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

by

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Abstract

DynaMIT is a Dynamic Traffic Assignment system that provides traffic information to travelers based on anticipated future conditions. Simulation tools are used for both transportation demand and supply, and interactions between the two are represented. The information strategy takes explicitly into account its predicted impact on traveler behavior in order to avoid adverse effects such as inaccuracy and over-reaction. The information is designed to be consistent with what travelers will actually experience.

In this thesis, a thorough evaluation of the DynaMIT system is conducted within a laboratory environment. A methodology for this work is provided that focuses specifically on two important aspects. The role of the origin-destination (O-D) flow estimation process is to replicate real-time observations from a network surveillance system. This component is evaluated based on various scenarios and criteria. Then, the impact of information provided by DynaMIT to travelers is analyzed. This includes an assessment of time savings experienced by travelers, as well as DynaMIT's ability to predict network conditions.

Results indicate that the O-D flow estimation process performs well and is robust in the presence of input errors. Estimation errors in percentage terms are generally kept within a range smaller than the percent error contained within the input data. The information generated by DynaMIT when provided to travelers was found to significantly reduce mean network travel times (by 29% for a base scenario). Prediction errors were negligible in the absence of congestion, and moderate when congestion occurs. These findings are very promising and demonstrate effective system performance.

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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 DynaMIT in a systematic and rigorous fashion. The demand estimation component will first be evaluated on the basis of estimation quality and robustness. The existing DynaMIT system will then be evaluated within a simulation laboratory environment. Criteria for evaluation will be the consistency of estimated and predicted link travel times, the impacts of the distributed travel information on both a user and a system basis, and observed levels of prediction stochasticity across replications. In this process, many research findings in the field of ATIS are developed.

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. Consistency means that the network conditions that travelers experience coincide with the predicted conditions on which the information was based.

Clearly, input and model errors mean that DynaMIT is 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, for example, 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.

DynaMIT does not generate system optimal information, which 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 contains historical data that represents typical traffic conditions, given as time-dependent origin-destination (O-D) matrix flows obtained from external surveys and off-line estimation. The database contains a network description: node and segment locations, segment capacities, and free-flow segment travel times. Also provided in the database are traveler socioeconomic characteristics (such as age, gender, income, auto ownership, trip purpose) by zone obtained from census
data and surveys. 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.

![Diagram of Demand Simulator](image)

**Figure 2: Demand Simulator**

Behavior models developed by Antoniou, Ben-Akiva, Bierlaire, and Mishalani (1997) estimate traveler decisions, including departure time, mode, and route choices, for each trip in order to complete the set of characteristics for drivers that are using the network. The models capture how real-time information distributed to travelers affects their travel decisions. These models are described in section 1.3. The O-D estimation process is
based on a Kalman Filter algorithm formulated by Ashok and Ben-Akiva (1993), and is summarized in section 1.4.

The supply simulator evaluated in this thesis, given in Figure 3, was developed by Yang and Koutsopoulos (1996). 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 motivated by the real-time operational requirement.

![Figure 3: Supply Simulator](image-url)
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 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 model groups that represent deterministic queuing and speed respectively. 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.

In prediction, there is one additional component to demand and supply that must be included. 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 information generation and simulation between demand and supply has to take place in order to identify an information strategy designed to lead towards 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 Bottom, Ben-Akiva, Bierlaire, and Chabini (1998), is used for information generation. It is based on a method of successive
averages. 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

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 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 horizon has rolled 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, as mentioned in section 1.2.5 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 prediction accuracy at the most distant end of the period. This is illustrated in Figure 5. Also, predictions made well into the future may not be
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 for 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 for DynaMIT 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 the models used for the evaluation conducted in this thesis. The evaluation used en-route traveler information provided by an ATIS system to on-board computers equipped within a certain percentage of vehicles. If desired, drivers can change routes from their habitual pattern in response to the messages. 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. A single habitual path is then assigned to each traveler. This is done through Monte Carlo simulation based on a C-logit model:

\[
P(p) = \frac{e^{V(p)}}{\sum_{i=1}^{n} e^{V(i)}}
\]
where: \( n \) = the total number of available paths in the network for the O-D pair of interest.

\[ V(i) = \text{the systematic utility of path } i. \]

\[ P(p) = \text{the probability that a traveler will choose } p \text{ as the habitual path. } p \text{ is a single path in the set of } n \text{ available paths connecting a particular origin and destination.} \]

\[ V(i) = (\beta_1) \cdot t^H_i + (\beta_2) \cdot CF_i + \delta(i) \]

\( H \) refers to historical path-level travel times.

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

\( t^H_i = \text{historical travel time for path } i. \)

\( CF_i = \ln \sum \omega_j N_j \), the commonality factor for path \( i \), capturing path overlapping.

This term \( CF_i \), or commonality factor, is described in more detail by Cascetta (1996). Its role in the route choice process is to deal with the independence for irrelevant alternatives (IIA) property discussed in Ben-Akiva and Lerman (1985).

\( \beta_1, \beta_2, \) and \( \delta(i) \) are coefficients that can be calibrated by maximum likelihood estimation from an off-line dataset of travelers. Such a dataset would contain the \( t^H_i \) and \( CF_i \) values for each available path, as well as the actual path selection that was made, for every traveler with their respective O-D pair. \( \delta(i) \) is an alternative specific constant associated with a particular path \( i \). \( \delta(i) \) can appear in the utility of no more than \( n-1 \) paths.

For this evaluation, \( \beta_1 \) is set to -5.0 and \( \beta_2 \) is set to -1.0. These values were chosen arbitrarily based on route choice behavior perceived to be realistic. The values are negative since a route with high travel time and greater commonality should be less likely to be selected by a particular driver. The value of \( \delta(i) \) is set to 0 for all network 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 in vehicles equipped to receive the real-time ATIS information via an on-board computer screen are called guided. Those who cannot receive the ATIS information are called unguided. Such unguided drivers are assumed to follow habitual travel choices.

Two separate en-route models were used for the behavior of guided drivers: descriptive and prescriptive. Which model is appropriate depends on how information was distributed to drivers. With descriptive information, the ATIS provides a full description of predicted route-level travel time conditions for each destination. With prescriptive information, only the final route recommendation from DynaMIT is listed by the ATIS.

The descriptive model for drivers who are guided is shown in Figure 6. Such drivers use the ATIS information to choose which path to select from the set of available paths. This does not imply a restricted path choice set, as drivers may choose a path based on real-time information that is the same as their habitual path selection.

![Figure 6: En-route Descriptive Choice Tree](image-url)
The path chosen by guided drivers is modeled by the following equation.

\[ P(p) = \frac{e^{V(p)}}{\sum_{i=1}^{n} e^{V(i)}} \]

where:

\[ V(i) = (\beta 1) \cdot tt_i^I + (\beta 2) \cdot CF_i + \delta(i) \]

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

\[ tt_i^I = \text{travel time provided by the information system for path } i \text{ in minutes. The superscript } I \text{ refers to the information strategy as generated by the DynaMIT system.} \]

The DynaMIT prescriptive en-route behavior model for guided drivers is shown in Figure 7. Drivers may stay on their habitual path, or select the path recommended by the ATIS system. Note that if \( i \) is the habitual path, \( \delta(i) \) captures the propensity for a driver to remain on the habitual path.

\[ \text{Habitual Travel Path} \]
\[ \text{Do Not Change Path} \quad \text{Change Path} \]

Figure 7: En-route Prescriptive Choice Tree

For simplicity, traveler socioeconomic characteristics and path-level features are not included in this evaluation process. However, such factors 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

The Kalman Filter algorithm combines historical and real-time data with an assignment matrix to obtain an estimation and prediction of O-D flows.

1.4.1 Inputs to Estimation Process

Figure 8 is a simplified diagram of how the O-D flow estimation process in DynaMIT works. The method used in DynaMIT involves estimating a vector of deviations between the true O-D flows and historical O-D flow values. This approach that works explicitly with such deviations is done primarily in order to use the historical database effectively. Historical data can be quite helpful, as it contains known relationships of travel demand and their variations over a set of previous days.

![Figure 8: O-D Flow Estimation](image)
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 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 translation 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 passed over each sensor in the network during the estimation time period of interest. For example, one line in an assignment matrix might look like this:

\[ 7:30-7:45 \quad H \quad #10003 \quad 0.5 \quad 7:15-7:30 \]

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 between 7:30 and 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 DynaMIT traffic simulator and appropriate historical demand by simulating the movement of vehicles in the network.
The traffic simulator keeps track of the departure time, origin, and destination of each vehicle that crosses every 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 here. Note that this discussion does not fully represent how the algorithm has actually been implemented in DynaMIT; it serves only to explain the general concepts. A more complete discussion of the algorithm and implementation is provided by Ashok (1996) and Antoniou (1997).

The current time interval for which an O-D flow estimate is desired is taken into account for all components. Some components must also 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. Some notation is presented here to assist in the explanation of algorithm components.

\[ c = \text{the number of sensors placed in the network.} \]
\[ n = \text{the number of O-D pairs to be estimated.} \]
\[ 1 = \text{the number one.} \]
\[ h = \text{an index integer referring to the current time period, or estimation interval, for which an O-D flow estimate is desired.} \]
\[ q = \text{the maximum number of time intervals needed to travel within the network of interest for vehicles from any O-D pair.} \]
$e$ = an index integer referring to the earliest previous time interval that must be considered. This is calculated as $h - q$.

$y_h = a_c \times 1$ vector of sensor counts for the time period $h$.

$x_k = an n \times 1$ vector that represents the number of vehicles from each O-D pair that enter the network from their origins during some time interval $k$.

$x^H_k = an n \times 1$ vector of historical O-D flows for time interval $k$.

The algorithm has three interacting components: the measurement equation, the transition equation, and the state vector. 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. This can be given in matrix form as:

$$Y_h = a^h \times x_h + v_h$$

where: $Y_h = y_h - \sum_{k=e}^{h-1} a^h_k \times x_k$

$a^h_k = a_c \times n$ assignment matrix that assigns the contributions of $x_k$ to $y_h$.

$v_h = a_c \times 1$ vector of measurement errors assumed to have an expected value of zero (unless the sensors are known to have systematic errors), and a $c \times c$ covariance matrix. Each diagonal term in the covariance matrix is the variance associated with a link count. The off-diagonal terms are the covariances between two link counts.
The *transition equation* describes the temporal evolution of deviations over time. This equation can be thought of as:

\[ X_h = \sum_{k=e}^{h-1} f_k^h X_k + w_h \]

where: \( X_k = x_k - x_k^H \), the deviation between actual and historical O-D flows.

