std Dev Across Vehicles (in seconds)	Std Dev Across Replics. (in seconds)
All Vehicles	**446.9**	**315.3**	**10.91**
7:00-7:15	291.7	152.5	2.97
7:15-7:30	326.7	189.0	1.25
7:30-7:45	417.0	267.6	8.47
7:45-8:00	520.9	336.3	13.27
8:00-8:15	565.3	381.5	22.69
8:15-8:30	548.9	371.4	27.85

Table 4: System Performance - No DynaMIT

	Mean (in seconds)	Std Dev Across Vehicles (in seconds)	Std Dev Across Replics (in seconds)
All Vehicles	**315.4**	**176.4**	**1.90**
7:00-7:15	293.3	153.3	3.17
7:15-7:30	318.5	178.6	4.51
7:30-7:45	336.5	200.1	4.03
7:45-8:00	326.5	183.0	3.75
8:00-8:15	311.3	170.2	6.50
8:15-8:30	297.9	156.2	1.92

Table 5: System Performance - With DynaMIT

With the use of DynaMIT, mean travel times in the network for all vehicles is lower by 29%. For the 7:00-7:15 time period, the travel time impact of DynaMIT is negligible as the incident has not yet started. For the 7:15-7:30 time period, the travel time impact is small. For the other four time periods, DynaMIT has a big effect on travel times due to the prevention of huge queue buildups in the network.

Travel time standard deviations across vehicles are significantly decreased from the no DynaMIT case. This is because the effects of the incident are mitigated, and prevailing traffic conditions are more free-flow and equitable for a larger number of vehicles. Travel time standard deviations across replications also are reduced when DynaMIT is in operation. The unstable traffic conditions and queues that occur within the MITSIM simulator without the presence of real-time information are avoided when the DynaMIT system is in operation.

Chapter 7

System Applicability

7.2 Percent of Informed Travelers

7.2.1 Background

Knowing how many travelers receive and comply with DynaMIT information is an important issue with respect to achieving consistency. It is hypothesized that a user-optimal outcome with respect to the distribution of real-time information is easier to accomplish when the percentage of informed travelers is smaller. This is because the response of travelers to the information, which is uncertain, has a greater effect on overall network conditions when the percent of informed travelers is higher.

The approach used here is to keep the assumed percentage of informed and compliant drivers within DynaMIT fixed at 50%, but to have conditions in the real world vary. The following percentages of informed and compliant travelers, also referred to as *guided* travelers, in reality will be investigated.

- 50% of travelers guided (base).
  (J-1, K-1, L-1, M-1, N-1, O-1, P-1, Q-1, R-1, S-1)

- 25% of travelers guided.
  (J-1, K-1, L-1, M-1, N-1, **O-2**, P-1, Q-1, R-1, S-1)
- 75% of travelers guided.
  (J-1, K-1, L-1, M-1, N-1, **O-3**, P-1, Q-1, R-1, S-1)

5.3 System Applicability

5.3.1 Presence of Stochasticity

The stochasticity of the DynaMIT system was tested by running multiple replications of the same base scenario. The first item to examine is prediction quality. This is shown in Figure 42 for five separate replications.

Figure 42: Predictions of Severity

The vertical axis shows the number of indices of the predicted severity of congestion in each zone for each replication from the mean of the five replications. One index is equal to one multiple of the free-flow travel time. As travel time is a time-dependent function, the measure is taken when congestion is predicted to be most severe. The horizontal axis refers to the same seven zones of the network that were identified in Section 5.1.2.

Figure 43: Predictions of Duration

Figure 43 provides a similar figure that examines the predicted duration of congested conditions (when travel times exceed free-flow conditions by a factor of 1.5 or more). The vertical axis shows the difference in minutes from the predicted zonal congestion duration of each replication to the mean of the five replications.

From these figures, it is clear that stochasticity of DynaMIT's predictions of congestion in the network is indeed present. For zones #3, #4, and #7 (the mainlines and on-ramps), this stochasticity is kept within a fairly small band of plus or minus 10%. There is zero stochasticity associated with the congestion duration of zones #3 and #7, since the duration is predicted to be zero in all cases.

For zones #1 and #2 (the main Sumner/Callahan Tunnel), the stochasticity is somewhat larger. Why this occurs is unclear, but the somewhat larger zone size may have something to do with the increased stochasticity. For the eastbound off-ramps (zone #5), the stochasticity is greatest.

One likely hypothesis for the presence of stochasticity in the predicted link travel times by DynaMIT is that the actual link travel times in the real world are also stochastic. In other words, the stochasticity of the prediction simply reflects differing conditions in the real world. Figure 44 and Figure 45 show the actual severity and duration of congestion that were experienced by drivers in five separate replications.

Figure 44: Actual Severity, With DynaMIT

The severity results in reality exhibited less stochasticity than the predictions in the main Sumner/Callahan Tunnel but more stochasticity than the predictions in the ramps and adjoining mainlines. Zones #5 and #6 in particular were extremely stochastic in reality.

Figure 45: Actual Duration, With DynaMIT

5.3.2 Stochasticity Relationships

The next issue is to observe whether these levels of stochasticity between DynaMIT and reality were correlated. If DynaMIT did provide perfectly consistent information, then the level of correlation should be high.

This section shows the resulting tests conducted on this basis, first for severity and then for duration. With seven zones and five replications, there are a total of 35 data points for each of the two measures. Linear regressions were run to determine if there is either a positive or negative relationship between the congestion conditions in the real world (used as the independent variable) and the predicted congestion by DynaMIT (used as the dependent variable). Confidence interval values and the t-statistics of the regression results are provided for severity in Table 6.

Table 6: Severity Regression Results

There is found to be a significant positive relationship between high congestion in the real world and high predicted congestion. The confidence interval is quite large. The adjusted R-square value for this regression was 0.175. The duration results given in Table 7 indicate again that a significant positive relationship exists for duration as well. The adjusted R-square value for this regression is 0.106.

Table 7: Duration Regression Results

6.2.3 Stochasticity Analysis

The stochasticity of the predictions in general was found to be greater as the rolling step size increased. The likely cause of this is the higher levels of stochasticity in reality. For longer rolling step sizes of 30 minutes and 60 minutes, the frequency of information update is low enough such that long queues are able to develop in the network near the incident location. This queue formation and dissipation in the real world was found to have greater stochasticity as the queue severity increased.

