Development of a Dynamic Traffic Assignment System for Short-Term Planning Applications

by

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Abstract

Evaluation of Intelligent Transportation Systems (ITS) at the planning level, as well as various short-term planning projects, require the use of appropriate tools that can capture the dynamic and stochastic interactions between demand and supply. The objective of this thesis is to develop a methodological framework for such applications and implement it in the context of an existing dynamic traffic assignment system, DynaMIT. The methodological framework captures the day-to-day evolution of traffic. Furthermore, it models traveler behavior and network performance, in response to special events and situations such as incidents, weather emergencies, sport events etc. The new planning tool DynaMIT-P, consists of a supply (network performance) simulator, a demand simulator and algorithms that capture their interactions. The supply simulator captures traffic dynamics in terms of evolution and dissipation of queues, spill-backs etc. The demand simulator estimates OD flows that best match current measurements of them in the network, and models travel behavior in terms of route choice, departure time choice and response to information. DynaMIT-P is particularly suited to evaluate Advanced Traffic Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS) at various levels of sophistication. The results of a case study, focusing on the evaluation of alternative designs of Variable Message Signs (VMS) using a network in Irvine, California, illustrate the functionality and potential of the system.

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Chapter 1

Introduction

Traditionally, traffic planners have been addressing the problem of traffic congestion and its mitigation. In order to alleviate traffic congestion, there are numerous choices regarding the enhancement and improvement of an existing transportation system. However, most of the alternatives involve a substantial amount of funding from multiple sources. Needless to say, judicious care has to be employed in selecting a particular alternative or a combination of various alternatives to enhance a particular transportation system. Recently, the emergence of Intelligent Transportation Systems (ITS) places more importance on the management of existing resources to increase the capacity of the system as opposed to new construction. In lieu of the above facts, it is imperative to possess analytical capabilities that would give a sense of the benefits of a particular project, especially ITS related. Thus stems the need for planning tools.

1.1 Background

Ever-increasing congestion, limited financial resources, time constraints and lack of proper tools to forecast the impact of proposed changes to the transportation system have been some of the deterrents to traffic planners. Transportation systems are complex systems involving various stake-holders; thereby making it impossible to isolate the benefits of a possible project without carefully outweighing the negative consequences that may be thrust by this project to other components of the system.

Decisions made by traffic planners usually have a bearing on long-term social, environmental and political consequences. An example of illustrating the above point is to consider the possible long-term effects due to enhancement of the infrastructure, say the addition of a new highway. Such a radical change in the transportation structure will perhaps lead to the establishment of new households and businesses along the highway. Industrial development around the region will be promoted and this may itself have both social and environmental consequences. Typically, these effects are due to the connection between transportation and land use patterns. Therefore planning tools are necessary to perform a thorough analytical analysis to measure the effects of a proposed transportation investment and as in the case above, assess long-term effects.

Recently, the focus of transportation planning has shifted from radical infrastructural changes to improvements of various components inherent to the system. The advent of ITS has provided an exciting breakthrough in this regard. It has been conjectured that developments in Advanced Traveler Information Systems (ATIS) and Advanced Traveler Management Systems (ATMS) can be viable alternatives to reduce congestion. However, it has generally been difficult to predict the benefits of such systems since the outcome of these strategies is highly dependent on traveler behavior and because of the fact that modeling traveler behavior in response to various ATIS/ATMS strategies has not been fully comprehended. It is also worth mentioning that effects due to information usually tend to be short-term and within-day effects, rather than long-term, since information to travelers is provided primarily during non-recurrent congestion conditions. Planning tools that would evaluate the impact of ITS technologies and in particular the impact of traveler information on the transportation system would be invaluable in this context.

In a nutshell, there is indeed a strong motivation to develop planning tools that would address either short-term planning applications, long-term planning applications or both and which could capture analytically the impact of a whole gamut of planning strategies, which may be infrastructural or operational in nature.

1.2 Short-Term Planning Applications

As briefly mentioned in the previous section, planning for transportation applications can address issues that are either long-term or short-term in nature. The focus of this thesis is on short-term planning applications, which assume that long-term behavior is not affected by the changes to the system.

1.2.1 Characteristics

Short-term behavior as the name suggests, refers to traveler behavior in response to events which tend to be of relatively shorter duration. While discussing short-term applications, some of the parameters that one usually addresses for transportation network analysis are assumed to be constant. In particular, it is assumed that the inputs to the short-term models consist of outputs from the long-term behavior. To be more precise, the Origin-Destination flows matrix (OD matrix) is assumed to be fixed, although unknown. Usually, determining the OD matrix constitutes the first three steps of the four-step planning process, namely trip production, trip distribution and modal split. Though there may be minor variations in the actual daily OD matrix, the input OD matrix available must more or less capture the actual combination of trip distribution and trip attractions.

In short-term planning, long term mobility decisions such as residential locations, auto ownership and ATIS/IT ownership are assumed to be fixed. Also assumed constant are long-term factors such as land-use and demographics. It is worth mentioning that any changes to the above factors, will initiate changes in travelers' long-term mobility decisions. Additionally, new business establishments can alter the trip generation and attraction process, thereby modifying the OD matrix.

Based on the above assumptions, one can think of short-term behavior as the response of travelers to changes in the characteristics of the system, given long-term decisions (day-to-day behavior) and it includes behavior of travelers in response to disturbances in the transportation system (within-day behavior). The concept of short-term behavior is expanded in the following chapter.

1.2.2 Examples of Short-Term Planning Applications

Some of the most common examples involving short-term planning applications include:

- Given specific long-term decisions, household and activity patterns and an existing transportation infrastructure, what habitual patterns do travelers currently follow? How is the traffic distributed on the network? Which areas are currently prone to congestion? Such questions can usually be answered with the help of a tool that focuses on short-term behavior and in this case on the day-to-day behavior of travelers.

- Special events such as sports events, political meetings and campaigns are ideal scenarios for the application of short-term planning tools. These events usually tend to either spike the demand on the system or inhibit the supply characteristics of the network or both. Planning tools can be used for the development of strategies for dealing with such events.

- Work zone activity, usually due to infrastructure activity, highway construction, maintenance or utility work tend to disturb the network features. Dealing with traffic issues is an important activity in designing work zone operation. Planning tools can come in handy to evaluate various work zone configurations and timing of activities proposed to mitigate the effects of the activity.

- Closure of lanes for a short duration due to various reasons.

- Operational evaluation of ATMS such as ramp metering, signal coordination and other control systems proposed to enhance the network can be examples of short-term applications. Effects of such control systems can be assessed with the help of short-term planning tools.

- Evaluation of ATIS strategies such as in-vehicle information and VMS information. The benefits from such information are derived from their use in non-recurrent situations, such as incidents, severe weather etc. Predicting the impact of information can be invaluable in the planning context.

- High occupancy vehicle (HOV) and High Occupancy tolls (HOT) are strategies to reduce the number of vehicles on the network. HOV lanes are special lanes earmarked for vehicles with multiple passengers such as car pools, buses etc. HOT lanes refer to HOV facilities that are open to lower-occupancy vehicles upon payment of a toll. As expected, HOV/HOT lanes usually have a better level of service in both of speed and reliability in order to attract usage. HOV/HOT scenarios that planners may wish to test include converting a general lane to a HOV lane, introducing preferential ramp treatments or implementing various HOT pricing strategies.

- Strategies used to mitigate the effects of serious accidents, unusual weather etc, can be studied and evaluated using short-term planning tools.

1.3 Literature Review

This section focuses on existing tools for transportation planning. A brief overview of the functionality of the existing tools is described. Also certain inadequacies of existing tools in dealing with short-term planning situations are presented. These shortcomings highlight the need to develop more sophisticated planning tools, that can handle a variety of situations, especially in the short-term context.