\( f_k^h = \) an \( n \) by \( n \) matrix that captures the temporal relationship between deviations.

Diagonal terms related one O-D pair to itself over time, while off-diagonal terms relate one O-D pair to another over time.

\( w_h = \) an \( n \) by \( 1 \) vector of gaussian errors assumed to have an expected value of zero (unless available data indicates otherwise), and an \( n \) by \( n \) covariance matrix. 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.
1.4.3 O-D Flow Prediction

Deviations between historical and predicted O-D flows are modeled in the O-D flow prediction process for each future time interval. This is done by the transition equation formulation described in the previous section. The notation changes as follows.

\[ h \] = the future time interval for which an O-D flow prediction is desired.

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

The problem of traffic congestion is one that continues to grow despite the incredible amount of resources devoted to its reduction. The complexity of both transportation systems and human behavior makes the process of finding effective solutions difficult for transportation professionals. DynaMIT is designed to explicitly model such complexity in order to improve traffic conditions in an intelligent fashion. The provision of traffic information to travelers based on anticipated conditions has tremendous potential for helping numerous people on a daily basis.

In this thesis, a framework for simulation-based evaluation and a high number of results from specific case studies are provided. This work helps in determining the role that DynaMIT would play for assisting travelers in an actual transportation network. Such an understanding is necessary for using DynaMIT effectively, and for the continued efforts in system evaluation and refinement. Research findings also describe how traffic information can be provided to travelers in the best manner possible.
Contributions to the assessment of DynaMIT performance are as follows:

- An evaluation of the DynaMIT demand estimation component using a range of input conditions is conducted. Errors are introduced within sensor counts, the historical database, and other algorithm inputs. The estimation accuracy of DynaMIT is then assessed for each case. DynaMIT estimates demand based on both historical and real-time data sources, and is shown to be robust with respect to errors contained in any one input.

- Demand estimation tests are analyzed under incident conditions. When an incident occurs within a network, traffic patterns tend to become more unstable. This affects the data that is provided to DynaMIT by the real-time surveillance system. The evaluation is important, as DynaMIT is expected to be of greatest benefit for travelers during incident conditions. Results are very encouraging and indicate that estimation accuracy is high when an incident has taken place.

- To understand DynaMIT's impact on traffic congestion, both congestion severity and duration levels in a realistic transportation network are studied in detail using travel demand that is representative of peak-hour conditions. Improvements in network performance achieved by distributing DynaMIT information to travelers are expected, even though this is not the primary objective of DynaMIT. Traffic information generated by DynaMIT was found to significantly reduce congestion when provided to travelers for a range of scenarios.

- The refinements necessary to improve system performance are identified. The ongoing testing and evaluation of DynaMIT is needed for the system to be most effective for travelers.
Contributions to research findings include:

- The impact of DynaMIT system parameters on predictive accuracy and network performance is identified. This has implications on how the DynaMIT system would ideally operate in a real-time environment. Parameters include the frequency of information update, the prediction period, and the number of system iterations. Because of computational efficiency issues, it may not be possible for all of these parameters to be set in an optimal fashion individually. Therefore, a trade-off analysis between sets of values is also conducted.

- Three varying types of information provision are examined. The level of detail associated with real-time information that is provided to travelers may differ. This analysis provides insight on the impact that such differences can have on travel time benefits.

- Network performance as a function of the percent of drivers able to receive ATIS information in real-time is investigated. A relationship between this percentage and mean travel time savings is proposed. This analysis also provides knowledge on the difference between achieving user benefits and overall system benefits from the provision of information.
1.6 Thesis Outline

A literature review is provided in Chapter 2 that discusses some of the previous research work related to dynamic traffic assignment, including results obtained from other simulation-based case studies. Chapter 3 provides a detailed methodology for how the evaluation will be conducted. This also serves as a useful starting point for additional work in the DynaMIT system evaluation.

Chapter 4 identifies how accurately the demand estimation component used in DynaMIT can estimate unknown O-D pair demand levels given some set of inputs. Chapters 5 and 6 assess the capabilities of the DynaMIT system in predicting traffic conditions and improving network performance.

Two types of prescriptive information are described in Chapter 7 and compared based on simulation case studies. A summary of all evaluation results, key research findings, and areas for future research are presented in Chapter 8.
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. This algorithm is capable of using historical and surveillance data and estimating O-D flows in real-time. Antoniou ran an evaluation of this Kalman
Filter algorithm using a simulation laboratory. What is needed as an extension is an evaluation that would assess algorithm robustness under varying levels of input quality. This is an important requirement for system accuracy and performance that, to a large extent, has not been addressed by other researchers.

2.2 Benefits of Information

Several papers have been written regarding the benefits of traveler information over the past few years. Some of these findings are discussed in this section. Results from the studies vary because of differences in the type of network, demand levels, and assumptions made regarding the information system.

An objective of this thesis is to evaluate the travel time benefits that information generated by DynaMIT has for drivers. As will be described in Chapter 3, this is done using a realistic network and demand levels that are representative of projected peak-hour conditions. Of course, results from this thesis are also scenario specific, so it is not a useful exercise to explicitly compare them with results from other papers. Nevertheless, this evaluation is extremely valuable for assessing DynaMIT's performance. It develops a number of research findings that have implications on how to achieve optimal ATIS performance given some prevailing network conditions.

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. This is consistent with findings using DynaMIT, as route choice traveler information cannot be as effective in improving travel times when all network routes are saturated.

Kaysi (1992) developed a framework and models for a dynamic traffic assignment system. He conducted simulation-based tests to observe the benefits of real-time information using two artificial networks for an analysis period of three hours. The term guided refers to travelers who receive and comply with the information. A maximum mean travel time benefit of 4.6% was obtained during incident conditions when the percent of guided drivers was between 20% and 30%. At higher percentages of guided drivers, congestion tended to form on alternative routes. Information based on anticipated traffic conditions was more effective than information based on instantaneous traffic conditions, except when the percent of guided drivers exceeded 80%.

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 guided drivers, of roughly 75%. At a lower MPR such as 20%, guided drivers can benefit by more than 25% but the benefits to unguided 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 principle 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. While findings from the studies differ, one overall point is the importance of behavioral considerations with respect to designing an effective ATIS. For consistency to be achieved, an anticipatory system such as DynaMIT must take into account how travelers are likely to respond to information that is provided to them.

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.

The simulation laboratory used for this thesis work contains certain assumptions regarding travel behavior, given in sections 1.3 and 3.2. Therefore, results provided in this evaluation are contingent upon these assumptions, as discussed in sections 6.2.2 and 8.2.1. Socioeconomic characteristics of drivers are not examined in detail due to the unavailability of actual travel data. This section describes what other researchers have determined regarding traveler behavior, and serves as a basis for which to develop future areas of DynaMIT system evaluation.

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.

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 more likely to switch routes, as opposed to a switch in departure times, 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%). 91% 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% of drivers in the Barfield et al. study preferred to receive traffic information pre-trip, while 44% preferred 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.

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. That motivates the detailed analysis conducted in this thesis.
Chapter 3

Evaluation Methodology

3.1 Simulation Laboratory

The evaluation in this thesis is 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’ responses 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.
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 incidents into account. Unguided drivers select routes based on historical travel times. Time-dependent travel times are updated periodically in real-time by DynaMIT at each rolling step size (defined in section 3.3.12). Guided drivers in MITSIM make route decisions based on the real-time travel times in the case of descriptive information. With prescriptive information, drivers who are guided use 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 DynaMIT 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

For the prescriptive information analysis provided in Chapter 8, the following dimensions are relevant: A-B-D-J-K
3.3.1 Network (A)

- A-1: Central Artery network.

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.

![Figure 10: Central Artery Network](image)

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 for travelers. 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.

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](image)

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 O-D pair, is shown in Table 1. The number in each cell represents the rate that vehicles from each O-D pair enter the network in vehicles/hour. 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.
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, while simplified, is fairly representative of actual peak hour conditions that are anticipated in the year 2004.

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 who 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 simulation ended.
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.

<table>
<thead>
<tr>
<th>Time Period</th>
<th>7:00-7:15</th>
<th>7:15-7:30</th>
<th>7:30-7:45</th>
<th>7:45-8:00</th>
<th>8:00-8:15</th>
<th>8:15-8:30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand at each O-D Pair in vehicles/hr</td>
<td>320</td>
<td>360</td>
<td>400</td>
<td>400</td>
<td>360</td>
<td>320</td>
</tr>
</tbody>
</table>

Table 2: Demand Peaking

For purposes of analyzing stochasticity across replications, two additional scenarios are also used that reduce the demand levels shown in Table 2 by 30% and 60% respectively.

- B-3: Fifty-six origin-destination pairs, reduced demand by 30%.
- B-4: Fifty-six origin-destination pairs, reduced demand by 60%.
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. The true demand is given in B-2.

- 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 algorithm operates without the assistance of any historical information. This is an extreme case used to test the limits of the algorithm performance.

3.3.4 Incident Conditions (D)

- D-1: No incident.
- D-3: Thirty-minute incident in Sumner/Callahan 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 described in the next two sections 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 is used for the impact of information analysis. This incident in the Sumner/Callahan Tunnel reduces vehicle speeds for all lanes in both directions to 10 mph from 7:15 to 7:45. DynaMIT is assumed to be aware of the incident one minute after its occurrence, and the system has good knowledge with respect to its severity and duration.

3.3.5 Sensor Counts (E)

Consistent with the simulation laboratory concept, surveillance system data needed for demand estimation are made available from the MITSIM traffic simulator. MITSIM provides link counts for each 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 traffic lanes 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. For this evaluation, three actual assignment matrices are computed using the MITSIM traffic simulator and are used as inputs to the Kalman Filter algorithm. Each matrix corresponds to vehicles that crossed sensors during the estimation interval of interest (7:30-7:45). One assignment matrix relates to vehicles that entered the network between 7:30 and 7:45. Another corresponds to vehicles that entered the network during the previous time interval (7:15-7:30), while a third corresponds to vehicles that entered during 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 O-D 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. Also, relationships between the inputs and the state variables to be estimated are not perfectly deterministic.

- I-1: Error covariance matrices as specified in the next three paragraphs.

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 input. 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 Guided Travelers (J)

The percent of travelers using the network who are guided 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 guided.
- J-2: 20% of travelers guided.
- J-3: 25% of travelers guided.
- J-4: 40% of travelers guided.
- J-5: 50% of travelers guided.
- J-6: 70% of travelers guided.
- J-7: 75% of travelers guided.
- J-8: 95% of travelers guided.