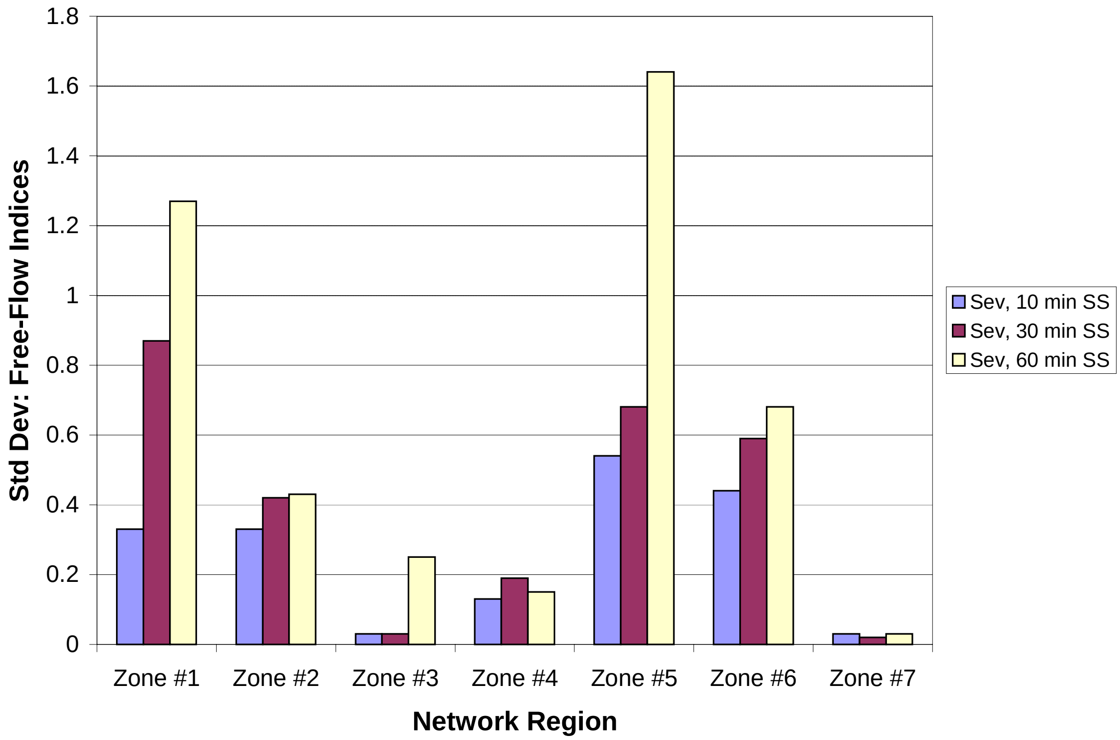

Figure 46: Severity Prediction Stochasticity, Step Size

Figure 46 shows, for each scenario, the standard deviation across five replications for predicted severity in the seven zones. For zones #1 and #5 (Sumner/Callahan Tunnel Westbound and the Eastbound off-ramps), the increase in prediction stochasticity going from a 30 minute to a 60 minute rolling step size was most evident.

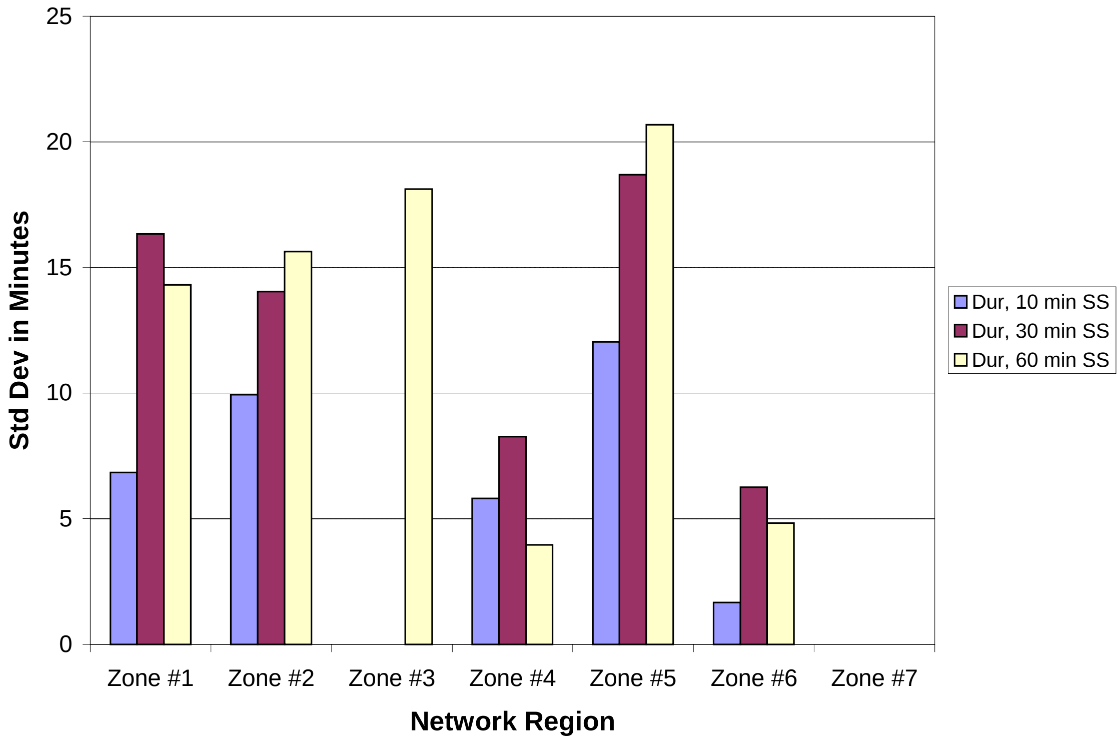

Figure 47: Duration Prediction Stochasticity, Step Size

Figure 47 shows, for each scenario, the standard deviation across five replications for predicted duration in the seven zones. For most of the zones, a fairly clear increase in stochasticity was observed in going from a 10 minute to a 30 minute rolling step size. One exception was zone #7, where no congestion was predicted in any scenario. Another exception was zone #3, where only the 60 minute rolling step size predicted any congestion in any replication and hence had any stochasticity.

6.3.3 Stochasticity Analysis

The stochasticity of the predictive quality with respect to rolling length was found to decrease as the rolling length increased. This is hypothesized to be the case since the total number of completed trips during the rolling length is higher as the rolling length increases. A higher number of completed trips is not only a more accurate reflection of what conditions in the network are likely to be, but also is more robust with respect to the output of predicted vehicle movements. In addition, as traffic conditions in the real world become more stochastic in the low rolling length scenarios, this affects the stochasticity of prediction. A feedback process of stochasticity thus ensues.

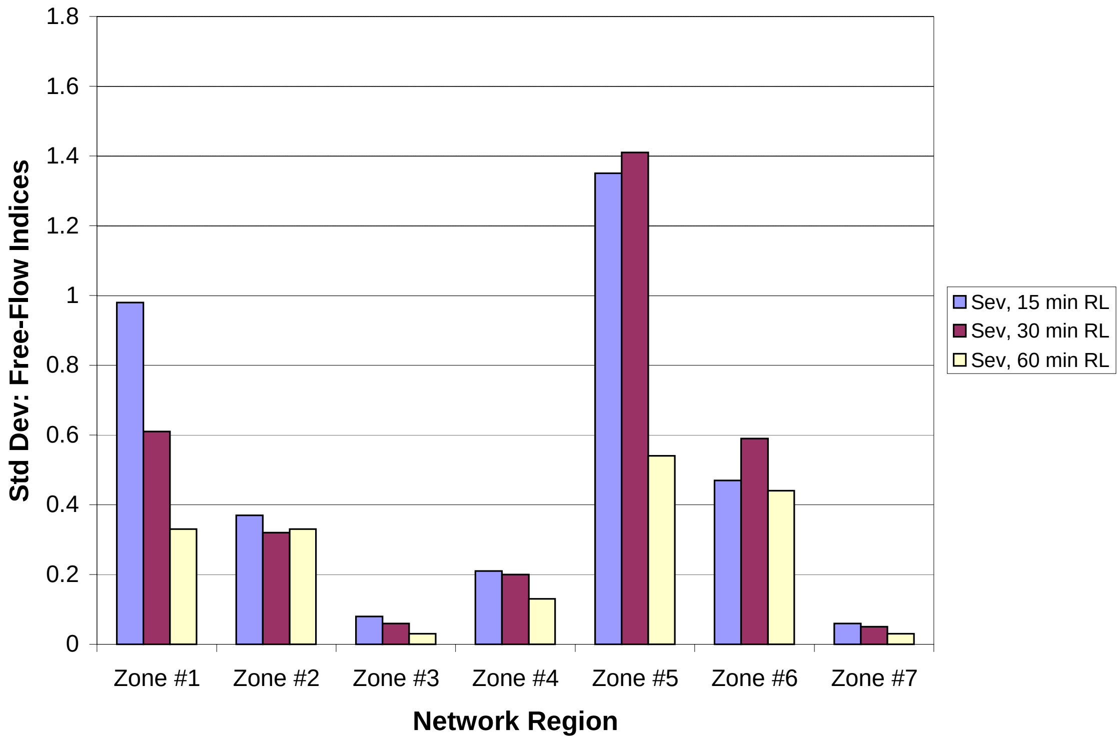

Figure 48: Severity Prediction Stochasticity, Rolling Length

Figure 48 shows, for each scenario, the standard deviation across five replications for predicted severity in the seven zones. The figure indicates a fairly clear trend of decreasing stochasticity with respect to predicted severity for zone #1, the Sumner/ Callahan Tunnel Westbound. For the other zones, the relationship is not as clear but is still found to be present.