1.3.1 Features of Existing Planning Tools

Traditional planning tools are based on the well established four-step planning process: trip production, trip distribution, modal split and assignment. Trip production or trip generation as the name suggests, forecasts the number of trips that will be made from particular locations. Trip distribution determines where the trips will be destined to. Modal split is concerned with how the trips will be divided among various modes of travel and finally trip assignment predicts the routes that the travelers will take resulting in traffic forecasts for the highway system and ridership forecasts for the transit system.

The history of transportation tools dates back to the 1970's when the UTPS (Urban Transportation Planning System) was developed by the Urban Mass Transportation Administration of the US Department of Transportation. This tool mainly accommodated models to capture the four-step process. The basic idea of UTPS has given rise to a plethora of other tools, which are aimed at capturing either one or more steps of the four-step process. Several variations of the main approach have also been proposed to correct limitations of the initial process. The general framework of the four-step model is shown in Figure 1-1.

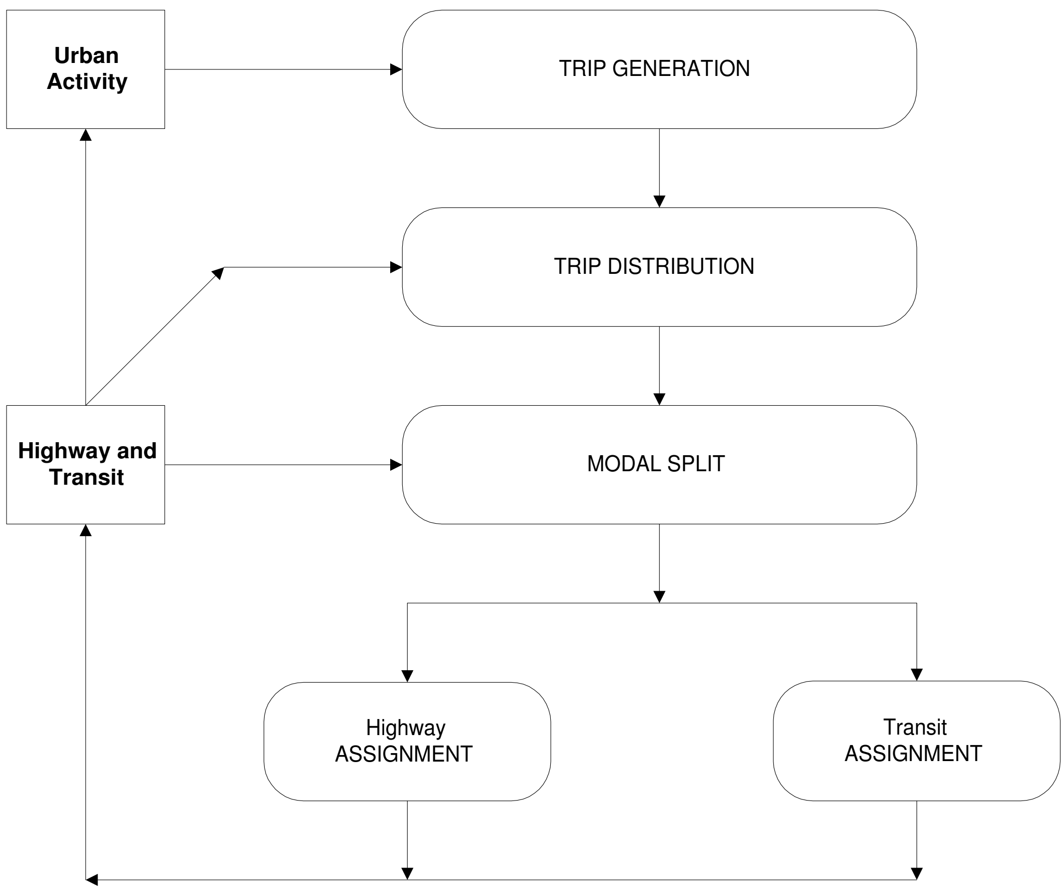

Figure 1-1: Four-step transportation planning process (UTPS).

Tools available to obtain trip productions (including the UTPS) recognize the strong interconnection between transportation and land use patterns. During this step, trip making ability is predicted based on the characteristics of the activity and some measure of transportation service to or from a section of the study area. These models typically employ statistical analysis and specifically regression analysis to relate the number of trips to land use patterns, socio-economic characteristics and activity patters of travelers. To facilitate this, the study area is usually divided into several zones called as TAZ's (Traffic Analysis Zones) and trips productions are computed zone-wise. Recently, GIS tools to perform trip productions have gained significance because of their ability to store and manipulate zonal data easily. Additionally, several new tools which incorporate sophisticated activity models of travelers are available. Trip attractions are similarly determined by these tools through regression analysis.

Gravity models, which postulate that the number of trips between two zones is directly related to the level of activities in each zones and inversely proportional to the separation between the two zones (as a function of an impedance), are primarily used to obtain trip distributions. Thus, trip distributions are determined by the relative attractiveness and accessibility to all possible attraction zones. Most of the tools used to perform trip distributions use variations of the gravity model such as incorporating friction factors (that reflect the effect of travel time on trip distribution) and/or socioeconomic factors (KF Factors). Separate gravity models based on trip purpose are also usually employed.

Modal split analysis has been addressed through discrete choice analysis and travel demand forecasting techniques. Modal split analysis models are usually based on the level of transit in a particular area. For example, there exist different modal split models based on whether the region falls under a non-transit, single-peak transit region or multi-peak transit region.

Examples of planning tools, which perform one or more of these above steps in addition to UTPS are EMME2, TRANSIMS, TRANPLAN, TransCAD, POLYDROM, OCTAM, FSUMTS etc.

The first three steps of the transportation planning process described above and the corresponding tools to address can be considered to fall under the category of long-term planning tools. This is because these steps address travelers' long term decisions and determine the overall level of travel in the network. For instance, based on the location of households and businesses and traffic zones, the first two steps help to establish the long term OD matrix. Modal split analysis can be considered to be sort of the transition analysis between long and short-term planning. This is because this depends not only on the location and the availability of other modes of travel, which is a long term aspect but also depends on short-term changes to the transportation system, that may cause travelers to temporarily resort to transit. An example of this is a severe weather day in which travelers may prefer transit for safety and convenience.

The focus of this thesis is on short-term behavior and it is hence imperative to understand the functionalities of existing short-term planning tools. This can be discussed by considering the fourth step in the transportation planning process, which tries to address the short-term nature of transportation planning. Traffic assignment is the final step in the planning process and it tries to establish routes that individual trips will follow. The objective of this step is to estimate what routes travelers follow and the resulting implication of travelers' decisions on the transportation network. Thus performing traffic assignment is exactly representative of short-term planning, wherein the focus is to establish travelers' habitual behavior and their behavior in response to various temporary events.

Traffic assignment has been the focus of intense research since its origin and the foundation of traffic assignment techniques was established on the seminal paper by Wardrop [54], which illustrated the concept of user and system equilibrium. Under user equilibrium conditions specified by Wardrop, all chosen paths by travelers have the same impedance. Thus under this principle, travelers tend to make decisions to minimize their individual travel times and in the process lead to equilibrium travel choices. System equilibrium on the other hand, although not attainable can be used by traffic planners to establish certain thresholds for comparison. Thus under system equilibrium, an optimization routine is usually employed to minimize system wide travel time. The key difference between the two techniques is that while establishing system equilibrium, it may so happen that some travelers are assigned to paths other than their preferred shortest paths.

In order to establish traffic assignment there are a variety of techniques and the planning tools mentioned in the above paragraphs use methods such as the all-or-nothing assignment, incremental-load assignment, incremental-reload assignment, assignment based on discrete choice models (e.g. the multinomial logit), price-time assignment and the Frank-Wolfe technique. While it is beyond the scope of this thesis to indulge in the specific details of each of the above procedures, it is important to mention that the above assignment techniques are static and do not explicitly model traffic dynamics and traffic demand-supply interactions. This deficiency has led to the development of tools based on Dynamic Traffic Assignment (DTA). The proposed planning tool as part of this research is based on DTA and the literature review of DTA systems is deferred to Chapter 2. As a final point, microscopic traffic simulators such as MITSIM, PARAMICS can also be used to evaluate certain planning strategies.