3.3.11 Type of Information Provided (K)

As described in section 1.3, there are two types of information that can be provided. With descriptive information, drivers are provided with travel times for a set of alternative routes. With prescriptive information, drivers are given 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. The motivation of 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 naive prescriptive information is provided.
• K-4: No information is provided.

3.3.12 Rolling Step Size (L)

The DynaMIT system is designed to operate continuously, as described in Chapter 1. Information is not necessarily generated and released to travelers at set times, but is done intermittently whenever the updated information strategy is ready. Increased computation power and efficiency will directly lead to more frequent updates. 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 should be preferable, assuming that the real-time system requirement is not violated. Some of these parameter values given here were evaluated briefly in the context of a trade-off analysis, introduced in section 5.4.

• L-1: Two minute rolling step size.
• L-2: 3.3 minute rolling step size.
• L-3: Five minute rolling step size.
• L-4: 6.7 minute rolling step size.
• L-5: Ten minute rolling step size.
• L-6: 13.3 minute rolling step size.
• L-7: Fifteen minute rolling step size.
• L-8: 16.7 minute rolling step size.
• L-9: Twenty 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, some for the trade-off analysis section in 5.4.

- M-1: Twelve minute rolling horizon.
- M-2: Fifteen minute rolling horizon.
- M-3: Thirty minute rolling horizon.
- M-4: Thirty-six minute rolling horizon.
- M-5: Forty-five minute rolling horizon.
- M-6: Sixty minute rolling horizon.
- M-7: Ninety minute rolling horizon.
- M-8: 120 minute rolling horizon.
- M-9: 180 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.

- N-1: One iteration.
- N-2: Two iterations.
- N-3: Three iterations.
- N-4: Four iterations.
- N-5: 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 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. This topic is discussed in Chapter 5.

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. The complete network performance analysis is provided in Chapter 6.
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

For Figure 13

Base: Base conditions, perfect inputs.
(A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1)
Cou+5: Sensor counts have systematically high errors of 5%.
   (A-1, B-1, C-1, D-1, E-2, F-1, G-1, H-1, I-1)
Cou-5: Sensor counts have systematically low errors of 5%.
   (A-1, B-1, C-1, D-1, E-3, 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-4, 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-5, F-1, G-1, H-1, I-1)
Cou+20: Sensor counts have systematically high errors of 20%.
   (A-1, B-1, C-1, D-1, E-6, F-1, G-1, H-1, I-1)
Cou-20: Sensor counts have systematically low errors of 20%.
   (A-1, B-1, C-1, D-1, E-7, 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. It has been checked that when these error-covariance matrix values are all set to values near zero, estimate errors are reduced to zero (not shown in the figure).

• The magnitude of the estimate error is roughly proportional to errors contained 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.

For Figure 14

Base: Base conditions, perfect inputs.
(A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1)
Hist+5: Historical demand is higher than the true demand by 5%.
(A-1, B-1, C-2, D-1, E-1, F-1, G-1, H-1, I-1)
Hist-5: Historical demand is lower than the true demand by 5%.
(A-1, B-1, C-3, D-1, E-1, 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-4, 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-5, D-1, E-1, F-1, G-1, H-1, I-1)
Hist+20: Historical demand is higher than the true demand by 20%.
(A-1, B-1, C-6, D-1, E-1, F-1, G-1, H-1, I-1)
Hist-20: Historical demand is lower than the true demand by 20%.
(A-1, B-1, C-7, D-1, E-1, F-1, G-1, H-1, I-1)
Changing the historical counts from the true O-D flows resulted in fairly small errors in the estimate. 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.

For Figure 15

Base: Base conditions, perfect inputs.
   \((A-1, B-1, C-1, D-1, E-1, F-1, G-1, H-1, I-1)\)
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).
   \((A-1, B-1, C-1, D-1, E-1, F-1, G-3, H-1, I-1)\)
Prev+20: Estimated demand for previous interval has a 20% error (too high).
(A-1, B-1, C-1, D-1, E-1, F-1, G-6, H-1, I-1)

Prev-20: Estimated demand for previous interval has a 20% error (too low).
(A-1, B-1, C-1, D-1, E-1, F-1, G-7, 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-4, 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-5, F-1, G-1, H-2, I-1)

Figure 15: Estimation Results #3

- Increasing the estimated O-D flows for the previous interval as compared to the actual O-D flows for that interval (Prev+10, Prev+20) resulted in O-D flow estimates for the current interval that were all somewhat low. The opposite effect occurred when the previous interval estimated flows were less than the actual flows (Prev-10, Prev-20). 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 pull the estimated O-D flows for the current interval closer to its historical values.

For Figure 16

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-8, D-1, E-1, F-1, G-1, H-1, I-1)

2xSigma: Historical matrix of zero, values in state variance matrix doubled.
(A-1, B-1, C-8, D-1, E-1, F-1, G-1, H-1, I-3)

3xSigma: Historical matrix of zero, values in state variance matrix tripled.
(A-1, B-1, C-8, D-1, E-1, F-1, G-1, H-1, I-4)

1000: Historical matrix of zero, values in state variance matrix set to 1,000.
(A-1, B-1, C-8, D-1, E-1, F-1, G-1, H-1, I-5)

5000: Historical matrix of zero, values in state variance matrix set to 5,000.
(A-1, B-1, C-8, D-1, E-1, F-1, G-1, H-1, I-6)

10000: Historical matrix of zero, values in state variance matrix set to 10,000.
(A-1, B-1, C-8, D-1, E-1, F-1, G-1, H-1, I-7)

- 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 16: Estimation Results #4

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.

- When the variance associated with the state vector is increased (2xSigma, 3xSigma), estimation errors are reduced since less reliability is being placed on the low quality historical matrix.

- If no historical matrix is available, it would probably not be evident what values to place on the state vector variance. Most likely, arbitrarily high values to the variance terms would be placed until an improved historical matrix can be built up over time. When this is done (1000, 5000, 10000), estimation errors can be reduced as low as an
average of 2% despite having a historical matrix of zero. This highlights the significant impact that the variance matrices can have on estimation quality.

4.3 With Incident Results

For Figure 17

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-4, 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-5, F-1, G-1, H-1, I-1)

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

(A-1, B-1, C-4, 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-5, 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)

- 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.
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. A minor increase of about 1% in estimation errors between the incident and the non-incident case was observed when previously estimated flows contained errors (IPrev+10, IPrev-10).

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.

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-8, D-2, E-1, F-1, G-1, H-1, I-1)

I2xSig: Incident, historical matrix of zero, values in state variance doubled.
(A-1, B-1, C-8, D-2, E-1, F-1, G-1, H-1, I-3)

I3xSig: Incident, historical matrix of zero, values in state variance tripled.
(A-1, B-1, C-8, D-2, E-1, F-1, G-1, H-1, I-4)

I-1000: Incident, historical matrix of zero, state variance values of 1,000.
(A-1, B-1, C-8, D-2, E-1, F-1, G-1, H-1, I-5)

I-5000: Incident, historical matrix of zero, state variance values of 5,000.
(A-1, B-1, C-8, D-2, E-1, F-1, G-1, H-1, I-6)

I-10000: Incident, historical matrix of zero, state variance values of 10,000.
(A-1, B-1, C-8, D-2, E-1, F-1, G-1, H-1, I-7)
With historical matrices set to zero (IHistZer), the effect on errors for the four O-D pairs from Logan Airport was 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%. However, when the variance of the state matrix was increased to reflect for the poor historical matrix quality, estimation errors were brought down. Even under incident conditions and a historical matrix of zeros, average estimation errors of just 8% were attainable when reliance on the state vector is low.

The with incident results 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.

For Figure 19

IncidRev: Fifteen-minute incident, fewer sensors.

(A-1, B-1, C-1, D-2, E-8, 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-9, 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-10, 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-4, D-2, E-8, 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-5, D-2, E-8, F-1, G-1, H-1, I-1)

IRPrev+10: Incident, fewer sensors, 10% error in previous interval estimate (too high).

(A-1, B-1, C-1, D-2, E-8, F-1, G-2, H-1, I-1)

IRPrev-10: Incident, fewer sensors, 10% error in previous interval estimate (too low).

(A-1, B-1, C-1, D-2, E-8, F-1, G-3, H-1, I-1)
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.

When input errors in the historical matrix or previous interval estimate are combined with a loss of sensor information (IRHist+10, IRHist-10, IRPrev+10, IRPrev-10), 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 is available for such O-D pairs without these four sensors, the algorithm sets the demand estimate close to historical matrix values.
4.4 Assignment Perturbation Results

For Figure 20

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)
AsI5: Incident, assignment matrix perturbed to maximum error of 5%.
    (A-1, B-1, C-1, D-2, E-1, F-2, G-1, H-1, I-1)
AsI10: Incident, assignment matrix perturbed to maximum error of 10%.
    (A-1, B-1, C-1, D-2, E-1, F-3, G-1, H-1, I-1)
AsI20: Incident, assignment matrix perturbed to maximum error of 20%.
    (A-1, B-1, C-1, D-2, E-1, F-4, G-1, H-1, I-1)

Figure 20: Estimation Results #8
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). Similar errors were observed during incident conditions.

This indicates that the algorithm is rather robust with respect to the assignment matrix input. This 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. Note that during an on-line state estimation, the assignment matrix will be computed and refined directly by DynaMIT in order to appropriately match real-time counts and historical values. The algorithm robustness therefore also indicates that the number of iterations needed for the state estimation process will be kept within a reasonable range.

4.5 O-D Flow Estimation Summary

The purpose of this chapter was to assess the accuracy of the O-D flow estimation algorithm used in DynaMIT under a range of input conditions. For the scenario that was used, the demand estimates from the algorithm were accurate when inputs were of high to moderate quality. Estimation errors were generally kept within a range equal to or smaller than the magnitude of errors contained within the inputs.

Variance-covariance matrices, which optimally are a reflection of input reliability, play their role as expected. They reduce the impact of input errors on estimation quality when these errors are known to be present. Therefore, a calibration of the error-covariance matrices off-line is important before using the Kalman Filter algorithm. Similarly, an accurate calibration of transition matrices is valuable since the transition equation input can also serve as a stabilizer for estimation quality. Transition matrix calibration is especially critical for traffic prediction.
Network incidents could have the effect of reducing the amount of measurement equation inputs available in real-time. If input quality for all sources is high, then such incident conditions do not appear to hurt the estimation accuracy significantly. This is extremely promising given that DynaMIT is expected to be of great benefit for travelers during incident conditions. Input errors, particularly with the historical matrix, in combination with incident conditions yielded higher estimation errors than for the no incident case. These errors are also kept within the same magnitude as the input errors.