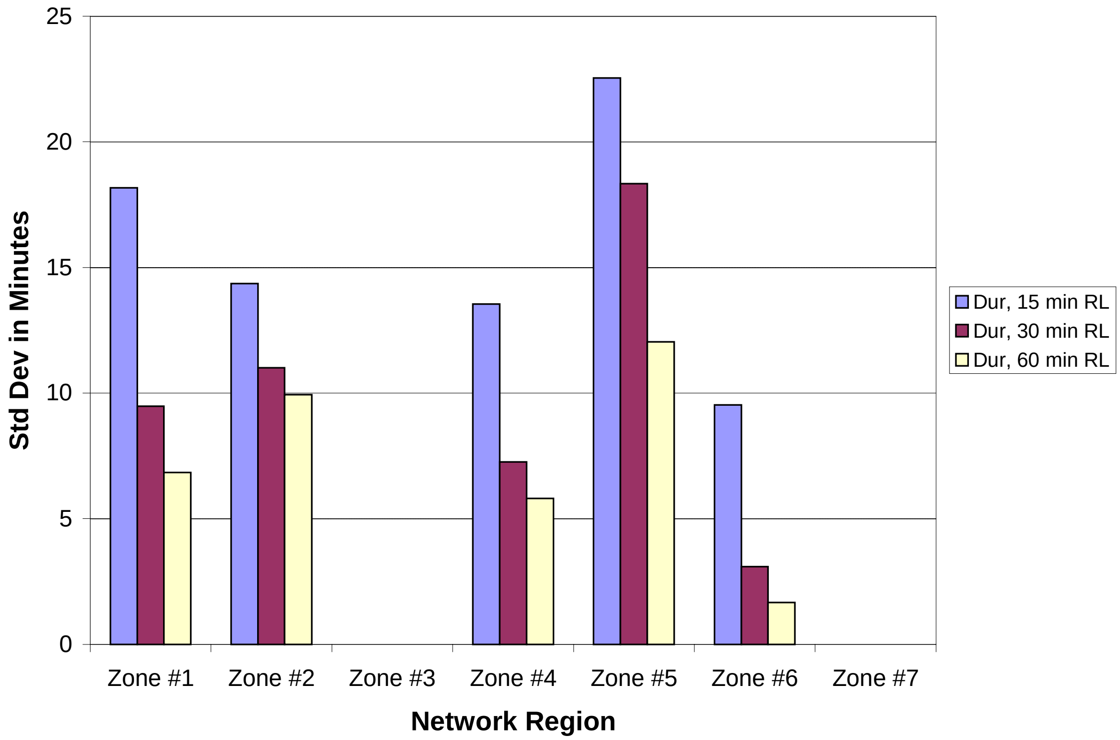

Figure 49: Duration Prediction Stochasticity, Rolling Length

Figure 49 shows, for each scenario, the standard deviation across five replications for predicted duration in the seven zones. Stochasticity in predicted duration decreases as the rolling length increases for all five zones in which congestion is predicted.

6.4.3 Stochasticity Analysis

Stochasticity of the prediction quality is expected to be reduced as the number of iterations run increases. The iterative process used by DynaMIT in its information generation function is intended to hone in on some fixed point. The exact fixed point may not be the same in each replication, particularly due to stochastic real-world inputs. However, conducting fewer iterations would not be thought of as favorable in this regard.

Figure 50 shows, for each scenario, the standard deviation across five replications for predicted severity in the seven zones. For zones #1 and #5, a clear relationship is found between a higher number of iterations and lower prediction stochasticity. For the other zones, particularly #6, the relationship is not as clear. The stochasticity results for duration are shown in Figure 51. Zones #1, #5, and #6 show the hypothesized relationship, while zones #2 and #4 do not.