To summarize the discussion in this section, traditional transportation planning is based on the four-step process and associated tools employ techniques to address each of the four steps. In particular, traffic assignment (the final step of the process) is the step that concerns itself with short-term planning. Further, it was highlighted that there exist a new class of tools that employ dynamic assignment techniques, which will be discussed in Chapter 2.

1.3.2 Limitations of Existing Planning Tools

This main limitations of the above tools for short-term planning applications, especially in the presence of ITS, is their inability to capture the following aspects:

- Traffic Dynamics
- Dynamic Demand-Supply Interactions
- Characteristics of ATIS/ATMS

The ability of capture traffic dynamics and explicitly model congestion build up and dissipation is critical for certain short-term planning applications. To illustrate this further, suppose that the planning strategy being evaluated is a ramp metering strategy. In this case, since the evaluation of the strategy requires explicit modeling of queues and interactions at a detailed level; the usual planning tools which are static are not adequate. Microscopic traffic simulators can be used for this purpose, but they may not be able to capture all the effects over a large area as well as route choices that may result from the strategy. Further, it is to be noted that, ultimately the network performance is due to the individual decisions of travelers and it is necessary to use disaggregate models to capture traveler behavior and also distinguish between users based on their socio-economic characteristics. Such a rich and explicit modeling of traveler behavior is not captured by existing planning tools.

One of the most important reasons for developing a new planning tool is to address ITS in the planning context. It has been stressed before that the focus of transportation planning has shifted towards ITS deployments that will ease traffic congestion. ATIS/ATMS deployments are specially useful only under non-recurrent congestion conditions. Currently there are very few tools which give a sense of the benefits of ITS deployments. IDAS (Intelligent Deployment Analysis Software) is a recent tool that has been developed by FHWA (Federal Highway Authority Association, USA). However, existing tools (including IDAS), which are based on static techniques are not very effective in evaluating ITS strategies.

A brief review of various studies for evaluating ITS and other strategies and the limitations of the techniques used to evaluate them are summarized below:

- **Demand Management Strategies:**

  Common demand management strategies include the use HOV/HOT lanes. The key difficulty in evaluating HOV/HOT lanes is to predict whether travelers will perform mode shifts to justify the infrastructural costs and to assess the network performance impacts.

Several studies have tried to assess the impact of HOV/HOT lane strategies. Based on a queuing model, Dahlgren [28], illustrated that HOV lanes may not always be more effective than general purpose lanes. He argues based on the model that construction of a mixed flow lane is better than constructing either a HOV/HOT lane if the initial delay is not high. Johnston and Ceerla [35], used travel demand forecasting techniques to demonstrate that HOV lanes may not be as effective as transit alternatives. However, the above approaches do not explicitly consider traffic dynamics and it is very difficult to analyze for example a strategy such as converting an already existing general purpose lane into a HOV/HOT lane. Further, a range of pricing strategies cannot be analyzed using these static techniques. Thus there is a need to develop tools that would capture not only rich traveler choice models to estimate the mode shift associated with HOV lanes but that would capture traffic dynamics that will determine the network impacts of such strategies.

- **ATIS Strategies:**

  It has been pretty well established in the literature that provision of information is effective primarily under non-recurrent congestion conditions. Al-Deek and Kanafani [2], modeled the benefits of information in traffic corridors and based on a simulation study reported that travel time savings are significant of the order of 30 percent in a network with two routes. Simulation results in the Santa Monica Freeway corridor in Los Angeles (Gardes and May [29]), showed that in the presence of an accident, information provision can bring about 6.2 percent reduction in travel times.

  However, a few authors have questioned the significance of ATIS benefits (e.g. Arnott et al. [5], Hall [30]). Arnott argues that ATIS may counter-productively lead travelers to congested alternative routes. Hall questions whether the problem on non-recurrent congestion is as significant as claimed. The general conclusion however from available literature is that ATIS can be beneficial but this statement has to be verified, either by observing actual ATIS deployments or by conducting further studies. The need to investigate the effects of ATIS on complicated networks provides the motivation for a new planning tool.

Clearly, to analyze the impact of information either through in-vehicle guidance, VMS messages or other means, it is necessary to explicitly model both traveler behavior and traffic dynamics accurately. Existing planning tools lack one or more of these critical features. Further, with emphasis also being on traffic prediction and provision of predictive information to travelers, the static planning tools are in-equipped to handle such scenarios.

Specifically regarding in-vehicle information, several authors have tried to analyze the impact of in-vehicle information with market penetration (e.g. Jayakrishnan et al. [32], Walting and Van Vuren [52]). However, studies with respect to market penetration effects were based either on surveys or on queuing models and do not effectively capture traffic dynamics and traveler behavior in response to information.

Impacts of VMS messages also typically depends on driver responses to these messages and the resulting traffic conditions. Response behavior of drivers in the presence of a VMS have been addressed by the use of logit models based on SP (Stated Preference) surveys (e.g. Bonsall and Merall, [15]). The main drawback of these surveys is the well known problem with SP surveys (i.e. travelers do not usually respond in an actual situation in a manner concurrent with their survey responses). An example of this, is the study conducted by Chattergee et al. [26]. As reported in that study, only one-fifth of the drivers diverted as opposed to results based on SP surveys in one area but SP results were consistent with observed diversion rates in another location.

Based on the preceding discussion, there is indeed a strong motivation to develop planning tools that will encapsulate traveler behavior, capture traffic dynamics and can be used for a variety of planning applications (including ITS strategies).

1.4 Thesis Objective and Problem Definition

The focus of the thesis is on development of a Dynamic Traffic Assignment tool for short-term planning applications. The critical objective is to model day-to-day evolution of travel demand and network conditions in the context of a DTA system and capture the within-day dynamics in the case of stochastic events. With current emphasis on ATIS/ATMS strategies and ITS investments to improve traffic conditions, the developed planning tool must be capable of addressing these issues and be sensitive to ATIS/ATMS design parameters.

1.5 Thesis Outline

The thesis is organized as follows. Chapter 2 deals with recent advances in planning tools that are based on DTA, rather than the traditional static planning tools. Chapter 3 deals with the framework of the planning system being developed. It discusses in detail the various components of the planning tool and illustrates how day-to-day and within-day behavior of travelers is modeled. An implementation of the planning framework in a DTA system DynaMIT to obtain DynaMIT-P is then discussed in Chapter 4. Chapter 5 presents results obtained using the planning framework applied in a case study related to a network in Orange County, Los Angeles. Directions for further research and possible expansion of this planning tool to suit long-term planning applications are presented in the concluding Chapter 6.

Chapter 2

Dynamic Traffic Assignment Systems for Short-Term Planning Applications

As briefly mentioned in Chapter 1, there exist a new class of tools that are being used for transportation analysis, based on the concept of Dynamic Traffic Assignment (DTA). This chapter focuses on the advantages of using DTA tools for short-term planning analysis. However, the concept of short-term planning is first broadened to provide a better understanding of the issues involved. Following this, certain key requirements that any system must satisfy to be useful for short-term planning applications are presented. The advantages of using DTA systems in this context are then highlighted, followed by a literature review of DTA systems and the model components that DTA systems consist of.

2.1 Elements of Short-Term Planning

Decisions made by travelers vary with regard to the time horizon in which decisions are made. This is depicted in Figure 2-1, which displays long-term, short-term and within-day time horizons.