The algorithm performance was quite robust with respect to errors in the assignment matrix. In an operational context, this is a positive finding for reasons of computational efficiency. The assignment matrix will be adjusted iteratively to improve the O-D flow estimation solution, as described in section 1.4.1. Since robustness is high, fewer iterations will be necessary for this purpose.
Chapter 5

System Accuracy

5.1 Objective

The purpose of this chapter is to describe results related to the estimation and prediction of traffic conditions by DynaMIT in a simulation environment. Tests were conducted in both an open loop and a closed loop fashion.

- **Open-loop:** Information generated by the DynaMIT system is not distributed to travelers. In other words, DynaMIT has no effect on network conditions.

- **Closed-loop:** Information generated by the DynaMIT system is distributed to travelers. This affects traveler behavior and network conditions, which in turn impact the surveillance data inputs to DynaMIT. This interactive process affects both DynaMIT’s performance and network conditions.

Open-loop testing allows for certain features of DynaMIT to be isolated in greater detail since there is no interaction with other parts of the laboratory. Closed-loop testing more
closely approximates how DynaMIT is expected to be used in a real world setting, and will be the focus of this chapter.

5.2 Open-Loop Tests

5.2.1 Free-Flow Conditions

Tests were conducted for traffic conditions that are approximately free-flow throughout the simulation. Using notation introduced in Chapter 3, this scenario is:

\[(A-1, B-4, D-1, J-5, K-4, L-5, M-6, N-3)\]

This involves using a fairly low demand pattern of about 9,000 vehicles/hr and no incident occurrence. Results from fifty replications each of MITSIM (the real world simulator) and DynaMIT were conducted. Actual and predicted vehicle speeds across each network link were averaged during the 2.5 hour simulation period for each replication. The mean link speed values across the replications were then compared.

The prediction accuracy of DynaMIT in the free-flow tests never differed from reality by a mean of more than three miles per hour for any network link. Under these stable traffic conditions, DynaMIT is shown to be an accurate traffic prediction tool.

5.2.2 Congestion Locations

A significantly more interesting analysis involves examining the prediction accuracy of DynaMIT under highly unstable, congested traffic conditions. For this purpose, network demand was raised to about 22,000 vehicles per hour with a thirty-minute incident occurrence in the Sumner/Callahan Tunnel. Using notation provided in Chapter 3, this scenario is defined:

\[(A-1, B-2, D-3, J-5, K-4, L-5, M-6, N-3)\]
As a result of the Sumner/Callahan Tunnel incident, congestion occurs on many links in
the upper part of the network. Six primary zones of congestion were identified:

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 section, Third Harbor Tunnel near Airport

<table>
<thead>
<tr>
<th>Zone</th>
<th>Length</th>
<th># of lanes</th>
<th>Free-Flow Travel Time</th>
<th>Free-Flow Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone #1</td>
<td>6043.3 ft</td>
<td>two</td>
<td>103.5 sec</td>
<td>39.8 mph</td>
</tr>
<tr>
<td>Zone #2</td>
<td>6264.1 ft</td>
<td>two</td>
<td>107.9 sec</td>
<td>39.6 mph</td>
</tr>
<tr>
<td>Zone #3</td>
<td>1654.8 ft</td>
<td>two</td>
<td>27.7 sec</td>
<td>40.8 mph</td>
</tr>
<tr>
<td>Zone #4</td>
<td>605.1 ft</td>
<td>one</td>
<td>12.9 sec</td>
<td>32.0 mph</td>
</tr>
<tr>
<td>Zone #5</td>
<td>1890.9 ft</td>
<td>two</td>
<td>34.2 sec</td>
<td>37.7 mph</td>
</tr>
<tr>
<td>Zone #6</td>
<td>795.2 ft</td>
<td>three</td>
<td>16.8 sec</td>
<td>32.2 mph</td>
</tr>
</tbody>
</table>

Table 3: Zone Characteristics

The free-flow travel times and speeds are empirical means taken from the free-flow
simulation results discussed previously. They are not purely free-flow conditions since
there are still some interactions occurring between vehicles. Note that the free-flow
speeds are relatively low compared to other controlled-access highways. Much of the
proposed Central Artery network is underground with many turning movements required,
so speed limits were set accordingly.

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 (zone 1, zone 2), queues push out onto the tunnel on-ramps (zone 3, zone 4). Off-ramp congestion begins to develop (zone 5) 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 both on- and off-ramps is caused partially by the lane changing that must occur for vehicles to access the ramp. Lane changing causes delays in congested conditions as some vehicles must wait for a suitable gap.

If queues in the on-ramps are severe, they start to push back to the adjoining freeway mainlines (zone 6). In this simulation, this occurs in an area near the Logan Airport. 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. Mainline congestion can slow down drivers in all lanes, not just the ones leading to on-ramps, because of lane changing impacts.
5.2.3 Results

When DynaMIT is not providing information to travelers, the congestion caused by the incident within the network is extreme. Results from fifty open-loop replications each of the MITSIM real-world simulator and DynaMIT were compared across the six zones. This is done through two measures, severity and duration.

- **Severity**: The minimum speed experienced or predicted for a zone, averaged across all vehicles, for any two-minute period during the simulation.

- **Duration**: The amount of time during the simulation that experienced or predicted travel times for vehicles through a zone equals or exceeds an average of 1.5 times or more of the free-flow travel time. This was defined in such a way as to exclude minor traffic condition deviations from the congestion duration measure.

Results from these tests, averaged over fifty replications, are provided in Table 4. Actual refers to the MITSIM microscopic simulator, while predicted refers to the DynaMIT mesoscopic simulator.

<table>
<thead>
<tr>
<th></th>
<th>Zone #1</th>
<th>Zone #2</th>
<th>Zone #3</th>
<th>Zone #4</th>
<th>Zone #5</th>
<th>Zone #6</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Actual Severity</strong></td>
<td>7.5 mph</td>
<td>13.5 mph</td>
<td>5.7 mph</td>
<td>6.3 mph</td>
<td>4.2 mph</td>
<td>20.3 mph</td>
</tr>
<tr>
<td><strong>Predicted Severity</strong></td>
<td>12.7 mph</td>
<td>10.2 mph</td>
<td>6.2 mph</td>
<td>10.2 mph</td>
<td>4.0 mph</td>
<td>23.3 mph</td>
</tr>
<tr>
<td><strong>Actual Duration</strong></td>
<td>79.0 min</td>
<td>49.0 min</td>
<td>31.0 min</td>
<td>22.0 min</td>
<td>54.0 min</td>
<td>6.0 min</td>
</tr>
<tr>
<td><strong>Predicted Duration</strong></td>
<td>80.9 min</td>
<td>65.8 min</td>
<td>40.4 min</td>
<td>84.7 min</td>
<td>38.1 min</td>
<td>0.3 min</td>
</tr>
</tbody>
</table>

**Table 4: Open-Loop Incident Results #1**

Without traveler information from DynaMIT, congestion is high for much of the simulation in five of the zones. With the exception of zone #2, DynaMIT tended to
predict somewhat less severe traffic conditions than what occurred in reality. In four of the zones, DynaMIT tended to predict a longer period of congestion than what took place in reality. This was quite pronounced for zone #4, the on-ramps Eastbound.

An additional exercise involved an examination of open-loop prediction accuracy under conditions of slightly lower network demand. Demand was lowered by 30% from the previous scenario (about 15,000 vehicles per hour) with the thirty-minute incident and fifty replications of each simulator were compared. The results may be different since the time period of heavy congestion is reduced. This scenario is described as:

(A-1, B-3, D-3, J-5, K-4, L-5, M-6, N-3)

<table>
<thead>
<tr>
<th></th>
<th>Zone #1</th>
<th>Zone #2</th>
<th>Zone #3</th>
<th>Zone #4</th>
<th>Zone #5</th>
<th>Zone #6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td>28.0 mph</td>
<td>19.2 mph</td>
<td>33.1 mph</td>
<td>28.8 mph</td>
<td>16.8 mph</td>
<td>21.5 mph</td>
</tr>
<tr>
<td>Severity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted</td>
<td>21.2 mph</td>
<td>24.0 mph</td>
<td>39.0 mph</td>
<td>31.4 mph</td>
<td>20.0 mph</td>
<td>22.8 mph</td>
</tr>
<tr>
<td>Severity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual</td>
<td>0.3 min</td>
<td>23.5 min</td>
<td>0 min</td>
<td>0 min</td>
<td>41.1 min</td>
<td>4.4 min</td>
</tr>
<tr>
<td>Duration</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted</td>
<td>14.9 min</td>
<td>21.1 min</td>
<td>0 min</td>
<td>0 min</td>
<td>30.2 min</td>
<td>0.3 min</td>
</tr>
<tr>
<td>Duration</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 5: Open-Loop Incident Results #2**

When demand in the network is reduced 30%, congestion is reduced significantly in the six zones. This is particularly true for on-ramp locations, where queues tend to form last and end first. DynaMIT again predicts slightly less severe congestion for most of the zones. The predicted duration by DynaMIT is high for zone #1 and low for zone #5, but fairly close for the other zones.

An interpretation of these findings will be discussed in conjunction with the closed loop discussion in the next section.
5.3 Closed-Loop Tests

5.3.1 Congestion Severity

The next part of the analysis is to observe prediction accuracy during closed-loop testing. The information strategy produced by DynaMIT is distributed to drivers in the simulated reality. Additional complexity is present in this case, as DynaMIT must include the anticipated response of drivers to the information strategy in its prediction of traffic conditions. The same 22,000 vehicles/hour scenario with a thirty-minute incident described in the open-loop testing section is analyzed here. Results provided in this section represent an average of twenty replications in the simulation environment.

(A-1, B-2, D-3, J-5, K-1, L-5, M-6, N-3)

The first column series in Figure 22 shows the free-flow speeds for each zone. The second column series gives the actual congestion severity in the network that occurs without DynaMIT in operation. The third series shows the severity for each zone that occurs in reality with DynaMIT in operation, and the fourth column series shows the severity that is predicted by DynaMIT.

When the information strategy generated by DynaMIT is distributed to drivers, congestion is reduced for each of the six zones. The reduction is greatest for zone #3, the Westbound on-ramps. Comparing the DynaMIT-Actual and DynaMIT-Predicted bars gives the quality of DynaMIT's prediction. For zones #1 and #3, the predictions made by DynaMIT of the congestion severity is quite good. For the other zones, DynaMIT predicts somewhat less congestion than what actually occurs. Errors are slightly larger than what was observed during the open-loop testing.
The prediction quality results 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 six miles per hour. Vehicle movements in these other links were predicted and actually were generally at or near free-flow speeds.