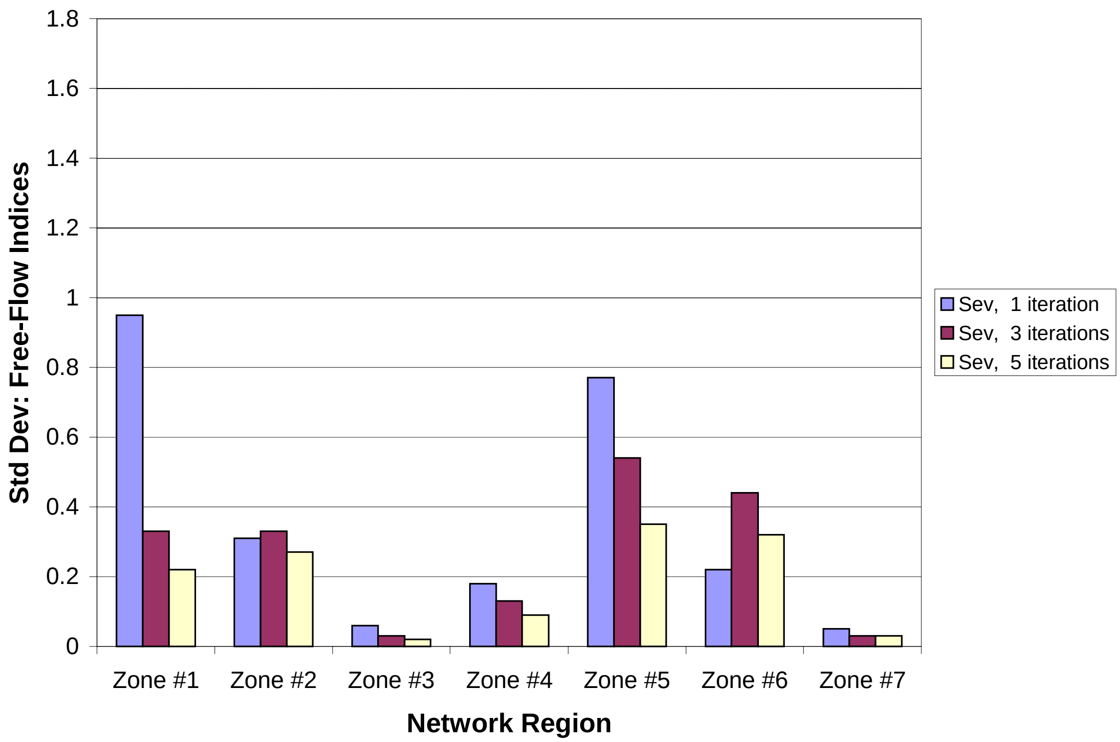

Figure 50: Severity Prediction Stochasticity, Iterations

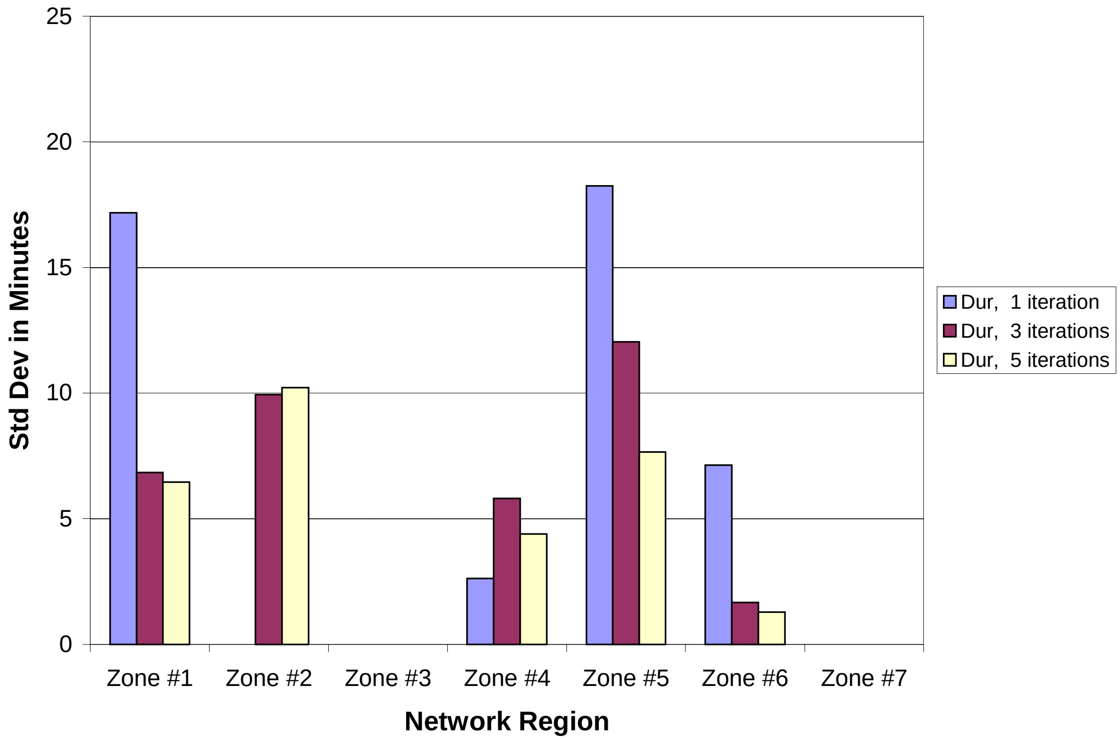

Figure 51: Duration Prediction Stochasticity, Iterations

7.2.4 Stochasticity Analysis

Traffic conditions occurring in the real world were more stochastic in the real world when 25% of travelers were guided because of higher levels of queue formation in the Sumner/Callahan Tunnel. In the following three tables, A refers to Group A drivers and B refers to group B drivers.

Percent of Drivers Chose Sumner/Callahan Tunnel

	A, 25% g	A, 50% g	A, 75% g	B, 25% g	B, 50% g	B, 75% g
Mean	**88.7 %**	**81.9 %**	**76.0 %**	**34.4 %**	**31.3 %**	**26.8 %**
Std Dev	**0.8 %**	**0.4 %**	**1.2 %**	**1.2 %**	**1.5 %**	**2.1 %**

Table 8: Route Choices - Function of % Guided

Travel Times for Sumner/Callahan Tunnel Route

	A, 25% g	A, 50% g	A, 75% g	B, 25% g	B, 50% g	B, 75% g
Mean	**566.3**	**433.4**	**415.7**	**575.0**	**485.6**	**462.2**
Std Dev	**26.8**	**5.4**	**5.9**	**33.6**	**15.3**	**7.6**

Table 9: S/C Travel Times - Function of % Guided

Travel Times for Third Harbor Tunnel Route

	A, 25% g	A, 50% g	A, 75% g	B, 25% g	B, 50% g	B, 75% g
Mean	**662.4**	**602.6**	**607.8**	**343.2**	**343.6**	**348.6**
Std Dev	**9.1**	**4.4**	**6.5**	**2.7**	**2.8**	**3.1**

Table 10: TH Travel Times - Function of % Guided

Chapter 8

Special Topics

8.1 Purpose

The purpose of this chapter is to examine two special topics, supply parameter sensitivity and prescriptive information, that are of interest from a research standpoint.

As highlighted from results in Chapter 5, the supply simulator could benefit from the adjustment of certain parameters. While an extensive calibration of the supply component is outside the scope of this thesis, a more limited sensitivity analysis demonstrates the impact that various parameters have on system results. With additional effort, it appears possible to significantly reduce the prediction quality errors that were observed from the scenario testing.

With prescriptive information, a single route recommendation from the DynaMIT system is provided to travelers rather than a full description of route travel times. The advantage of this from a user standpoint is the ease of comprehension. This could be particularly important for VMS, since only limited time may be available for travelers to interpret the information. The disadvantage from a user standpoint is a less complete picture of what conditions are actually taking place in the network.

The prescriptive information analysis presented here is not particularly rigorous. The results are not intended to be indicative of DynaMIT's capabilities. These tests instead were conducted primarily to address the user benefit potential related to different types of information provision, to be expanded upon by future research. With some further model development in the simulation laboratory, a more complete analysis of prescriptive information could be readily conducted.

8.2 Supply Sensitivity

8.3 Prescriptive Information

8.3.1 Naive vs. Specific

The following scenarios of prescriptive information are evaluated in this section. Each scenario consists of the following three dimensions:

- Percent of guided, or both informed and compliant, travelers (Guid),
- Duration of information provision (Dur), and
- Recommendations provided to travelers (Rec).

Figure 52 shows the Central Artery network with origins and destinations. There is a recognition that the incident, while severe, does not delay travelers excessively enough such that it makes sense for travelers moving in the upper portions of the network, shown above the curved line, to use the Third Harbor (lower) tunnel. Therefore, with specific information, travelers from O-D pairs A-F, B-F, F-A, and F-B are instructed to use the Sumner/Callahan (upper) tunnel despite the incident occurrence. Other travelers with two feasible route choices are instructed to use the Third Harbor tunnel. There is still a net diversion of travelers away from the incident location.

Figure 52: Specific Prescriptive Information

Naive information should reduce congestion in the incident location more significantly, but at the possible cost of over-reaction for travelers from certain O-D pairs.

8.3.2 User Benefit

With prescriptive information, user optimal criteria are more adequately met as compared to descriptive information. Travelers who are informed and compliant (guided) are more consistently selecting the most optimal path available in the network with respect to time-dependent travel times. Therefore, guided travelers are found to generally experience shorter travel times as compared to unguided travelers from each O-D pair in the network. However, the magnitude of this result varies considerably depending on the scenario.

For comparison purposes, the analysis concentrates again on the two groups of travelers defined in Chapter 6 that have considerable flexibility with respect to available route choices in the network. These groups are shown again for convenience, with locations for the origins and destinations referenced in Figure 11.

Group A	Group B
I-93 North to Route 1A	Mass Pike to Route 1A
Route 1A to I-93 North	Route 1A to Mass Pike
Storrow Drive to Route 1A	
Route 1A to Storrow Drive	

With naive recommendations, travelers from both groups are instructed to use the Third Harbor tunnel during the time that the information is distributed. For specific recommendations, travelers from Group A are instructed to use the Sumner/Callahan Tunnel (despite the incident occurrence) while travelers from Group B are instructed to use the Third Harbor Tunnel. Therefore, examining travel time results from these two groups will highlight differences between the two types of information.

Figure 53 shows the mean travel times experienced by travelers from Groups A and B, split into unguided and guided, for scenarios BPres and Naive. In the horizontal axis labels, the letter U stands for unguided, G stands for guided, S stands for specified, and N stands for naive. The time periods listed refer to departure time intervals.