Long-term mobility decisions include, for example, residential location, auto and

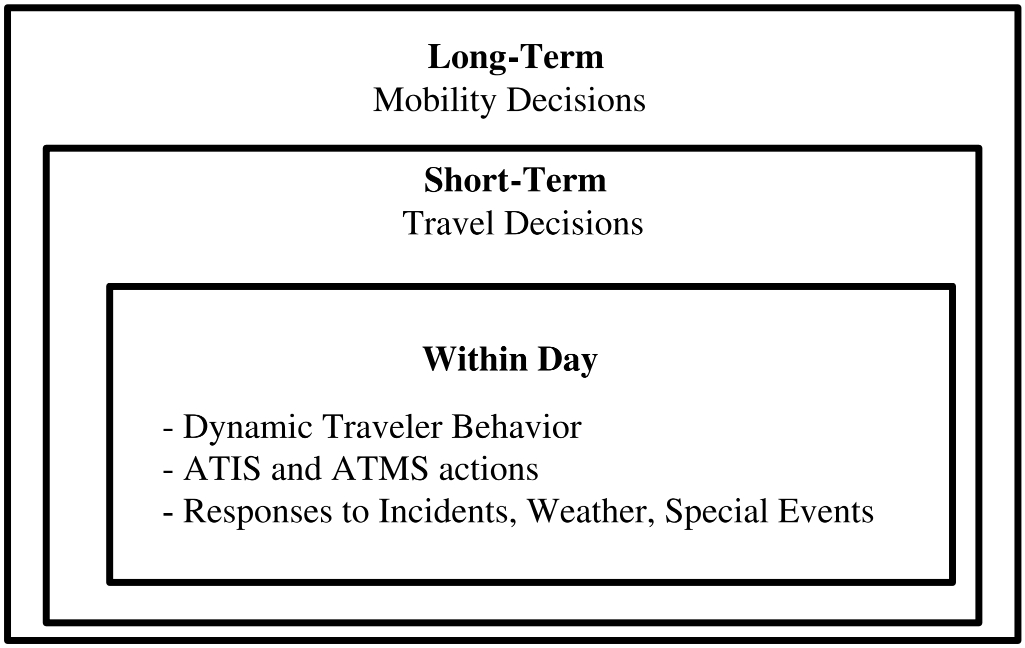

Figure 2-1: Levels of traveler behavior.

ATIS/IT ownership. Adjustments at this level are typically made only after observing conditions over a period of months or years. The outputs from the long-term decisions can be considered as inputs to the short-term behavior.

Short-term travel decisions include choices of departure time, mode, route choices and responses to ATIS products. Adjustments in short-term decisions are sometimes made in response to changes in long-term decisions such as land use, demographics and infrastructural enhancements to the transportation network. An example of this is to consider how auto ownership (a long-term decision), affects mode choice (a short-term decision). Traffic conditions is another important factor for adjustments in short-term behavior (e.g a longer travel time will cause a route-shift). Travelers may make these adjustments every few weeks or days, depending on how quickly traffic conditions in the network are evolving. Thus the short-term behavior can be considered as the behavior that leads to "equilibrium" decisions. The short-term travel behavior is also called the day-to-day behavior model. Short-term travel behavior results in habitual travel patterns, which travelers usually follow on a day-to-day basis.

The deviation of travelers from their habitual paths on a particular day is captured by the within-day decisions that travelers make. There are a multitude of reasons as to why travelers may depart from their habitual patterns. Examples of such events could be special events, accidents on the network, closure of lanes, unusual weather etc. Further, ATMS strategies and ATIS strategies such as traveler information (In-vehicle/VMS) assume significance usually in the face of such unusual situations or disturbances in the network. Responses to these ATIS/ATMS strategies constitute within-day behavior.

To summarize, in short-term planning we need to model both the day-to-day and within-day dynamics of travelers. Thus any tool to address short-term planning applications has to capture the above dimensions of traveler behavior.

2.2 Requirements for Modeling Short-Term Behavior

The main requirements to capture day-to-day and within-day decisions are:

- Realistic Models for Traveler Behavior (Demand)
- Dynamic Network Performance (Supply)
- Demand-Supply Interactions and Dynamics
- Representation of Stochasticity
- Sensitivity to ATIS/ATMS Modeling

2.2.1 Realistic Models for Traveler Behavior (Demand)

The system should capture traveler behavior through travel behavior models that are sensitive to the policy variables of interest, such as capacity, pricing and information systems. These models must also reflect heterogeneity among travelers, both to provide accurate forecasts of network performance and to estimate impacts across different classes of users. This necessitates the fact that the demand simulator has to be microscopic, wherein a population of drivers is generated and each driver has his/her own socio-economic characteristics and each driver makes his/her decisions regarding route choice etc.

The demand models must be able to capture how travelers react to ATIS and ATMS strategies.

2.2.2 Dynamic Network Performance (Supply)

The other important module that a system must possess to be valuable for short-term planning applications is the representation of the performance of the network. This is required because several planning applications usually involve assessing changes in traveler behavior due to changes in the network characteristics. It is thus necessary to simulate the real-life traffic conditions to accurately model day-to-day and within-day behavior of travelers in response to a variety of scenarios. The level of detail required in the representation of the supply depends on the planning scenario of interest. For an alternative involving a major change to the infrastructure, a macroscopic representation such as the average flow on a path may suffice for evaluation. However, for an operational or informational planning alternative, such as ramp metering or signal co-ordination, a finer level of detail is needed in which traffic dynamics such as formation and dissipation of queues, link-specific effects of queuing, spill-backs and speed-flow relationships with variations of traffic conditions along the links are explicitly represented. Thus in order to cope with planning requirements, the system must be able to represent these varying levels of network detail. To satisfy this requirement, typically a mesoscopic traffic simulator is recommended that can capture the necessary complexity without sacrificing computational time.

2.2.3 Demand-Supply Interactions and Dynamics

The level of service of the transportation network is endogenous to the system: travelers make their decisions based on travel times and their decisions, in turn affect the travel times. In planning applications changes in the demand and/or the supply side are made. Therefore the interaction between demand and supply is critical. The demand-supply interactions are particularly important in the day-to-day behavior of travelers. The tools employed for short-term planning applications must be able to replicate the demand-supply interactions and must capture the intermediate states of the system as it tends towards equilibrium. Furthermore, it is necessary to capture the dynamics in the system such as the estimation of time-dependent OD matrices.

2.2.4 Representation of Stochasticity

Stochastic events, such as accidents or poor weather, can have major impacts on the performance of a transportation network on a particular day and influence the within-day behavior of travelers. Therefore the planning system must be able to represent such stochasticity. This is particularly important in the context of ATIS evaluation, in which much of the benefit derives from providing information under atypical travel conditions.

2.2.5 Sensitivity to ATIS/ATMS Modeling

The planning system should be able to evaluate the impact of both ATMS and ATIS. ATIS may have different levels of capabilities and sophistication. For instance, information provided to travelers could be based on current network conditions (instantaneous information) or it could be based on anticipated network conditions (predictive information). This information may be broadcast either through VMS signs on the network or through in-vehicle units in equipped cars. The evaluation of ATIS systems requires a planning tool that can generate both the guidance and the traveler response to guidance. Further, the system must be able to incorporate various design parameters of ATIS strategies such as the frequency with which the information is updated, delay of information and type of information (prescriptive or descriptive).

This concludes the discussion on the various requirements for effective short-term planning analysis. The next section illustrates the advantages that DTA systems can have in addressing these planning issues instead of the static planning tools described in Chapter 1.

2.3 Advantages of Dynamic Traffic Assignment Systems for Short-Term Planning Applications

Traditional planning methods, such as the widely used four-step process are primarily composed of static and deterministic models. These methods treat demand as uniformly distributed in a fixed time interval. Furthermore, due to limitations in analytical models, they treat the network in a simplistic manner and at a very aggregate level. This static representation fails to capture essential features of traffic congestion (such as congestion build-up and dissipation), and therefore cannot predict network performance accurately. Analyzing short-term behavior of travelers however, hinges upon this very ability to capture traffic dynamics (as outlined in the previous section) and hence traditional planning tools are not very effective for short-term planing applications, in the presence of ITS. The shortcomings of the traditional static planning tools are overcome by DTA systems, which capture traffic dynamics in a realistic manner by modeling time varying OD demands, queues and spill-backs.