5.3.2 Congestion Duration

Figure 23 provides similar information for congestion duration. DynaMIT is successful in reducing the duration of congestion for all zones except #2. Congestion is virtually eliminated for zones #3 and #6; 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.

A topic related to duration is the predicted starting and ending time of the queues, shown in Table 6 averaged over twenty 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. The congestion start times

![Figure 23: Congestion Duration](image)
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 and been detected (which in this case is one minute after its occurrence).

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.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Without DynaMIT-Actual</th>
<th>With DynaMIT-Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1: Tunnel</td>
<td>7:19-8:42</td>
<td>7:18-7:38</td>
</tr>
<tr>
<td>#2: Tunnel</td>
<td>7:17-8:07</td>
<td>none</td>
</tr>
<tr>
<td>#3: On-ramps</td>
<td>7:54-8:34</td>
<td>7:35-7:49</td>
</tr>
<tr>
<td>#4: On-ramps</td>
<td>7:29-7:52</td>
<td>7:47-8:03</td>
</tr>
<tr>
<td>#5: Offramps</td>
<td>7:47-8:40</td>
<td>none</td>
</tr>
<tr>
<td>#6: Mainline T Harbor</td>
<td>8:01-8:06</td>
<td>none</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Zone</th>
<th>Without DynaMIT-Actual</th>
<th>With DynaMIT-Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minutes Reduction</td>
<td>63</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>37</td>
<td>6</td>
</tr>
<tr>
<td>With DynaMIT-Predicted</td>
<td>7:42-8:14</td>
<td>8:06-8:31</td>
</tr>
<tr>
<td></td>
<td>none</td>
<td>7:23-8:44</td>
</tr>
<tr>
<td></td>
<td>7:39-8:17</td>
<td>none</td>
</tr>
<tr>
<td>Start Time Error</td>
<td>-24</td>
<td>-51</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>+12</td>
</tr>
<tr>
<td></td>
<td>+8</td>
<td>0</td>
</tr>
<tr>
<td>End Time Error</td>
<td>-36</td>
<td>-38</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>-55</td>
</tr>
<tr>
<td></td>
<td>-14</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 6: 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.

5.3.3 Explanation of Findings

Results presented from tests in both an open-loop and a closed-loop fashion have been promising. Errors of moderate magnitude are restricted to only a few links in the network during unstable, incident conditions. While a detailed analysis of the exact sources of error is beyond the scope of this thesis, it is hypothesized that some of the following factors could be at work:

- In the microscopic real-world representation, individual vehicles are moved in a highly detailed fashion. Vehicles check for acceptable gaps when making lane changes. This action occurs frequently near on-ramp and off-ramp merging locations. In congestion situations, vehicles are likely to queue up for some time if no gap is acceptable. DynaMIT may need to take account of this.

- Vehicle speeds in DynaMIT appeared too fast in highly congestion situations. This can be corrected through adjusting speed-density functions.

- The acceptance capacity of downstream links during incident conditions appeared to be high during queue formation but low during queue dissipation. Parameter calibration in these models could result in improved prediction accuracy.

5.3.4 Rolling Step Size

An extensive evaluation of predictive quality as a function of DynaMIT system parameters (rolling step size, rolling horizon, number of system iterations) is outside the scope of this thesis. However, a more limited analysis based on five replications for a set of alternative scenarios yields considerable insight on the effect that these parameters have on system performance.
Changes in the rolling step size definitely had an effect on user and system performance, to be described in Chapter 6. The reason for this depends specifically on predictive quality. Graphing a congestion profile for a particular zone will assist here. A congestion profile shows the actual and predicted congestion levels over the course of the simulation.

Such profiles are shown in the following three figures for Zone #4, the Eastbound on-ramps. These three scenarios are evaluated here.

- **10SS**: Rolling step size of ten minutes (base).
  
  (A-1, B-2, D-3, J-5, K-1, L-5, M-6, N-3)

- **30SS**: Rolling step size of thirty minutes.
  
  (A-1, B-2, D-3, J-5, K-1, L-10, M-6, N-3)

- **60SS**: Rolling step size of sixty minutes.
  
  (A-1, B-2, D-3, J-5, K-1, L-11, M-6, N-3)

![Figure 24: Zone #4 Congestion Profile, 10 SS](image-url)
Figure 25: Zone #4 Congestion Profile, 30 SS

Figure 26: Zone #4 Congestion Profile, 60 SS
The figures indicate that in all scenarios, the actual congestion severity spikes 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 about 5 mph greater 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.

It is important to distinguish here between the information itself and the information strategy. At a rolling step size of sixty minutes for example, the DynaMIT system would not necessarily provide the same information to drivers who enter the network at 7:15 and drivers who enter the network at 7:25. However, the information strategy provided by DynaMIT is only updated every sixty minutes. Therefore, any unexpected changes such as an incident that may have taken place are accounted for in the information strategy less frequently with a longer rolling step size.

5.3.5 Rolling Horizon

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

- **15RH**: Rolling horizon of fifteen minutes.
  
  \[(A-1, B-2, D-3, J-5, K-1, L-5, M-2, N-3)\]

- **30RH**: Rolling horizon of thirty minutes.
  
  \[(A-1, B-2, D-3, J-5, K-1, L-5, M-3, N-3)\]

- **60RH**: Rolling step size of sixty minutes (base).
  
  \[(A-1, B-2, D-3, J-5, K-1, L-5, M-6, N-3)\]

![Figure 27: Zone #1 Congestion Profile, 15 RH](image-url)
Figure 28: Zone #1 Congestion Profile, 30 RH

Figure 29: Zone #1 Congestion Profile, 60 RH
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 60 minute rolling length. As this information is distributed, more 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 for zone #1 is underpredicted in all three scenarios. At the sixty minute rolling horizon, this error is rather small (20 mph vs. 21 mph). However, the magnitude of underprediction appears to be greater for shorter rolling horizons. 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 good network performance, prevention of queue buildup is crucial. 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 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 overall network travel times 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.

5.3.6 Number of Iterations

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). With one iteration, a time lag occurred
between when actual congestion started and when congestion was predicted. DynaMIT with one iteration generally did not predict congestion until at least 15 minutes after it had already started. The difference in predictive quality between three iterations and five iterations was extremely minimal.

The results associated with the one iteration scenario indicate a poorer identification of a fixed point between demand, supply, and information. This illustrates the importance of consistency in the information strategy and the need to properly anticipate drivers' responses to the information provided. It is important to conduct the iterative process more than once such that the consistency question can be visited during the calculations.

5.4 System Accuracy Summary

Results in this chapter assessed DynaMIT's ability to accurately predict network conditions in a simulation environment. Prediction tests were first run when information generated by DynaMIT is not distributed to travelers. In conditions that were roughly free-flow, mean prediction errors throughout the network were negligible. As would be expected, the prediction quality is reduced for network regions where traffic conditions are congested and more unstable. Prediction appeared to be most difficult in the regime between free-flow speeds and heavy congestion.

When DynaMIT information is provided to travelers during the simulation period, results indicated that DynaMIT tended to over-estimate speeds by a mean of 7 mph during the most congested times of the simulation. Also, DynaMIT had a tendency to predict congestion in certain areas for a longer period than it actually lasted. This was particularly true for on-ramp sections. The mesoscopic nature of the DynaMIT traffic simulator may be a cause of this result. More investigations in this direction is desired.
Overall, the DynaMIT system performed well in a simulation environment, with its primary objectives of unbiasedness and consistency being closely met. While errors were moderate, some results indicate that supply simulator refinement in certain areas would be beneficial. An enhanced supply simulator is currently in development in part to address these issues. Additional model calibration using field data may also be required to improve the global prediction quality in congested situations.

Results presented in this chapter also highlighted the effects of DynaMIT system parameters on prediction accuracy. The a priori expectation that DynaMIT performance depends partially on a set of system parameters were confirmed.

- As expected, a reduction in the rolling step size (frequency of information update) increases DynaMIT effectiveness. At frequencies equal to or lower than thirty minutes, there is danger that incident occurrences will not be taken into account by the DynaMIT system until it is too late to provide benefit for many affected travelers. Frequent updates are desirable for maintaining system accuracy.

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 be directly controllable via a system parameter. Reducing the information update interval in this case will be primarily a function of computational power and system operational efficiency. This motivates the development of DynaMIT within a distributed computing environment. Additional software engineering is necessary to optimize the system.
• An increase in the rolling horizon, or prediction period, improves the effectiveness of DynaMIT. A short rolling horizon results in predictions that tend to underestimate the amount of congestion. This is a function of how the DynaMIT network simulator treats unfinished trips that are left in the network when the simulation period ends.

• An increase in the number of iterations, designed to generate a more consistent information strategy, 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 generated information that is based on erroneous predictions, inconsistent with traffic conditions that actually occur.
Chapter 6

Network Performance

6.1 Traveler Behavior

The link travel time predictions made by the DynaMIT system are released to travelers in the MITSIM network and affect their route choices accordingly. This section highlights these effects, which is useful for understanding other parts 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 30 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.
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 31 shows the route choices made by travelers in the two groups during the simulation when no information is provided. This scenario uses the same primary
demand pattern of about 22,000 vehicles/hour. An incident occurrence takes place in the Sumner/Callahan tunnel from 7:15 to 7:45. This is described, using the notation from Chapter 3, as:

\[(A-1, B-2, D-3, K-4)\]

![Route Choices With No DynaMIT](image)

**Figure 31: Route Choices With No DynaMIT**

Traveler route choices for the same scenario made with DynaMIT in operation at the base system parameters (10 minute rolling step size, 60 minute rolling horizon, 3 iterations, 50% of drivers are guided) are shown in Figure 32. Many drivers avoid using the Sumner/Callahan Tunnel because of the information provided by DynaMIT. The ATIS system has informed drivers that travel times in that tunnel have gone up as a result of the incident, particularly from 7:30 to about 8:00. The base DynaMIT scenario is described as:

\[(A-1, B-2, D-3, J-5, K-1, L-5, M-6, N-3)\]
Figure 32: Route Choices With DynaMIT

Figure 33: Route Choices, Guided and Unguided

Recall that in this scenario, half of the travelers (guided-G) choose their route based on information from DynaMIT while the other half (unguided-U) do not. Figure 33 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.