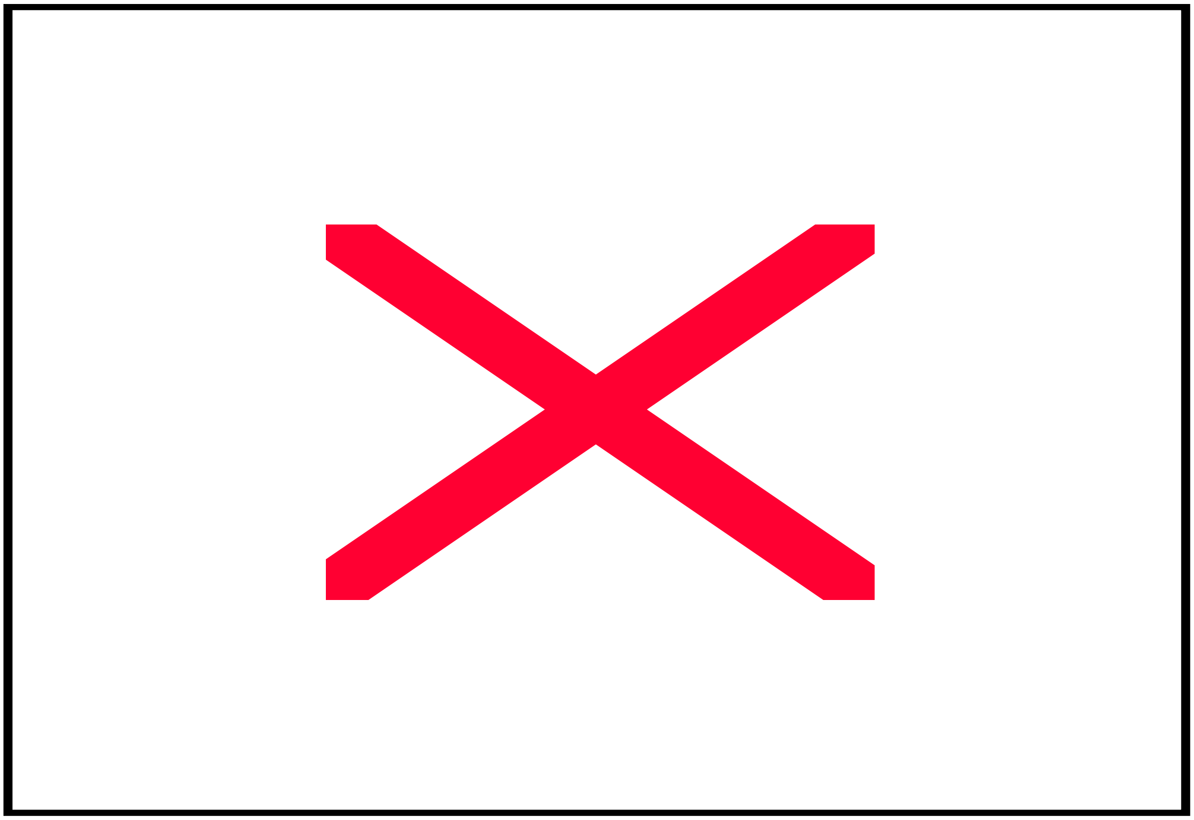

Figure 53: User Optimality for BPres, Naive (40% Guided)

For travelers in Group A, guided travelers with naive information experience significantly longer mean travel times than unguided travelers. They are being informed to take the circuitous Third Harbor Tunnel even though the Sumner/Callahan Tunnel is faster despite the incident occurrence. When specific information is provided, travelers in Group A experience roughly the same mean travel times regardless of whether they are unguided or guided. The vast majority of unguided Group A travelers habitually select the Sumner/Callahan Tunnel, while Group A travelers who comply with the specific information are choosing the same tunnel as well.

Note that with specific guidance, unguided travelers are hurt somewhat as compared with naive guidance since fewer travelers have been diverted away from the incident location. Thus, system-wide benefits of specific versus naive information is questionable for Group A travelers. However, the user benefits of specific information for travelers who are informed and compliant are clearly superior to the user benefits of naive information.

For Group B travelers, the user benefits for guided travelers are positive in both the specific and naive information scenarios. This makes sense, since the recommendation for both scenarios for such travelers is to avoid the incident location. Such a diversion, however, is slightly more effective in the specific case as opposed to the naive. This is because in the naive case, a greater number of total travelers were diverted to the Third Harbor Tunnel, and travel time is a function of use.

Figure 54 plots the same travel time results for the scenarios in which just 10% of travelers were guided as opposed to 40%. The mean travel times that travelers experienced overall were greater, which makes sense since fewer travelers were diverted away from the incident location. In addition, the difference between the specific and the naive information cases was more evident.

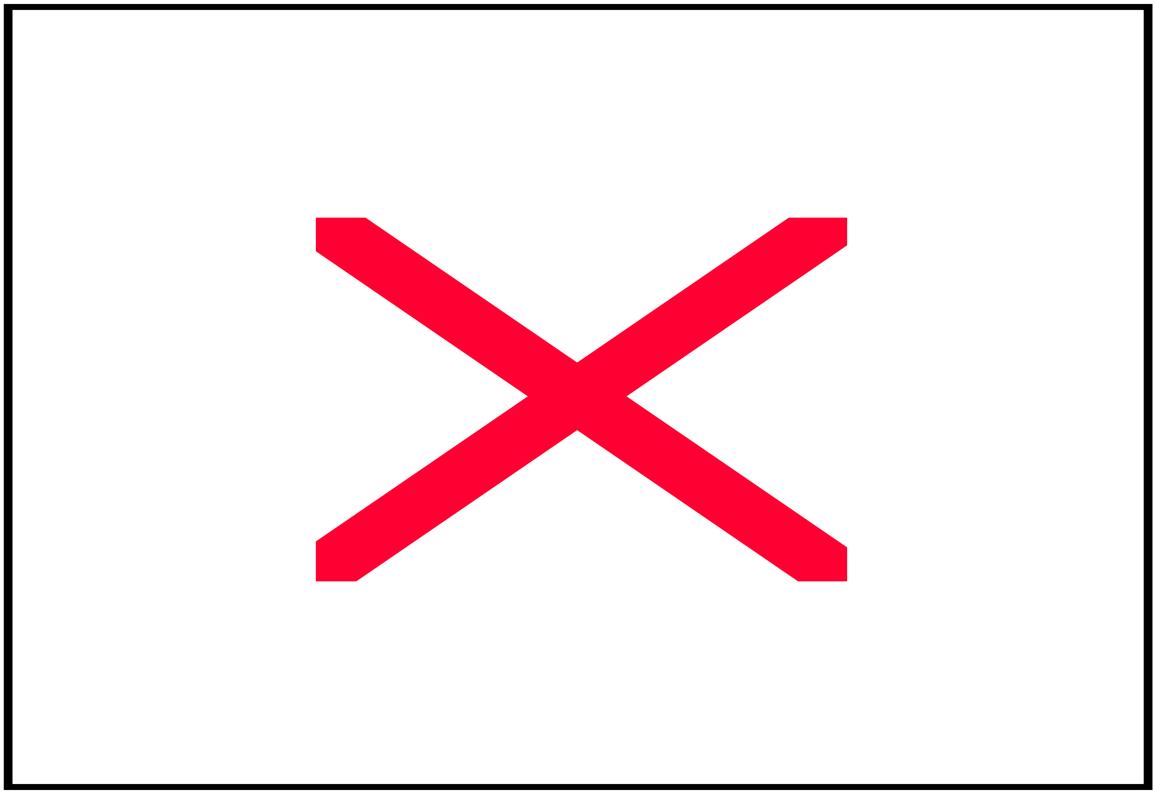

Figure 54: User Optimality for 10%, 10%N (10% Guided)

In the naive case, guided Group A travelers suffered from larger mean travel times than unguided travelers. This is similar to the 40% guided scenarios, but the magnitude of this was less particularly as the simulation proceeded. Since a smaller total number of travelers was diverting to the Third Harbor tunnel in the 10% guided case, the extra travel time from choosing the circuitous route becomes less significant relative to the delays encountered at the incident location.

For Group B travelers in the 10% case, informed travelers benefited more as compared to the 40% guided case. This is again a result of fewer overall vehicles, and thus lower travel times, for travelers using the Third Harbor Tunnel. This supports the general finding proposed by other researchers that the benefit of traveler information for individual users often diminishes as a greater number of travelers are informed. Travel time results from the 20% and 20%N scenarios were found to lie in-between the 10% guided and 40% guided cases.