DTA systems can be categorized into either analytical-based DTA systems or simulation-based DTA systems. Analytical-based DTA tools usually formulate the problem as an optimization problem and employ mathematical techniques to solve it. However, as the problem size grows larger, these tools are computationally cumbersome and are not practical. Furthermore, they are not capable, due to their analytical nature, to capture all the details of the problem. The advent of large and powerful computers has prompted simulation techniques to gain significance. One such promising improvement to traditional planning tools is the use of DTA and simulation to model network performance. The key advantages of using simulation-based DTA tools for planning applications include:

- Simulation-based DTA systems capture the time-dependent interactions between the demand for the network and the supply of the network.

- Simulation-based DTA systems are able to predict the locations and impacts of traffic congestion by modeling the dynamic nature of the network and explicitly capturing critical aspects such as congestion buildup, queues, spill-backs and congestion dissipation.

- Simulation-based DTA systems are able to capture the effects of segment-level operational changes such as ramp meters and traffic lights by incorporating the operation control logic (through its impact on link capacities) into the representation of the supply simulator.

- Simulation-based DTA systems can model effectively various ITS strategies, in particular ATIS/ATMS strategies and the impact of information. This is possible by incorporating rich traveler behavior models to represent individual travel behavior and simulation to model traffic dynamics at the required level of detail.

- Simulation-based DTA systems can represent the travel choices in great detail.

2.4 Literature Review of DTA Systems

Several simulation-based DTA systems exist and they are reviewed in this section. The literature review of is organized as follows:

- Simulation-based DTA systems

- Model components of simulation-based DTA systems

2.4.1 Literature Review of Simulation-Based DTA Systems

Examples of systems that employ DTA techniques in a simulation environment for planning as well as real-time applications are CONTRAM, DynaMIT and DYNASMART-P.

CONTRAM developed by Taylor [50], is a DTA tool employing simulation to model the congestion that occurs during the day and to represent the peaks of congestion as well as off-peak conditions. It is a tool that can model unexpected events such as incidents that reduce network capacity and specific scenarios such as modeling special lanes for buses in certain situations. Additionally it provides fuel consumption and emissions results. To achieve its functionality, CONTRAM divides the planning horizon into time slices used to model the build up and decline of traffic. Vehicles are assigned to their minimum cost routes, taking into account the traffic interactions and delays caused by other vehicles on the network. A trip occurs across several time slices during which traffic demand and network conditions can vary and over-saturated conditions may occur temporarily. Some of the modeling features include different vehicle classes, advanced intersection modeling and dynamic matrix estimation. However, the drawback of this system in the context of the planning scenarios of interest is that it does not explicitly capture individual traveler decisions and does not model travel behavior. These elements are critical for accurate evaluation of the impact of ATIS. Furthermore, the model does not capture the critical day-to-day traveler learning experiences that are relevant for short-term travel decisions.

DynaMIT [44], is a state-of-the-art real-time computer system for traffic estimation, prediction and generation of traveler information and route guidance. DynaMIT supports the operation of ATIS and ATMS at Traffic Management Centers (TMC). The key to DynaMIT's functionality is its detailed network representation, coupled with models of traveler behavior. Through an effective integration of historical databases with real-time inputs from field installations (surveillance data and control logic of traffic signals, ramp meters and toll booths), DynaMIT is designed to efficiently achieve:

- Real time estimation of network conditions.
- Rolling horizon predictions of network conditions in response to alternative traffic control measures and information dissemination strategies.
- Generation of traffic information and route guidance to steer drivers towards

optimal decisions.

A more comprehensive review of DynaMIT is presented in Chapter 4.

DYNASMART-P, (Mahmassani et al. [40]) on the other hand is a planning tool that models the evolution of traffic flows in a network that result from travelers seeking to fulfill a chain of activities at different destinations over a planning horizon. DYNASMART-P is a confluence of two major categories of tools; network assignment tools which are used primarily in conjunction with demand forecasting procedures for strategic (long-term) planning applications and traffic simulation tools, used primarily for traffic operational studies. DYNASMART-P serves to support strategic and operational planning decisions by helping to identify deficiencies, designing and evaluating the impact of alternative course of actions, in the context of the broader set of policy objectives for the study area. It achieves its objective using richer representation of traveler behavior decisions than static assignment models, explicit description of traffic properties and a more complete representation of network elements including signal control strategies. Some of the applications of DYNASMART-P include evaluation of HOV lane pricing schemes, HOT lane assessment (e.g. Abdelghany et al. [28]), signal control strategies, VMS and incident management.

2.4.2 Literature Review of Model Components in DTA Systems

The key components of simulation-based DTA systems are the traveler behavior models(demand), models used to capture supply characteristics of the network and models to capture demand-supply interactions (day-to-day learning models).

Demand Modeling

The models required pertain to mode, departure time and route choice. The standard available models capture day-to-day behavior of travelers. However, with importance being laid on ITS, there have been efforts to enhance traveler behavior models to capture ATIS/ATMS strategies. Examples include route choice models and departure time models in lieu of information to travelers and mode choice models in light of HOV lanes. In addition, the demand component of DTA tools may include an OD estimation module which adjusts the OD flows to reflect the latest traffic counts in the network. Ben-Akiva et al. [14], have proposed an overall framework for a dynamic demand simulator, which can be implemented in simulation-based DTA systems. A literature review of traveler choice models and OD estimation is presented below.

- **Route Choice**: Route choice models are typically based on the multinomial logit structure (MNL), in which the choice is among the set of generated paths for each OD pair. The utility for any path is a function of factors that influence the route choice decision, including socio-economic characteristics of the traveler, travel times, network topology and traveler information. Standard route choice models suffer from the limitations due to the Independence of Irrelevant Alternatives (IIA) property of the multinomial logit models (unobserved factors of the alternatives are uncorrelated). The example in Figure 2-2, which is one of the classical examples of the IIA, illustrates this fact. The three routes depicted in the figure all have the same impedance T. Paths 1 and 2 share a common segment, with impedance T - d, and are distinct for d units. Assuming that route utility is based on distance only, the MNL model will predict a share of one-third for each of the routes irrespective of the value d. MNL is thus consistent with our intuition when the overlap between Paths 1 and 2 is very small. However as the value of d approaches T, we expect that Path 3 would have a share of one-half, while Paths 1 and 2 would each receive one-quarter of the traffic.

  The above limitations lead to the development of the C-Logit route choice model (Cascetta et al. [25]). The C-Logit model adds an adjustment to route utilities based on the amount of overlap with other routes. The model therefore maintains the computational simplicity of the logit form, but produces more intuitive route shares. There are several forms for the C-Logit commonality factor correction, yet there has been a lack of theory or guidance as to which form of

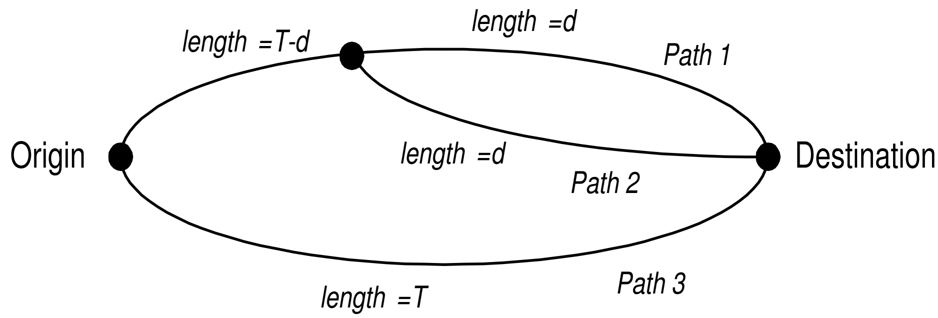

Figure 2-2: Overlapping path problem.

correction is to be used. The Path-size (PS) logit model (Ramming, [47]) represents an effort to incorporate behavior theory in the C-Logit adjustment process. The key to path-size logit is that correction terms are derived from discrete choice theory (Ben-Akiva and Lerman, [11]). For a detailed review of standard route choice models, the reader is referred to Ramming [47].