Figure 34 shows the travel time results from the simulation for the two groups when no information is provided. The vertical axis indicates the time savings experienced by drivers who chose the Sumner/Callahan tunnel. This can be expressed as:

\[
\text{Time savings} = \frac{(TT_{TH} - TT_{SC})}{TT_{TH}}
\]

where: \(TT_{TH}\) = mean travel time experienced by travelers from a particular O-D pair group and departure time interval who chose the Third Harbor Tunnel,

\(TT_{SC}\) = mean travel time experienced by travelers from a particular O-D pair group and departure time interval who chose the Sumner/Callahan Tunnel.

![Figure 34: Travel Times With No DynaMIT](image-url)
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. This is shown in the figure as reduced travel time savings for travelers in Group A, and increased travel costs for travelers in Group B. However, 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.

The travel times of travelers in the two groups with the presence of DynaMIT under incident conditions are shown in Figure 35.

![Figure 35: Travel Times With DynaMIT](image)

The effects of the incident on travel times in the Sumner/Callahan tunnel are greatly reduced in this case. For drivers in Group A, travel time savings from using the Sumner/Callahan tunnel route are a minimum of about 21% from 7:15 to 7:45 when the incident is in effect. For drivers in Group B, travel time costs from using this route are greatest from 7:30 to 7:45 at about 35%. Because many drivers diverted away from the
incident when provided with information from DynaMIT (shown in Figure 32), the Sumner/Callahan tunnel is less congested than when DynaMIT is not in operation.

6.2 User Benefit

6.2.1 Benefit Results

Chapter 5 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 benefited travelers with respect to experienced travel times.

Figure 36: Mean Travel Times for all Travelers

Figure 36 shows the mean travel time in seconds for all travelers in the network under incident conditions. One bar series shows travel times experienced by drivers when DynaMIT is not in operation (A-1, B-2, D-3, K-4). The other bar series shows travel times experienced by drivers when DynaMIT is in operation at base system conditions (A-1, B-2, D-3, J-5, K-1, L-5, M-6, N-3). In the figure, the letter G refers to drivers who are guided and the letter U refers to unguided drivers.
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 guided travelers do not differ much from others with respect to their mean travel times. These results initially appear to be surprising. One would expect the 50% of drivers who are guided to have lower average travel times than others as a result of basing their decisions on information provided by DynaMIT.

This calls into question whether the information provided by DynaMIT is informing drivers to select a user-optimal outcome. Inconsistency between DynaMIT's predicted link travel times and reality as described in Chapter 5 may have contributed to this. Recall from Figure 22 that the mean error between predicted and actual severity levels for six zones affected by the incident was about 7 miles per hour (DynaMIT tended to overpredict speeds). From Figure 23, DynaMIT had a mean error in predicted vs. actual congestion duration of about 23 minutes for four of the six zones.

However, there is another issue in addition to inconsistency taking place that affects the travel time comparison between guided and unguided travelers. To determine what this is requires examining again the travel times for specific O-D pairs. This is shown in Figure 37 for the same two groups A and B used in the previous section.
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 6.1 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.

6.2.2 Explanation of Findings

In the MITSIM reality, guided drivers make their route choice decisions using a logit model based on the updated travel times from the information system. Therefore, 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 result indicates the need for further calibration of the behavior models using field data. Namely, it may be desirable to add and estimate an alternative specific constant $\delta(i)$ to the habitual paths of drivers in MITSIM. As mentioned in section 1.3.3, this would capture the propensity of drivers to remain on their habitual path until travel times on that path exceed the travel times for alternative routes.

### 6.2.3 Rolling Step Size

![Figure 38: User Benefit, Rolling Step Size](image)

Figure 38 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 of ten minutes, thirty minutes, and sixty minutes. 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.

The inconsistency levels in prediction provide insight on the source of differences in user benefit levels. This is shown in Table 7 for three measures found to be most relevant in their influence on travel behavior and network performance. In particular, the predicted start time of congestion had a key influence on network performance. To achieve travel time benefits, it was important that information regarding the incident was provided to travelers as quickly as possible after its occurrence and detection. Results shown are based on five replications of each scenario.

- **Severity**: Inconsistency between the predicted minimum speed and the actual minimum speed of drivers, averaged over six zones, for any two-minute period during the simulation. Positive numbers indicate that DynaMIT overpredicted these minimum speeds.

- **Start Time, tunnel**: Inconsistency between the predicted starting time and actual starting time of congestion in the Sumner/Callahan tunnel (zones #1 and #2). Congestion is defined to start when mean travel times through the tunnel for vehicles equals or exceeds 1.5 times or more of the free-flow travel time.

- **Start Time, ramps**: Inconsistency between the predicted starting time and actual starting time of congestion in ramp locations (zones #4 and #5). The other zones, #3 and #6, were not included because the operation of DynaMIT successfully eliminated congestion in these zones for most scenarios.

For the start time numbers, a positive number indicates that DynaMIT predicted congestion to occur before it actually started. A negative number indicates that DynaMIT predicted congestion to occur after it actually started. The tunnel and ramp zones are
shown separately, since as mentioned in section 5.3.2 DynaMIT tended to predict congestion in ramp sections early and congestion in the tunnel late.

<table>
<thead>
<tr>
<th>RSS</th>
<th>Severity</th>
<th>Start Time, tunnel</th>
<th>Start Time, ramps</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>+ 7.0 mph</td>
<td>- 37 min</td>
<td>+ 10 min</td>
</tr>
<tr>
<td>30</td>
<td>+ 8.7 mph</td>
<td>- 34 min</td>
<td>+ 2 min</td>
</tr>
<tr>
<td>60</td>
<td>+ 7.5 mph</td>
<td>- 44 min</td>
<td>- 25 min</td>
</tr>
</tbody>
</table>

Table 7: Inconsistency, Rolling Step Size

For longer rolling step sizes, the consistency of severity prediction was found to be slightly worse. The consistency of congestion start times was affected fairly significantly by the rolling step size. In this series of tests, a longer rolling step size means that DynaMIT is not able to account for the incident until later in the simulation. This was mentioned in section 5.3.4.

6.2.4 Rolling Horizon

Because of differences in DynaMIT’s predictions and information strategy, fewer travelers divert away from the incident when a shorter rolling horizon is used. Figure 39 shows the mean travel times experienced in the network for guided and unguided drivers for the rolling lengths of fifteen minutes, thirty minutes, and sixty minutes (averaged over five replications of each). Benefits of information provision in these scenarios begin to differ beyond 7:30, and the gap closes somewhat only after 8:15.
Consistency measures for the rolling horizons are given in Table 8. As opposed to changes in the rolling step size, changes in the rolling horizon tended to impact consistency results more with respect to predicted congestion severity. At the shorter rolling horizons, probably due to incomplete trips as discussed in section 5.3.5, severity is underpredicted to a greater extent for shorter rolling horizons. This affects network performance because congestion due to the incident is reported by DynaMIT to be less severe than it actually is. Fewer drivers divert routes as a result.

<table>
<thead>
<tr>
<th>Rolling Horizon</th>
<th>Severity</th>
<th>Start Time, tunnel</th>
<th>Start Time, ramps</th>
</tr>
</thead>
<tbody>
<tr>
<td>15 RH</td>
<td>+ 14.5 mph</td>
<td>- 33 min</td>
<td>+ 3 min</td>
</tr>
<tr>
<td>30 RH</td>
<td>+ 8.8 mph</td>
<td>- 32 min</td>
<td>+ 11 min</td>
</tr>
<tr>
<td>60 RH</td>
<td>+ 7.0 mph</td>
<td>- 37 min</td>
<td>+ 10 min</td>
</tr>
</tbody>
</table>

Table 8: Inconsistency, Rolling Horizon

Figure 39: User Benefit, Rolling Horizon
6.2.5 Number of Iterations

Fewer travelers divert away from the incident when a lower number of iterations is used due to lower predictive quality. Figure 40 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 40: User Benefit, Number of Iterations](image)

The consistency measures as a function of the number of system iterations is provided in Table 9. Similar to the rolling horizon, changes in the number of iterations impacted the predicted congestion severity to a large extent. This is particularly true for the 1 iteration scenario. The predicted starting time of congestion was also affected by the number of iterations used.
Table 9: Inconsistency, Number of Iterations

<table>
<thead>
<tr>
<th></th>
<th>Severity</th>
<th>Start Time, tunnel</th>
<th>Start Time, ramps</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 iteration</td>
<td>+ 22.7 mph</td>
<td>- 35 min</td>
<td>-10 min</td>
</tr>
<tr>
<td>3 iterations</td>
<td>+ 7.0 mph</td>
<td>- 37 min</td>
<td>+ 10 min</td>
</tr>
<tr>
<td>5 iterations</td>
<td>+ 5.6 mph</td>
<td>- 30 min</td>
<td>+ 17 min</td>
</tr>
</tbody>
</table>

6.3 Percent of Guided Drivers

Fewer travelers divert away from the incident when the percent of guided travelers is smaller. The experienced travel times for the two groups A and B are shown in the next two figures for additional scenarios of the guided driver percentage. 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.

- **25%G**: 25% of drivers are guided.
  
  (A-1, B-2, D-3, J-3, K-1, L-5, M-6, N-3)

- **75%G**: 75% of drivers are guided.
  
  (A-1, B-2, D-3, J-7, K-1, L-5, M-6, N-3)
Figure 41: Travel Times, 25% Guided

Figure 42: Travel Times, 75% Guided
The next two figures show how unguided travelers compared to guided 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 base scenario.

Figure 43: 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 44: Unguided vs. Guided, 75% Guided

Figure 45 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 guided as compared to when 25% of travelers are guided. 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 relatively small, guided travelers really benefit from the information in terms of travel time as compared to unguided travelers.
This discussion highlights distinctions between user benefit and system benefit. When the percent of travelers provided with real-time information is fairly small and a severe incident occurs, guided travelers can benefit substantially in terms of travel time compared to unguided travelers. Improvements 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 guided travelers relative to unguided travelers will be reduced. If over-reaction occurs, guided travelers can face longer travel times than unguided travelers even if system-wide benefits are impressive. This relationship will be discussed further in Chapter 7.
6.4 System Travel Times

The mean travel times experienced across all fifty-six O-D pairs are provided in the next two tables 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.