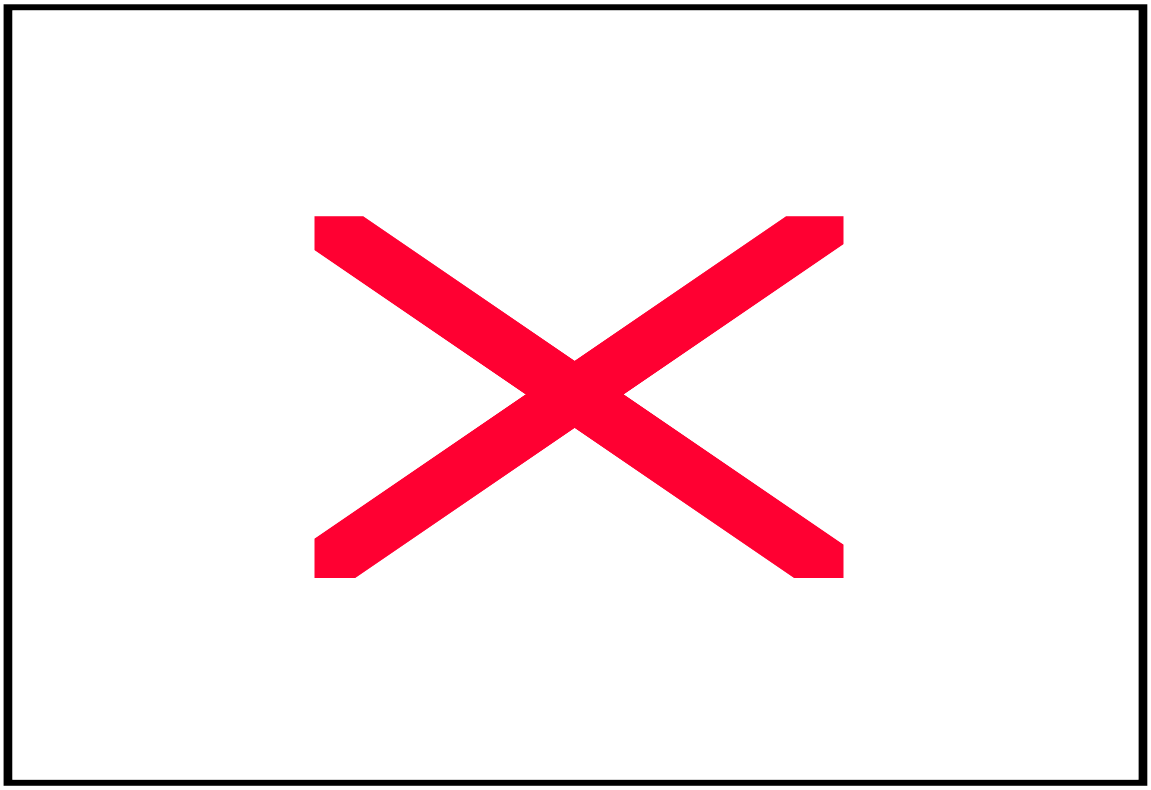

Figure 55: User Optimality for 70%, 70%N (70% Guided)

Figure 55 shows user optimality results associated with the scenarios where 70% of travelers were guided. In the specific case, over-reaction does not materialize; overall travel times are reduced as compared to the 40% guided scenarios. Indeed, mean travel times between the four departure time intervals are quite similar for both Group A and Group B travelers, which indicates that the effects of the incident have been stabilized. This, however, diminishes the benefit of the information for guided travelers as compared to unguided travelers.

In the naive case, over-reaction is severe since a high number of travelers have been diverted to the Third Harbor tunnel. Guided group A travelers in the naive case experience increased travel times as compared to previous scenarios. For Group B, guided travelers benefit in terms of travel time earlier in the simulation. But as the simulation proceeds and effects of the incident dissipate, guided travelers begin to experience longer mean travel times than unguided travelers.

For the scenarios 95% and 95%N, the findings were similar to those given for 70% and 70%N except for more extreme. For specific information, travel times are up slightly as compared to the 70% case as some over-reaction occurs. For naive information, the vast majority of travelers are selecting the Third Harbor tunnel in the 95% case, and congestion has simply shifted from one tunnel to the other. Mean travel times for guided Group A and all Group B travelers are up significantly from the 70%N case.

For the Delay and Del30 scenarios, overall mean travel times have gone up since the incident is allowed to have a greater impact. The user benefit, however, of providing information to guided travelers has increased during the time that information is distributed. Diverting away from the incident becomes more important as the effects of the incident worsen.

The key finding from the other scenarios that were run is as follows. For scenarios where the effects of the incident are high because of a delay in information release, naive information becomes an increasingly powerful method of reducing mean overall travel times as compared to specific information. Shifting certain guided travelers away from the incident to a more circuitous route may be poor for them from a user-optimal perspective, but user benefits enjoyed by unguided travelers (and overall system benefits) increase. In other words, the tension between satisfying user-optimal and system-optimal criteria increases as congestion goes from mild to severe.

Of course, if congestion is extremely severe, both individual users and the system could benefit from having travelers divert to circuitous routes. This is true if the circuitous routes in question have shorter travel times than habitual routes because of the incident occurrence. Therefore, at some point of high congestion severity, tension between meeting user-optimal and system-optimal criteria may start to lessen.

Chapter 9

Summary and Conclusions

This thesis conducted a number of simulation-based case studies related to dynamic traffic assignment. The two main areas that were examined were network demand estimation using the Kalman Filter algorithm and the impact of en-route traveler information on travel times at both the user and the system level. Results from the case studies serve the following main purposes:

- They assess the performance of the existing DynaMIT system, a dynamic traffic assignment system developed at MIT, and
- They yield interesting research findings in the field of ATIS that are useful on their own and provide many ideas for additional research as well.

Results provided in this thesis are a subset of the evaluation work that has been conducted for the DynaMIT system. A detailed description of methodology and results for other components of DynaMIT (effect of pre-trip behavior update, supply simulator model validation, simulation computational efficiency, and the testing of different information generation strategies) are contained in other documents. A smaller case study related to the impact of traveler information on network performance, described in the DynaMIT Task G report, yielded results similar to those in Chapters 5, 6, and 7.

For each of the two areas covered in this thesis (demand estimation and impact of traveler information), this concluding chapter will be presented in the following manner.

- DynaMIT system performance is summarized,
- Research findings are presented,
- Possible system enhancements to DynaMIT are proposed, and
- Future case studies and directions for ongoing research are provided.

9.1 Demand Estimation

9.1.1 System Performance

Chapter 4 validated the performance of the Kalman Filter algorithm off-line through inputs generated from a simulated demand scenario on the Central Artery network. The Kalman Filter algorithm is shown to be a highly effective method of demand estimation when no errors are present in the algorithm inputs. As the lack of inputs errors is not expected to be common in reality, the Kalman Filter has been designed specifically for robustness with respect to input quality. This made the testing of the algorithm given a variety of input errors an important step of the evaluation process.

Estimation results with input errors were intuitive. For the no incident scenario, errors in the O-D estimation process were kept within a range roughly proportional to the amount of input error. Drastic input errors, such as a historical matrix of zero in combination with other problems, yielded O-D flow estimates with errors of up to about 40%. Such a scenario was designed to be extreme and test the limits of the algorithm performance. Given the magnitude of the error, the algorithm performance is quite reasonable.

9.1.2 Research Findings

The specification of the error-covariance matrices was found to have a significant impact on estimation results. If values in the associated error-covariance matrix of a particular input source are small, this has the following implications:

- Errors in that input source have a more severe effect on estimation quality,
- Errors in other input sources have less of an effect on the estimation. Small error-covariance matrix values in conjunction with high quality for the corresponding input serves as a stabilizing force for estimation accuracy.

Large error-covariance matrix values for a particular input source has these implications:

- Errors in that input source have less of an effect on estimation quality,
- Errors in other input sources have a greater effect on the estimation.

An accurate off-line calibration of the error-covariance matrices before the Kalman Filter algorithm is used in real-time applications therefore is an important task. Similarly, an accurate calibration of transition matrices is valuable since the transition equation input can also serve as a stabilizing force for estimation quality.

Network incidents have the effect of reducing the amount of measurement equation inputs available in real-time. If input quality for all sources is high, this appears to not be a severe problem in terms of estimation accuracy. Input errors in combination with incident conditions, however, yield higher estimation errors.