The route choice models discussed above are standard models that focus primarily on day-to-day behavior and do not take into account ATIS information. However, *en-route choices that travelers make in the presence of information* is a critical aspect regarding traveler response to ATIS and are required for evaluation of within-day dynamics. There have been two main approaches employed to model this behavior of travelers. One of them is based on discrete choice analysis, in which additional factors that are thought to be critical in light of information provision, are incorporated in the standard route choice models. The other approach is based on the concept of bounded rationality, Simon [48]. Mahmassani and Chang [39], modeled response based on bounded rationality concepts. According to bounded rationality concepts, travelers make en-route decision simply based on their satisfaction level. Thus, if the travel time savings on the recommended route exceed a threshold value, travelers will comply with the information. Mahmassani et al. [40], explicitly modeled route-choice behavior using the bounded rationality concept. Other approaches such as Lotan and Koutsopoulos [37], are also proposed that employ fuzzy theory to model route-choice in the presence of information.

Based on discrete choice analysis, Bonsall and Parry [16] and Abdel-Aty et al. [1], tried to enumerate the important factors that travelers consider for performing en-route choice. They suggest that the nature of information (prescriptive or descriptive), extent and the quality of information are important determinants of driver response to information. Mahmassani et al. [27], used logit regression models to analyze compliance behavior of commuters. According to this study, the quality of information was found to be a major factor toward commuters' compliance. Additionally, commuters tend to comply with (in order) predicted information, prevailing information, perturbed information, differential predicted, differential prevailing and lastly random information. The study also revealed that drivers tend to comply when no switching is required and the cost of switching (e.g additional delays) is very critical otherwise. Moreover, it was reported that travelers in general comply more with information that is prescriptive rather than descriptive and travelers who experience high variance in trip times tend to comply more with pre-trip information than en-route information. Mahmassani and Srinivasan [49], discussed in detail inertia and compliance mechanisms in en-route choice. Using multinomial probit models and employing a simulation approach, they showed that inertia to shift from the current path is reduced with increasing congestion and with decreasing information quality errors. Compliance likewise, is increased with larger trip saving and reduced cost of switching and is decreased with inaccurate information or any negative experience recently faced by the traveler.

Specifically regarding in-vehicle systems, Mannering et al. [41], conducted ordered logit and regression analysis based on a Stated Preference (SP) survey to quantify traveler ratings of the importance of in-vehicle system attributes. Travelers' socio-economic characteristics, their habitual travel patterns, congestion levels are determinants of importance ratings. For examples, households with more vehicles per person, people with flexible work hours who perform frequent departure time shifts, younger people, people with low income are more likely to think that in-vehicle information is important. Thus these travelers are more likely to comply with in-vehicle information.

Under VMS information, studies based on SP surveys by Wardman et al. [53], Bonsall and Merall [15] and Peeta et al. [45], emphasize that relative journey times, delay on the current route, age, sex and previous network knowledge as being important factors that govern travelers' route choice decisions. Mc Arthur [42], used behavioral rules employed in PARAMICS-CM and found that diversion is based on whether the savings that travelers perceive lie above a threshold and on the travelers' patience and trust in the system.

- **Departure Time Choice:**

  A critical behavioral response to congestion, incidents or strategies such as pricing, is that travelers adjust their times of departure. Therefore, the departure time choice model is an important aspect. The important traveler characteristic that determines departure time choice is the preferred arrival time of the traveler. However, this attribute is usually measured with significant errors. A key issue of departure time models is defining an acceptable range of departure time intervals considered by an individual. This is an intricate problem, because continuous time is usually discretized and hence the correlation of unobserved effects among alternatives cannot be ignored. Secondly, the perception of the alternatives depends upon travel time. In traditional planning methods, data on this attribute are rarely available and it is conveniently assumed to be constant across the peak period.

  Regarding departure time choice models, typically probabilistic choice models such as the Logit model and generalizations of the Logit model such as Generalized extreme value, Logit kernel probit are employed. However, these Logit models suffer from the IIA property, especially if departure times choices are close together (in which case they may be correlated). Departure time switching models are also common, particularly for ATIS applications, in which the choices are to leave at a habitual departure time or to switch to an earlier or later departure time slot. The appeal of these models is that they circumvent the IIA property, even if the Logit model is used for this purpose. Choice models with latent variables in which the preferred arrival time is treated as a latent variable are also employed. Finally, departure time choice models have been estimated using Revealed and Stated preference survey data (RP and SP). Logit models based on RP surveys were estimated by Cascetta et al. [24]. Models for departure time choice based on a Nested Logit model estimated from SP data were proposed by Antoniou et al. [4].

- **Mode Choice:**

  Planners are often interested in strategies that aim to reduce vehicle miles traveled and/or increase use of transit and non-automated modes. To evaluate the benefits of such strategies it is necessary to make mode choice decisions. The corresponding models are random utility models (logit or nested logit) assessing the choice between car, transit, and other available modes, Ben-Akiva and Lerman [11]. Factors affecting mode choice include purpose of trip, in-vehicle travel time, out-of-vehicle travel time, travel cost, car availability, destination and travelers' socio-economic characteristics.

  Additionally, mode choice needs to be performed to model demand management strategies such as HOV lanes. Typically, logit models which consider relative attributes of the HOV and non-HOV lanes are employed for this purpose.

- **OD Estimation:**

  OD estimation techniques serve the purpose of obtaining a set of OD flows from historical OD matrices and field sensor counts which are desired to be matched. OD estimation techniques are based on either a sequential or a simultaneous approach. Common techniques of OD estimation are the Kalman Filter and the Generalized Least Squares (GLS). Pioneering work in this area has been reported by Cascetta [20], Cascetta et al. [23], Ashok and Ben-Akiva [7]. For a comprehensive literature on OD estimation, the reader is referred to Ashok [6], Brandriss [18] and Balakrishna [8].

Supply Modeling

As mentioned earlier, the supply simulator has to capture traffic dynamics, has to be flexible in order to represent varying levels of detail and it also has to be computationally efficient. Thus simulation approaches as in DynaMIT, DYNASMART-P and CONTRAM employ a mesoscopic supply simulator that use aggregate macroscopic relationships but at the same time have sophisticated models to represent traffic dynamics (e.g. queuing behavior). Further the supply component must be able to interact with the demand component. Details on supply simulation techniques in a DTA system can be found in Ben-Akiva et al. [12].

Further, the supply simulator models have been enhanced to simulate ATMS strategies through their impact on intersection capacities. Tian [51], proposes a model of such a capacity translator, which can be implemented in DTA systems.

Models of Demand-Supply Interactions

These models are particularly critical for establishing the day-to-day learning behavior of travelers. In traditional planning applications, the demand-supply interaction model takes a static or equilibrium approach, where the only state of interest is the fixed point in which supply and demand are perfectly balanced. However, the day-to-day learning approach for demand-supply interaction concerns itself with the sequence of states that occur as the system works towards equilibrium. These intermediate stages are important for evaluation, because the transportation system is often in disequilibrium due to travelers' gradual response to non-standard conditions such as incidents, weather, special events etc.

Horowitz [31], suggested an equilibrium model in which the travel choices on each day are based on weighted averages of measured travel times on previous days. An extension of the above model to specify different weights to different individuals was also proposed.

Mahmassani and Chang [38], proposed a myopic adjustment approach in which driver's travel choices are based on previous days experience. Further, the model incorporates the schedule early or late arrival of a driver on the previous day (including relative weights for early and late arrivals).

Cascetta and Cantarella [21], have developed day-to-day dynamic stochastic assignment models. The behavioral principle is that users make their choices according to pre-trip expectations of travel times. These expectations are a result of experience, memory and learning, and are generally different from actual path costs, which the traveler will not know until the path is complete. The day-to-day model reflects the travelers' learning and forecasting mechanisms: it predicts the travelers' expected travel times for any given day based on his or her expected travel times and experienced travel time in the previous days.

Ben-Akiva et al. [9], proposed a convex combination approach for information integration in day-to-day learning models. According to this approach, the updated estimation of travel time on a path is given as a convex combination of the driver's historical perception of information and information provided by ATIS.