<table>
<thead>
<tr>
<th></th>
<th>Mean (in seconds)</th>
<th>Std Dev Across Vehicles (in seconds)</th>
<th>Std Dev Across Replics. (in seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All Vehicles</strong></td>
<td>446.9</td>
<td>315.3</td>
<td>10.91</td>
</tr>
<tr>
<td>7:00-7:15</td>
<td>291.7</td>
<td>152.5</td>
<td>2.97</td>
</tr>
<tr>
<td>7:15-7:30</td>
<td>326.7</td>
<td>189.0</td>
<td>1.25</td>
</tr>
<tr>
<td>7:30-7:45</td>
<td>417.0</td>
<td>267.6</td>
<td>8.47</td>
</tr>
<tr>
<td>7:45-8:00</td>
<td>520.9</td>
<td>336.3</td>
<td>13.27</td>
</tr>
<tr>
<td>8:00-8:15</td>
<td>565.3</td>
<td>381.5</td>
<td>22.69</td>
</tr>
<tr>
<td>8:15-8:30</td>
<td>548.9</td>
<td>371.4</td>
<td>27.85</td>
</tr>
</tbody>
</table>

Table 10: System Performance - No DynaMIT

<table>
<thead>
<tr>
<th></th>
<th>Mean (in seconds)</th>
<th>Std Dev Across Vehicles (in seconds)</th>
<th>Std Dev Across Replics (in seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All Vehicles</strong></td>
<td>315.4</td>
<td>176.4</td>
<td>1.90</td>
</tr>
<tr>
<td>7:00-7:15</td>
<td>293.3</td>
<td>153.3</td>
<td>3.17</td>
</tr>
<tr>
<td>7:15-7:30</td>
<td>318.5</td>
<td>178.6</td>
<td>4.51</td>
</tr>
<tr>
<td>7:30-7:45</td>
<td>336.5</td>
<td>200.1</td>
<td>4.03</td>
</tr>
<tr>
<td>7:45-8:00</td>
<td>326.5</td>
<td>183.0</td>
<td>3.75</td>
</tr>
<tr>
<td>8:00-8:15</td>
<td>311.3</td>
<td>170.2</td>
<td>6.50</td>
</tr>
<tr>
<td>8:15-8:30</td>
<td>297.9</td>
<td>156.2</td>
<td>1.92</td>
</tr>
</tbody>
</table>

Table 11: 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 reduced when the DynaMIT system is in operation.

The With DynaMIT results given in Table 12 are for the base scenario of a ten minute rolling step size, sixty minute rolling length, three iterations, and 50% drivers guided. The mean benefits in system travel time over the simulation period as compared to the no DynaMIT scenario, averaged over five replications, are provided in Figure 46. Results are indicative of what were discussed in sections 6.2 and 6.3.
6.5 Trade-off Analysis

6.5.1 Set-Up

In an actual traffic management center application, there exists trade-offs between the DynaMIT system parameters that have been examined: rolling step size, rolling horizon, and number of iterations. These tradeoffs exist because of probable limits associated with available computational power and the real-time system requirement.

For example, while extending the rolling horizon may be desirable from a predictive quality standpoint, it also increases the amount of calculation time needed for DynaMIT to operate at each iteration. Therefore, a rolling horizon extension may only be possible to achieve if the number of system iterations is reduced. However, reducing the number
of system iterations may hurt predictive quality. In this sense, choosing optimal system parameters becomes a balancing act between conflicting objectives.

As an addition to results presented thus far, this section provides a brief analysis of scenarios designed to investigate trade-offs between these DynaMIT system parameters. Note that each scenario described here contains results from only one replication, so this analysis is not conclusive. However, it does provide an indication of which parameters may be most important for system performance in a particular scenario.

For continuity, the same main closed-loop scenario is used for analysis in this section. There are about 22,000 vehicles/hour using the Central Artery network with a thirty-minute incident occurrence in the Sumner/Callahan tunnel. 50% of drivers are guided. Using notation introduced in Chapter 3, this is described as:

\[(A-1, B-2, D-3, J-5, K-1)\]

Recall that for this analysis, the base system parameters were set as: 10 minute rolling step size, 60 minute rolling horizon, three system iterations. This section assumes that certain trade-offs can be made between these parameters at fixed percentages. As examples, a reduction in the rolling step size of 50% means that the rolling horizon must be reduced by 50%. A decrease in the rolling step size of 33% means that the number of system iterations must be cut by 33%. If the rolling horizon is extended by a multiple of three, the number of system iterations must be cut back by a multiple of three.

With these assumptions set, twelve scenarios were developed. With each scenario, one parameter is fixed at the base level. The other two scenarios are traded off for each other at some proportion, resulting in a new set of parameters. Rolling step size is abbreviated as RSS, rolling horizon as RH, and number of iterations as IT. Results from these sets in a simulation environment are compared with the base parameters.
5, 30, 3: Five minute RSS, 30 minute RH, three IT.
   (A-1, B-2, D-3, J-5, K-1, L-3, M-3, N-3)
2, 12, 3: Two minute RSS, 12 minute RH, three IT.
   (A-1, B-2, D-3, J-5, K-1, L-1, M-1, N-3)
15, 90, 3: Fifteen minute RSS, 90 minute RH, three IT.
   (A-1, B-2, D-3, J-5, K-1, L-7, M-7, N-3)
20, 120, 3: Twenty minute RSS, 120 minute RH, three IT.
   (A-1, B-2, D-3, J-5, K-1, L-9, M-8, N-3)
6.7, 60, 2: 6.7 minute RSS, 60 minute RH, two IT.
   (A-1, B-2, D-3, J-5, K-1, L-4, M-6, N-2)
3.3, 60, 1: 3.3 minute RSS, 60 minute RH, one IT.
   (A-1, B-2, D-3, J-5, K-1, L-2, M-6, N-1)
13.3, 60, 4: 13.3 minute RSS, 60 minute RH, four IT.
   (A-1, B-2, D-3, J-5, K-1, L-6, M-6, N-4)
16.7, 60, 5: 16.7 minute RSS, 60 minute RH, five IT.
   (A-1, B-2, D-3, J-5, K-1, L-8, M-6, N-5)
10, 90, 2: Ten minute RSS, 90 minute RH, two IT.
   (A-1, B-2, D-3, J-5, K-1, L-5, M-7, N-2)
10, 180, 1: Ten minute RSS, 180 minute RH, one IT.
   (A-1, B-2, D-3, J-5, K-1, L-5, M-9, N-1)
10, 45, 4: Ten minute RSS, 45 minute RH, four IT.
   (A-1, B-2, D-3, J-5, K-1, L-5, M-5, N-4)
10, 36, 5: Ten minute RSS, 36 minute RH, five IT.
   (A-1, B-2, D-3, J-5, K-1, L-5, M-4, N-5)

6.5.2 Results

The following three figures evaluate mean travel times experienced in the network for these scenarios. In each figure, the base scenario with the parameters 10,60,3 (a 10 minute rolling step size, 60 minute rolling horizon, and 3 system iterations) is given a value of 0%. All other scenarios are then compared to the base. For example, a value of
3% means that the mean travel times experienced by drivers in the network improved (went down) by 3% relative to the base.

**Figure 47: System Results – RSS-RH Tradeoff**

The 5,10,3 scenario had the best system performance overall. The other sets of parameters did not perform as well as the base.

**Figure 48: System Results – RSS-IT Tradeoff**
The base scenario outperformed the other scenarios listed in Figure 48. In particular, the scenario involving the operation of DynaMIT with one iteration (with a rolling step size of 3.3 minutes and a rolling horizon of 60 minutes) was not effective.

![Figure 49: System Results – RH-IT Tradeoff](image)

The 10,45,4 scenario and the 10,60,3 scenario yielded system travel time results that were quite similar. The other three scenarios listed were not as successful. Again, the scenario involving the use of DynaMIT with one iteration did not perform well.

From these results, it appears that some form of parabolic relationship exists between the system parameter settings and the benefits associated with the traveler information. When any of the three parameters is set to a value that is extreme in an undesirable way, the prediction accuracy and the resulting information impact go down. This provides some evidence that unless data suggests otherwise, it is best to choose fairly modest values for each of the parameters (close to the base parameters given here) rather than trade off one for another too heavily.
6.6 Network Performance Summary

This chapter discussed the impact that information from DynaMIT had on network performance when distributed to travelers. Results indicated that the information strategy provided by DynaMIT is effective. Mean travel times experienced by drivers in the network are significantly lower with DynaMIT in operation during incident conditions. Many drivers chose a beneficial alternate route after being informed that travel times on their habitual path had increased relative to historical levels. The information strategy provided by DynaMIT did not result in over-reaction, and as the incident began to clear travelers increasingly returned 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 suitable for use in future evaluations. Work in the development and implementation of additional algorithm strategies is ongoing, to be compared with the current algorithm.

As the number of guided drivers increased, mean network travel times improved. This is because more drivers were able to take advantage of DynaMIT's real-time information. Changes in DynaMIT system parameters were found to affect network performance rather significantly. This is due to varying levels of prediction accuracy, as discussed in section 5.4. A trade-off analysis indicated that for optimal system performance, DynaMIT parameters need to be set in such a way as to avoid extreme values.
For future evaluation, behavior model refinements would be valuable. This can be done in the following way.

- Include an alternative-specific constant that gives drivers a preference for habitual routes. For this to occur, habitual paths should be stored as an input for each driver in the simulation laboratory.

- Collect field data, and calibrate behavior models based on this data.

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. This is likely to be a fairly realistic representation of actual travel behavior.
Chapter 7

Prescriptive Information

7.1 Purpose

The purpose of this chapter is to examine the distribution of prescriptive information to travelers. 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 obtaining and comprehending the information. The disadvantage is a less complete picture of what conditions are actually taking place in the network. This trade-off is a factor to consider when designing an ATIS distribution system. This is especially true for variable message signs, since only limited time may be available for travelers to interpret the information.

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.
7.2 Naive vs. Specific

As mentioned briefly in Chapter 3, there are two different types of prescriptive information, naive and specific, used in this evaluation. They can be defined as:

- **Naive**: The same recommended route is given to all travelers who are guided, such as "Accident ahead. Use the Third Harbor Tunnel". In other words, the recommendation is not destination-specific.

- **Specific**: The recommended route from the ATIS system differs depending on the specific destination of the traveler. An example is "Accident ahead. Use the Third Harbor Tunnel to access the Mass Pike, use the Sumner/Callahan Tunnel to access I-93 North".

Naive information is easier for drivers to interpret quickly. However, it can lead to some problems depending on the exact scenario, as described here. Figure 50 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. Such a diversion is quite circuitous for such travelers, although it makes more sense for others to take.

Therefore, with specific information, travelers from O-D pairs A-F, B-F, F-A, and F-B are instructed by the ATIS system to use the Sumner/Callahan (upper) tunnel despite the incident occurrence. Other travelers with two feasible route choices are instructed by the VMS to use the Third Harbor tunnel. There is still a net diversion of travelers away from the incident location with specific information, although not as large as for naive information assuming a fixed percent of guided travelers. Thus, 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.
7.3 User Benefit

The prescriptive information scenarios evaluated in this section, defined in terms of the dimensions described in Chapter 3, are as follows. The first two prescriptive scenarios are set as base conditions. The same demand pattern and incident location from the descriptive closed-loop tests are examined. Recall that guided drivers follow the route recommended by the ATIS system. Unguided drivers continue to follow their historical route selection. The recommendations are active from 7:15 to 8:15.