This highlights the importance of adequate sensor allocation in the network. In general, sensors placed near network origins are probably more useful for demand estimation than sensors placed near network destinations. Counts from sensors near origins are more current and are less likely to be impacted by incident occurrences in the network. Developing strategies for sensor allocation is an interesting area for future research.

9.1.3 System Enhancements

The case study indicates that the Kalman Filter algorithm is an effective and robust method of demand estimation. The next step for enhancement involves validating algorithm performance in operation with the complete DynaMIT system.

9.1.4 Future Research

Areas for future research related to demand estimation include the following:

- Additional case studies with more complex demand patterns,
- A more complete investigation of demand prediction,
- Development and testing of methods for error-covariance matrix calibration,
- Strategies to optimally allocate network sensors for real-time demand estimation.

9.2 Impact of Traveler Information

9.2.1 System Performance

Operation of the DynaMIT system in a simulation environment was shown to be highly effective in terms of improving mean vehicle travel times in a situation of non-recurrent congestion. DynaMIT has been shown to predict travel conditions to a reasonable degree of accuracy, and provide travelers with a beneficial information strategy based on its predictions. Overall, the results are quite strong and encouraging. The system functions well in a simulation environment, and closely meets its primary objectives of unbiasedness and consistency. Some results indicate that system refinement in certain areas would be desirable. These findings are summarized here.

- Supply simulator: For certain links, DynaMIT predicted less congestion that what was actually observed. A more careful investigation is required to determine what link conditions lead to this outcome. The result indicates that speed-density function parameters in DynaMIT may benefit from adjustment.

  For large complex weaving sections, DynaMIT encounters more difficulty with its prediction quality. Some model adjustments could assist with this problem, but some discrepancy is probably unavoidable stemming from inherent differences between mesoscopic and microscopic representations with respect to the treatment of lane changing, merging, yielding, nosing, etc.

  In the MITSIM reality, congestion begins at the incident location and then starts working its way back. This seems to be logical. However, within DynaMIT, in certain cases congestion started upstream of the incident instead. This probably has to do with segment-level acceptance capacity parameters.

  DynaMIT tends to err on the side of slow queue dissipation. This outcome can likely be overcome easily by adjustments to the queuing model.

  Some stochasticity was associated with DynaMIT's prediction across replications. The magnitude was relatively small, and was partially influenced by stochasticity that took place in the real world independent of DynaMIT. Stochasticity of actual network performance was reduced when DynaMIT was in operation versus when DynaMIT was not present.

- Demand simulator: The route choices and experienced travel times of drivers in reality raised a key question of whether information provided by DynaMIT is actually leading towards a user-optimal outcome. However, such results do not appear to relate specifically to DynaMIT's prediction quality and information strategy. Rather, results are more a function of the treatment of traveler behavior in the MITSIM reality.

Chapter 6 contained a discussion of this issue. To recap, the issue is whether the provision of en-route descriptive information would actually lead informed travelers to select a non-habitual route that the information system states is inferior to their habitual route. In the case study, this occurred regularly because the stated travel times given to informed travelers by the information system were closer together than the habitual travel time values were.

If this outcome is deemed to be realistic, this is an indication that descriptive information is potentially dangerous for travelers. The provision can lead to informed decisions by users that are worse than their habitual decisions would have been, even if the information is consistent with what occurs in reality.

If this outcome is not realistic, than the traveler processing of descriptive information in MITSIM should be adjusted. This can be done in two ways:

1) Include a travel time threshold that gives a preference for the habitual route. Most travelers will not be induced to switch routes unless informed travel times on one or more non-habitual route(s) is lower than the habitual route informed travel time by some threshold.

2) Use a nested logit model for informed travelers who respond to descriptive information. The decision to switch routes should be made first, followed by the selection of which non-habitual route to switch to.

With either of these options, the goal is to have a behavior model where most drivers do not switch paths until doing so would save them travel time, as indicated by the information system.

- Information Generation: When provided with information regarding an incident occurrence, DynaMIT generated an en-route information strategy that successfully diverted a number of travelers away from the incident location. DynaMIT was able to avoid over-reaction, and as the incident area began to clear travelers were increasingly informed to return back to their habitual route choices.

  The time smoothing algorithm currently used by the DynaMIT system performed well for this set of case studies, and is deemed to be adequate for use in future evaluations. Work in the development and implementation of additional algorithm strategies is ongoing, to be compared with the current algorithm.

9.2.2 Research Findings

Results presented in Chapters 5, 6, 7, and 8 were instrumental in identifying key dynamic traffic assignment research findings. The a priori expectation that DynaMIT performance depends partially on a set of system parameters were confirmed.

- A reduction in the rolling step size, or information update interval, increases DynaMIT effectiveness. If information is distributed less frequently than roughly every fifteen minutes, there is great danger that incident occurrences will not be taken into account until it is too late to provide benefit for many affected travelers.

  It is useful to note again that the rolling step size is a feature used only for research purposes in a simulation environment. When the DynaMIT system is operated in real-time for an actual traffic management center, the rolling step size will not exist. Reducing the information update interval in this case will be primarily a function of computational power and system operational efficiency.

- An increase in the rolling length improves the effectiveness of DynaMIT. A short rolling length results in predictions that tend to underestimate the amount of congestion. This could be a function of how the DynaMIT network simulator treats unfinished trips that are left in the network as the simulation ends.

- An increase in the number of iterations improves the effectiveness of DynaMIT. The use of a single iteration fails to properly close the loop between demand, supply, and information. This results in the distribution of information based on erroneous predictions.

- An increase in the percent of informed drivers generally improves the effectiveness of DynaMIT. More travelers can be diverted away from incident locations to reduce the incident's impact. Benefits for unguided travelers typically increase as the percent of informed travelers go up. However, the benefits for guided travelers from increasing the distribution of information can vary. The effect differs across O-D pairs.

- Studies run regarding the provision of prescriptive information showed that when using recommendations that are specific to O-D pairs, user criteria for all travelers can be achieved in addition to system criteria.

9.2.3 System Refinements

Chapter 5 highlighted the need for additional calibration work for the supply simulator to address the predictive quality of congested links and slow queue dissipation. The case studies use demand estimates as given rather than as an unknown to be estimated. Testing of the DynaMIT system with O-D estimation and prediction included is a high priority for future evaluation work.

Another priority for future system evaluation involves the development of comprehensive pre-trip traveler behavior models in the MITSIM reality. The main addition that pre-trip information provides is the inclusion of departure time activity, where congestion can be alleviated through the shifting of traveler demand in time as well as space.

An additional area in the demand simulation area is the implementation of a route switching model in the MITSIM reality that utilizes a nested structure or a threshold value. While such a model would need to be calibrated, it seems reasonable to assume that route switching would be minimal until the point where the informed travel time for a habitual route exceeds the informed travel time for one or more non-habitual route(s).

Ongoing work in the testing of new or improved strategies for information generation will continue. Refined algorithms may potentially improve the consistency check process and/or locate a fixed point solution more rapidly.

9.2.4 Future Research

Additional case studies could be conducted that would further assess levels of DynaMIT accuracy and stochasticity. Relationships between system performance and key parameters including the rolling horizon, rolling length, and number of iterations that were proposed in this thesis could be studied in more detail. MITSIM laboratory enhancements would allow for an improved study of various types of information, particularly those to be distributed at the pre-trip stage.

Additional areas of future research include:

- The installation and evaluation of the prototype DynaMIT system at a traffic management center location. This would begin by acquiring relevant data from the network of interest in order to calibrate DynaMIT models. Off-line testing can be conducted by using the network and associated demand pattern in a simulation environment. Ultimately, actual real-time data could be fed into the DynaMIT system. Another key area here involves assessing computational efficiency.

- The development of a framework and modeling approach that integrates the control logic of traffic lights and ramp meters with real-time information. This means thinking of control logic not just as an input, but as an element that could possibly be changed in an integrated fashion to work with traveler information.

- The inclusion of incident detection strategies with dynamic traffic assignment.