Jha et al. [34], use Bayesian updating techniques to update driver's perception updating from one day to the next in light of experienced travel time and available information. Their approach also tries to capture driver's confidence in travel information by considering both experienced and perceived travel times as random variables with the variances of the travel time distributions representing driver's confidence in information.

2.4.3 Summary of Literature Review

Summarizing the discussion in the previous sections, simulation-based DTA system presents the best technique to evaluate short-term planning applications. A few tools such as DynaSMART-P and CONTRAM have tried to address such applications. Various modeling issues regarding the components of simulation-based DTA systems were discussed. However, the key functionality being addressed in this research is the capability of the planning system to model various ATMS/ATIS strategies with varying levels of sophistication. This is particularly important in the event of information provided to travelers. This information provided to travelers can be of completely contrasting natures. As mentioned earlier, this information could range from instantaneous travel times to predictive travel times. The planning system, as already mentioned must not only incorporate traveler behavior models that capture response to information, but must also be able to generate instantaneous or predictive travel times depending on the scenario being analyzed. Further, it is desired that the planning system be sensitive to various design parameters of ATMS/ATIS. Incorporation of the above features in the context of short-term planning applications and developing a planning tool that encapsulates day-to-day behavior and within-day dynamics (with emphasis on ITS strategies) is critical and is the objective of this research.

2.5 Summary

So far in this thesis, we have described the nature of short-term planning applications and have provided a summary of various static planning tools in Chapter 1. The context of short-term planning applications was further expanded in this chapter and various requirements that have to be met by tools to capture short-term planning were highlighted. The advantages of DTA systems for planning as opposed to traditional static planning tools were presented. Following upon the potential of such DTA systems, a review of existing DTA systems was presented. Further, an in-depth literature review of components in DTA systems pertinent to this study were described with significant focus on ITS applications.

The next chapter presents a detailed framework of the planning tool being developed and describes how day-to-day and within-day dynamics (with ITS emphasis) can be modeled using a DTA system.

Chapter 3

Framework of the Planning Tool

This chapter develops a framework to address short-term planning applications. The framework illustrates the mechanism of establishing the habitual behavior and provides the methodology to capture various scenarios, especially ITS related. The framework described can be implemented in a simulation-based DTA system to result in a planning tool for short-term applications.

3.1 System Framework of the Planning Tool

Based on the levels of traveler behavior outlined in Chapter 2, the conceptual overall system framework of the planning tool is presented in Figure 3-1.

The inputs to the system are the best available OD flows and the most recent counts about flows in the network. These OD flows reflect long-term factors such as residential locations, ATIS/IT characteristics and auto ownership. Land use factors such as locations of activities (businesses, schools etc) and demographics are assumed to be constant during the analysis. Further, actual field sensor counts are used to update the available OD flows to flows best reflecting the current measurements. The outputs from the system are the performance of the transportation and information systems, which can be translated into consumption of resources and benefits.

The first stage of the model is the day-to-day behavior of travelers. This behavior tries to establish the network conditions resulting from travelers' habitual decisions.

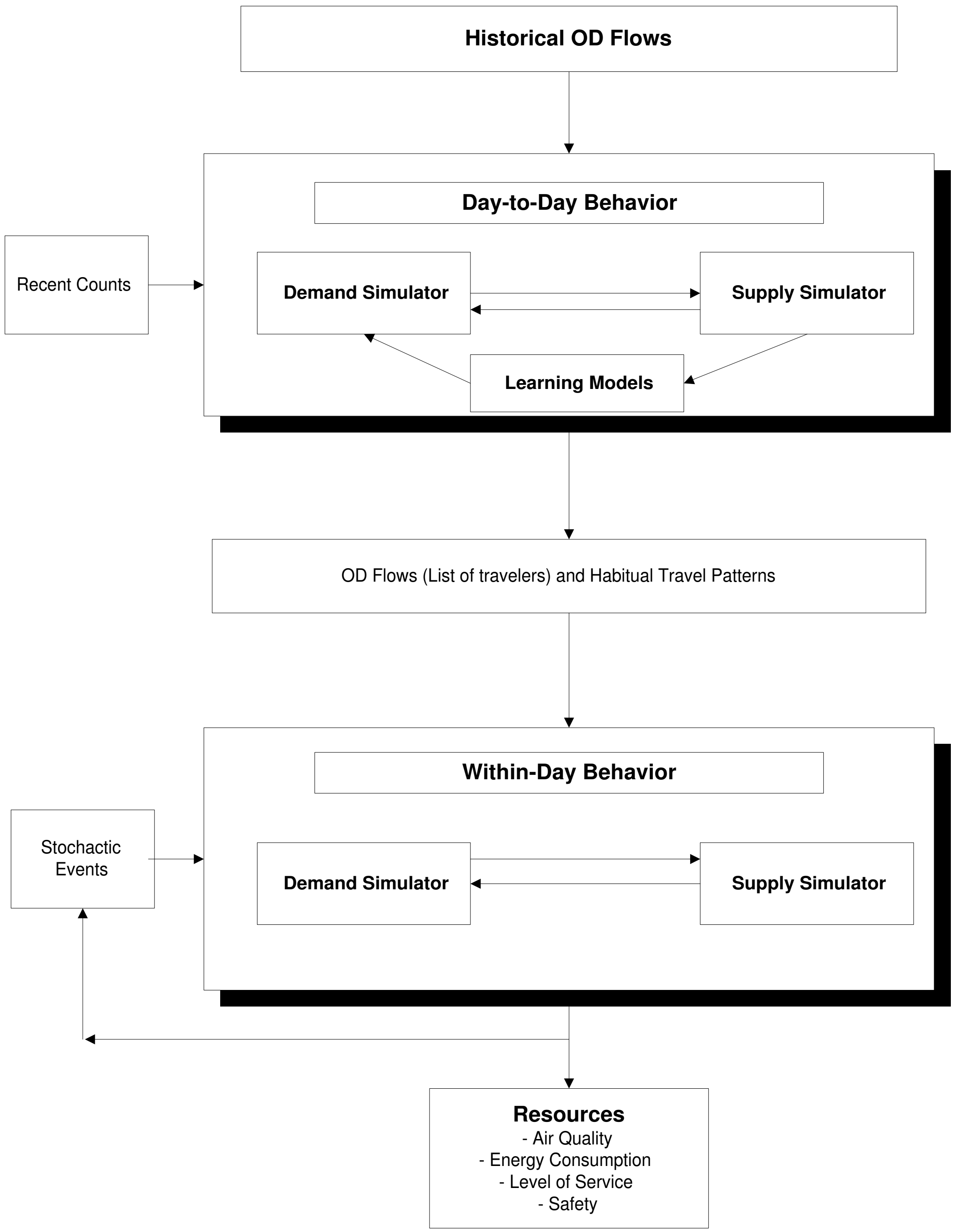

Figure 3-1: System framework of the planning tool.

It establishes the network conditions that would be fairly typical of a normal day, in the absence of special events, accidents, severe weather conditions etc. The model depicted in the figure constitutes three main components for the day-to-day behavior analysis, namely the demand simulator, the supply simulator and the learning models. The demand simulator predicts the decisions regarding destination, departure time and mode/route choice for each of the travelers. Further, the demand simulator includes OD estimation capabilities. The resulting actual travelers with their trip characteristics are then loaded onto the supply simulator, which results in a new level of service. Learning models are utilized to perform adjustments to the habitual travel characteristics from day-to-day, based on travelers' experienced versus realized travel times. The outputs from the day-to-day models are the habitual travel patterns. Specifically, the outputs are a set of time-interval based link travel times referred to as the *Equilibrium travel times* and the *Planning OD matrix* that best describes the observed sensor counts.