- **40%S**: 40% guided, specific information.
  
  \((A-1, B-2, D-3, J-4, K-2)\)

- **40%N**: 40% guided, naive information.
  
  \((A-1, B-2, D-3, J-4, K-3)\)
With prescriptive information, user benefit criteria are, for the most part, more adequately met as compared to descriptive information. Guided travelers 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. The O-D pairs contained in these groups are listed again for convenience, with locations for the origins and destinations referenced in Figure 11.
With naive recommendations, travelers from both groups are instructed to use the Third Harbor tunnel during the 7:15 to 8:15 time period 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 51 shows the mean travel times experienced by travelers from Groups A and B, split into unguided and guided, for scenarios 40%S and 40%N. In the horizontal axis labels, the letter G stands for drivers who are guided, U stands for unguided drivers, S stands for specific information, and N stands for naive information. The time periods listed refer to departure time intervals.
For travelers in Group A, guided travelers in 40%N experience significantly longer mean travel times than others. They are being informed to take the circuitous Third Harbor Tunnel although the Sumner/Callahan Tunnel is faster (despite the incident occurrence). In 40%S, travelers in Group A experience roughly the same mean travel times regardless of whether they are guided or not. 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 in 40%S, travelers who are unguided are hurt somewhat as compared with 40%N 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 guided travelers 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 40%S and 40%N 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 52 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 52: User Benefit for 10%S, 10%N](image)

In 10%N, 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%N 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 10%S and 10%N, guided travelers benefited more as compared to 40%S and 40%N. 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 who comply often diminishes as a greater number of travelers are informed. Travel time results from the 20%S and 20%N scenarios were found to lie in-between the 10% and 40% cases.

Figure 53 shows user optimality results associated with the 70% guided scenarios. In the 70%S scenario, over-reaction does not materialize; overall travel times are reduced as compared to 40%S and 40%N. 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 drivers as compared to unguided drivers.

In 70%N, over-reaction is severe since a high number of travelers have been diverted to the Third Harbor tunnel. Guided group A travelers in 70%N experience increased travel times as compared to previous scenarios. For Group B, guided travelers benefit earlier in the simulation. But as the simulation proceeds and effects of the incident dissipate, guided travelers begin to experience longer travel times than others.
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 travelers and all Group B travelers are up significantly from the 70%N case.

Figure 53: User Benefit for 70%S, 70%N
7.4 Proposed Relationship

Some key findings from this chapter can be summarized in the following two figures. Figure 54 shows the mean travel time experienced by drivers for four different levels of guidance during the time that specific prescriptive information is provided. The percent of guided travelers will be referred to here as the \textit{market penetration rate} (MPR).

![Figure 54: User Benefits as Function of MPR](image)

As the MPR increases, unguided drivers can benefit substantially. An increased MPR has a tendency to spread out congestion between alternate routes as more drivers are diverting from incident locations. Unguided drivers have more of a tendency of pass through incident locations since they are not reacting to the traveler information. This accounts for the large benefits to unguided drivers at a high MPR.

For guided drivers, the story is different. In the absence of mainline queue backups that could affect all drivers, those who are guided tend to have somewhat smaller travel time
benefits as the MPR goes up. At a low MPR, since few drivers are reacting to the information, those who do divert do not encounter much congestion on the alternative routes. At a high MPR, when many drivers respond to information, the congestion on such alternative routes increase.

Figure 55: Benefit Relationship

This discussion is highlighted in Figure 55, based on prescriptive simulation results for drivers in Group B. The travel time benefit is measured against what was experienced by the same group of drivers without the provision of information. The line named "All" is an average of all drivers. At an increased MPR, this line moves closer to the guided line as more of the total drivers are guided.

For this particular set of tests, the mean travel times experienced by unguided and guided drivers occurs at about the 70% MPR. At the 95% MPR, some over-reaction has
occurred as guided drivers begin to experience longer travel times than unguided drivers in absolute terms.

This over-reaction effect does not necessarily need to occur if the information provided is consistent with a good prediction of how drivers will respond to the information in reality. For this prescriptive information analysis, the consistency criteria was not enforced due to assumptions made regarding the scenarios. Results are indicative of changes in the percent of guided drivers when the information strategy provided to the drivers does not change. A more complex prescriptive information analysis is left for further research.

7.5 Prescriptive Information Summary

This chapter compared two types of prescriptive information. One type (naive) gave the same recommendation to all travelers, while the other type (specific) gave recommendations that were specific to particular O-D pairs. At a low ATIS market penetration rate (MPR), naive information was found to reduce mean network travel times to a slightly greater extent. However, it often resulted in drivers choosing non-optimal paths from their point of view. Specific information was far more effective in achieving travel time benefits for all users.

As the MPR increased, the experienced travel times for guided drivers went up slightly as more drivers diverted to use alternate routes. However, travel times experienced by unguided drivers were substantially lower at high MPR values since congestion at the incident location was reduced. This indicates that as the MPR increases, travel time benefits from being equipped with an ATIS system may be lower but mean travel benefits for all travelers should be higher. In other words, a greater use of ATIS should result in an improvement of system performance and benefits for more travelers.
Chapter 8

Conclusion

This thesis contains results from a number of simulation-based case studies using DynaMIT, a dynamic traffic assignment system designed to generate traffic information for travelers in real-time. Tests were conducted using the Central Artery network in Boston with a realistic peak-hour demand pattern. This allowed for many performance measures to be adequately addressed. The three main areas examined were:

- **Demand Estimation**: the ability of DynaMIT to estimate demand patterns in a traffic network, given data from a surveillance system and historical sources, as a function of input quality.

- **Prediction Accuracy**: the accuracy associated with DynaMIT's predictions of anticipated traffic conditions for different levels of traveler demand.

- **Network Performance**: the travel time benefits associated with providing travelers with information generated by DynaMIT in incident conditions.
Additional areas evaluated include the impact of DynaMIT system parameters on performance, benefits as a function of the percent of informed travelers, and differences between various types of real-time information.

8.1 System Performance

The O-D flow estimation process used in DynaMIT has a key advantage that it develops its estimate of traveler demand based on both historical and real-time inputs. This design is intended to allow for greater robustness with respect to input errors. Results obtained from a series of tests indicate that this robustness is indeed high, as estimation errors were usually kept within a range smaller than the magnitude of errors in the inputs. This gives a strong indication that the DynaMIT estimation process can be applied effectively and reliably in real-time applications.

The prediction accuracy of DynaMIT for free-flow network conditions was nearly perfect. For network regions that are congested, DynaMIT's predictive accuracy was slightly lower. Queue dissipation for certain regions, particularly on-ramp sections, was slower than the MITSIM reality. It is probable that further calibration of system models will reduce such errors substantially.

The information generated by DynaMIT was successful in helping travelers when an incident occurred in the network. Drivers equipped to receive ATIS information received route-level travel times in real-time from DynaMIT, and were able to make beneficial travel choices. Congestion near the incident location was reduced significantly, while appreciable increases in congestion for other parts of the network were not observed. Travelers were informed to return to habitual route choices when the incident cleared. Mean network travel times were reduced by 29% or more for some scenarios.
8.2 Research Findings

For demand estimation to be most effective, it is valuable for input reliability to be taken into account through the proper selection of error-covariance matrix values. Inputs that are known to be of high quality can serve as an important stabilizing force for the estimation process. In incident conditions, the amount of real-time information available could be reduced due to fewer sensors being crossed by vehicles per unit time. Thus, the wise placement of sensors and an accurate historical database are both especially helpful when an incident occurs.

DynaMIT system parameters were found to have a significant influence on prediction quality. A more rapid calculation cycle reduces the risk of delay in reporting unexpected incident conditions to travelers. Longer prediction periods improve accuracy since the fraction of unrecorded trips in the simulated vehicle movements is lower. Two or more system iterations are necessary for the generated information to be consistent with actual network conditions. A trade-off analysis indicated that DynaMIT system parameters should ideally be set at fairly moderate values rather than extreme.

An increase in the market penetration rate (MPR), or the percent of drivers able to receive real-time information, generally improved network performance. More travelers are able to divert away from incident locations in the network. Benefits for unguided travelers were found to increase as the MPR went up. The benefits for guided travelers from raising the MPR went down slightly since more drivers were responding to the information. This increased the vehicle flow on alternate routes. In the case of prescriptive information, route recommendations that were specific to O-D pairs are most effective with respect to achieving user benefits for the greatest number of travelers.
8.3 Future Research

The scenarios used for the evaluation of prediction accuracy and network performance take 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 priority for future evaluation work. Other areas for future research related to demand estimation include:

- Additional case studies for other networks,
- An investigation of demand prediction in a closed-loop context,
- Development and testing of methods for error-covariance matrix calibration,
- Strategies to optimally allocate network sensors for real-time demand estimation.

The DynaMIT supply simulator could benefit from the adjustment of model parameters. With additional calibration, it appears possible to significantly reduce the prediction quality errors that were observed from the scenario testing. An upgraded supply component is currently in development for this purpose.

Another priority for future system evaluation involves the development of comprehensive pre-trip traveler behavior models in the MITSIM real world simulator. 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. Behavior model enhancements related to the treatment of route switching behavior should be implemented to improve laboratory results.

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

Additional case studies could be conducted that would further assess levels of DynaMIT accuracy and stochasticity. Other areas of future research include:
• Calibration and validation of models using field data. This presumably will result in enhanced system performance when the DynaMIT system is applied for an actual traffic management center.

• 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.
8.4 Final Comments

Numerous results were presented in this thesis related to the evaluation of DynaMIT, a real-time dynamic traffic assignment system. The evaluation was structured in a rigorous and systematic way. Findings from this research indicate that DynaMIT performed effectively in a simulation laboratory environment. The information generated by DynaMIT was consistent with actual traffic conditions and was highly successful in reducing the travel times and congestion that travelers experience. This is done in a way that does not require adding costly infrastructure or restricting people's travel choices.

This thesis, while comprehensive, has explored only some of the possibilities for system evaluation. Based on the given methodology, case study analysis should be continued by others so that DynaMIT can be most effective for travelers. With additional effort in this direction, DynaMIT will soon be available for field applications in actual transportation networks. This is where the system potential highlighted in this thesis could be realized and translated directly to user benefits.
Bibliography


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