- The use of DynaMIT as a planning tool. This involves conducting simulation-based studies to assess the impacts of demand and/or supply planning alternatives (congestion pricing, road expansion, etc.) on traveler behavior and network performance. A dynamic traffic assignment system has tremendous potential to improve transportation investment decisions through realistic traveler behavior models and vehicle simulation.

Bibliography

Abdel-Aty, M., R. Kitamura, and P. Jovanis. Using stated preference data for studying the effect of advanced traffic information on drivers' route choice. *Transportation Research (C)*, Vol. 5, No. 1, 1997, pp. 39-50.

Al-Deck, H. and A. Kanafani. Modeling the benefits of advanced traveler information systems in corridors with incidents. *Transportation Research (C)*, Vol. 1, No. 4, 1993, pp. 303-324.

Antoniou, C. *Demand Simulation for Dynamic Traffic Assignment*. Master's thesis, Massachusetts Institute of Technology, Cambridge, MA. 1997.

Ashok, K. *Estimation and Prediction of Time-Dependent Origin-Destination Flows*. Doctoral thesis, Massachusetts Institute of Technology, Cambridge, MA. 1996.

Barfield, W., M. Haselkorn, J. Spyridakis, and L. Conquest. Integrating commuter information needs in the design of a motorist information system. *Transportation Research (A)*, Vol. 25, No. 2, 1991, pp. 71-78.

Ben-Akiva, M., M. Bierlaire, J. Bottom, H. N. Koutsopoulos, and R. Mishalani. Development of a route guidance generation system for real-time application. *Proceedings of the 8th International Federation of Automatic Control Symposium on Transportation Systems*, IFAC, 1997.

Ben-Akiva, M., M. Bierlaire, H. Koutsopoulos, and R. Mishalani. DynaMIT: a simulation-based system for traffic prediction. *Paper presented at Daccord short term forecasting workshop*, 1998.

Ben-Akiva, M., A. de Palma, and I. Kaysi. Dynamic network models and driver information systems. *Transportation Research (A)*, Vol. 25, No. 5, 1991, pp. 251-266.

Canterella, G. and E. Cascetta. Dynamic processes and equilibrium in transportation networks: towards a unifying theory. *Transportation Science*, Vol. 29, No. 4, 1995, pp. 305-329.

Caplice, C. and H. Mahmassani. Aspects of commuting behavior: preferred arrival time, use of information, and switching propensity. *Transportation Research (A)*, Vol. 26, No. 5, 1992, pp. 409-418.

Chui, C. and G. Chen. *Kalman Filtering with Real-Time Applications*. Springer-Verlag Berlin Heidelberg, 1991.

Conquest, L., J. Spyridakis, M. Haselkorn, and W. Barfield. The effect of motorist information on commuter behavior: classification of drivers into commuter groups. *Transportation Research (C)*, Vol. 1, No. 2, 1993, pp. 183-201.

Daganzo, C. *Fundamentals of Transportation and Traffic Operations*. Elsevier Science Ltd, 1997.

Devore, J. *Probability and Statistics for Engineering and the Sciences*. Duxbury Press, 1991.

Emmerink, R., K. Axhausen, P. Nijkamp, and P. Rietveld. The potential of information provision in a simulated road transport network with non-recurrent congestion. *Transportation Research (C)*, Vol. 3, No. 5, 1995, pp. 293-309.

Emmerink, R., P. Nijkamp, P. Rietveld, and J. Ommeren. Variable message signs and radio traffic information: an integrated empirical analysis of drivers' route choice behavior. *Transportation Research (A)*, Vol. 30, No. 2, 1996, pp. 135-153.

Grewal, M. and A. Andrews. *Kalman Filtering: Theory and Practice*. Prentice Hall Inc., 1993.

Hall, R. Non-recurrent congestion: how big is the problem? Are traveler information systems the solution? *Transportation Research (C)*, Vol. 1, No. 1, 1993, pp. 89-103.

Hall, R. Route choice and advanced traveler information systems on a capacitated and dynamic network. *Transportation Research (C)*, Vol. 4, No. 5, 1996, pp. 289-306.

Houpt, P., M. Athans, D. Orlhac, and W. Mitchell. *Traffic Surveillance Data Processing in Urban Freeway Corridors Using Kalman Filter Techniques*. Technical report, Massachusetts Institute of Technology, Cambridge, MA. 1978.

Kanafani, A. and H. Al-Deck. A simple model for route guidance benefits. *Transportation Research (B)*, Vol. 25, No. 4, 1991, pp. 191-202.

Khattak, A., J. Schofer, and F. Koppelman. Commuters' en-route diversion and return decisions: analysis and implications for advanced traveler information systems. *Transportation Research (A)*, Vol. 27, No. 2, 1993, pp. 101-111.

Koutsopoulos, H. and H. Xu. An information discounting routing strategy for advanced traveler information systems. *Transportation Research (C)*, Vol. 1, No. 3, 1993, pp. 249-264.

Lam, W. and H. Lo. Accuracy of origin-destination estimates from traffic counts. *Traffic Engineering and Control*, Vol. 31, 1990, pp. 358-367.

Lotan, T. Effects of familiarity on route choice behavior in the presence of information. *Transportation Research (C),* Vol. 5, No. 4, 1997, pp. 225-243.

Mahmassani, H. and R. Jayakrishnan. System performance and user response under real-time information in a congested traffic corridor. *Transportation Research (B)*, Vol. 25, No. 5, 1991, pp. 293-308.

Pindyck, R. and D. Rubinfeld. *Econometric Models and Economic Forecasts, 4th Edition*. McGraw-Hill, 1998.

Polydoropoulou, A. *Modeling the Influence of Traffic Information on Drivers' Route Choice Behavior*. Master's thesis, Massachusetts Institute of Technology, Cambridge, MA. 1993.

Romph, E. Dynamic traffic assignment. *Transportation Modeling for Tomorrow*. Delft University Press, 1996, pp. 193-224.

Schofer, J., A. Khattak, and F. Koppelman. Behavioral issues in the design and evaluation of ATIS. *Transportation Research (C)*, Vol. 1, No. 2, 1993, pp. 107-117.

Shin, M., B. Ran, R. Oh, and K. Choi. Developing an evaluation tool for a real-time dynamic traffic assignment system. *Transportation Research Board Annual Meeting*, 1999, pp. 1-26.

Taylor, M., W. Young, and P. Bonsall. *Understanding Traffic Systems: Data, Analysis, and Presentation*. Avebury Technical, 1996.

Thakuriah, P. and A. Sen. Quality of information given by advanced traveler information systems. *Transportation Research (C)*, Vol. 4, No. 5, 1996, pp. 249-266.

Vythoulkas, P. A dynamic stochastic assignment model for the analysis of general networks. *Transportation Research (B)*, Vol. 24, No. 6, 1990, pp. 453-470.

Wardman, M., P. Bonsall, and J. Shires. Driver response to variable message signs: a stated preference investigation. *Transportation Research (C)*, Vol. 5, No. 6, 1997, pp. 389-405.

Wie, B., T. Friesz, and R. Tobin. Dynamic user optimal traffic assignment on congested multidestination networks. *Transportation Research (B)*, Vol. 24, No. 6, 1990, pp. 431-442.

Wu, J. A real-time origin-destination matrix updating algorithm for on-line applications. *Transportation Research (B)*, Vol. 31, No. 5, 1997, pp. 381-396.

Wu, J. and G. Chang. Estimation of time-varying origin-destination distributions with dynamic screenline flows. *Transportation Research (B)*, Vol. 30, No. 4, 1996, pp. 277-290.

Yang, Q. *A Simulation Laboratory for Evaluation of Dynamic Traffic Management Systems*. Doctoral thesis, Massachusetts Institute of Technology, Cambridge, MA. 1997.

Zijpp, N. Dynamic OD-matrix estimation from combined data. *Transportation Modeling for Tomorrow*. Delft University Press, 1996, pp. 95-128.