The habitual travel patterns are then the inputs to the within-day behavior models. The within-day dynamics is the next stage of the planning tool and it captures the network state that would result in the wake of unusual events that disturb the travelers' day-to-day equilibrium and measures employed to manage traffic in such situations. Stochastic events are also input into the within-day models to represent atypical conditions that might be present (e.g. poor weather or incidents). Any particular network characteristics or information characteristics for the scenario of interest may also be reflected in the inputs as modifications to the baseline scenario. The demand-supply interaction is then performed iteratively to obtain consistency between the two components. Further, one may want to sample stochastic events according to their frequency to get an idea of the performance of the network. This mechanism is indicated by the loop in Figure 3-1. The output from the short-term models is the performance of the transportation and information systems, in the presence of accidents, special events etc., as reflected by resource consumption and benefits.

3.2 Components of the Planning Tool

In order to achieve the functionalities described above, the main components required by the planning tool are:

1. **Demand Simulator:** The function of the demand simulator is to estimate the most up-to-date OD matrix and subsequently generate a population of travelers. Based on the available demographic data, the demand simulator assigns each traveler with socio-economic characteristics such as age, purpose of trip, value of time etc. In addition, the demand simulator contains the following models:

    - *OD Estimation Algorithm:* This algorithm updates the OD matrices to match the field sensor counts. This algorithm is required primarily for establishing the day-to-day behavior of travelers.
    - *Route Choice Models:* Route choice models are of three types namely habitual route choice models (for day-to-day behavior) and en-route choice models (for within-day dynamics). The habitual route choice model assigns travelers to paths based on their perceived travel times. En-route choice models represent traveler compliance in the case of prescriptive information and capture en-route decisions in the case of descriptive information.
    - *Departure Time Choice Models:* These models assign departure times to travelers and model shifts in departure time of travelers in response to information.
    - *Mode Choice Models:* These models predict the mode choice for the traveler, especially in the case of within-day behavior such as response to HOV lane strategies or special events.

2. **Supply Simulator:**

    The supply simulator has an input the list of travelers with their complete characteristics from the demand component including travel behavior and simulates their movement in the network in order to evaluate network performance and the level-of-service in the network. The supply simulator captures traffic dynamics and models the formation and dissipation of congestion (and queues) in the network. The supply simulator also models the ATMS system in place or under evaluation.

3. **Learning Models:**

   As described in Figure 3-1, the learning models capture demand-supply interactions. These models update the perceived travel time of travelers based on their trip experiences.

3.3 Modeling Day-To-Day Behavior

The procedure to establish the basic equilibrium conditions in the network through modeling day-to-day behavior is outlined in Figure 3-2.

1. Inputs: The main inputs to the process are

- *Historical OD Matrices:* The historical OD matrices are derived from long-term planning analysis. However, usually planning OD matrices are static, but for the purposes of the model discussed here, the estimated OD matrix is dynamic. For accurate replication of actual traffic conditions, it is incumbent that the input OD matrix adequately captures different OD flows during the morning and the evening peaks and changes in OD Flow to reflect peak periods etc.

- *Socio-economic Characteristics of Travelers:* The socio-economic information is required to assign the travelers with various characteristics, that are used in modeling traveler behavior.

- *Historical Travel Times:* Historical travel times, if available are the first estimate of the habitual travel times. However, unavailability of this data will not be critical since free flow travel times can be assumed otherwise.

- *Field Sensor Counts:* Field sensor counts are important inputs to the planning process and are used for updating the original (seed) OD matrix. Field sensor

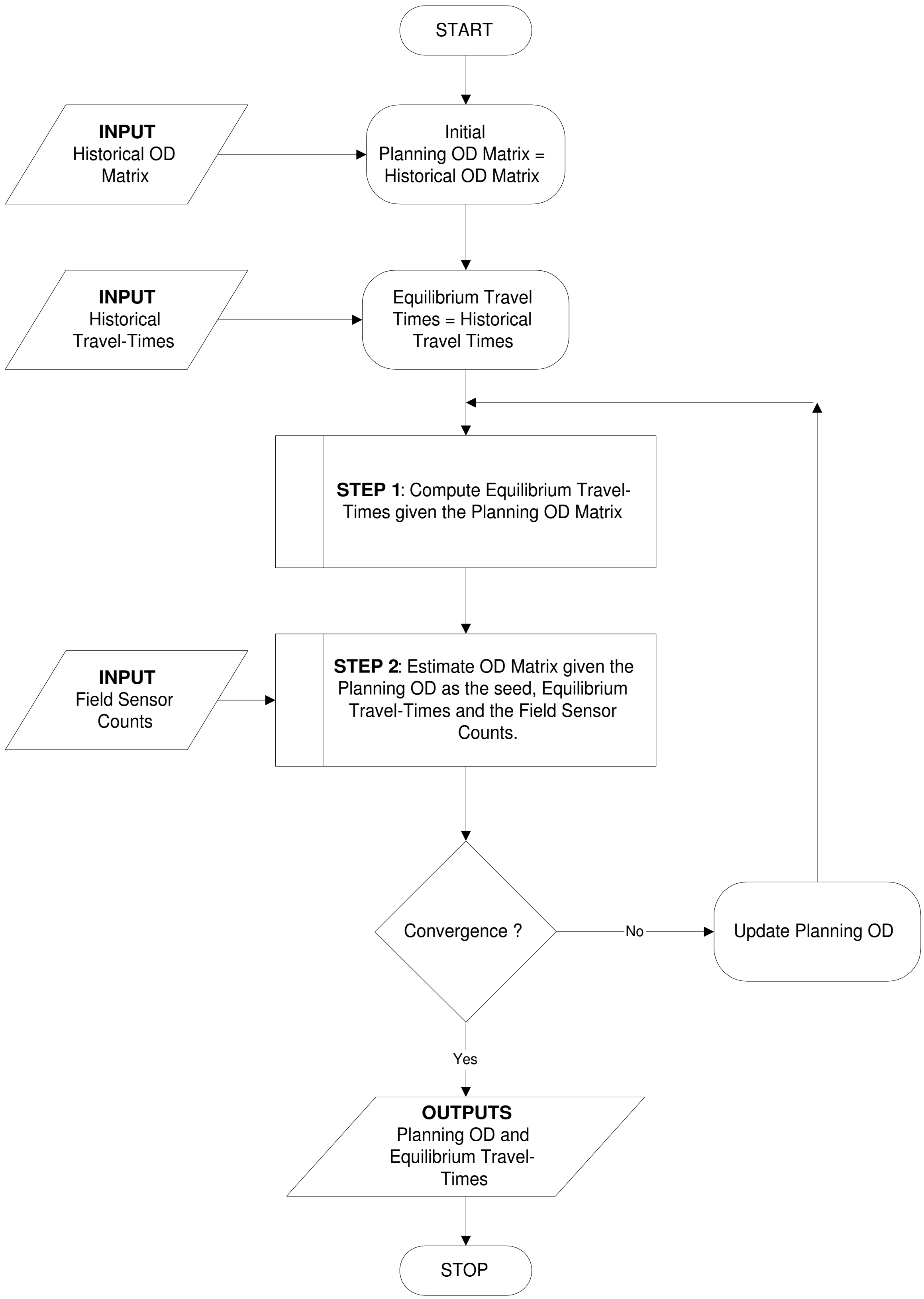

Figure 3-2: Modeling day-to-day behavior.

counts again must be time interval based to capture varying traffic volumes by day. The availability of a good set of sensor data assumes greater significance in the absence of accurate historical OD matrices.

2. Outputs: The outputs from the day-to-day behavior models are

- *Equilibrium Travel Times:* These are a set of time-interval based link travel times representing equilibrium conditions.

- *Planning OD matrix:* These matrices result after updating the historical OD matrices to match the field sensor counts and they reflect the current load on the network.

3. The Process: The process of establishing the day-to-day behavior is iterative in nature. The historical OD matrices and the corresponding set of travel times are used as the starting values of the planning OD matrices and the equilibrium travel times respectively. This is captured by the first two steps in Figure 3-2. The next important step is the computation of the equilibrium travel times for the current planning OD (which during the first iteration is the historical matrix). This computation, labeled as Step 1 in the flowchart, tries to establish the habitual behavior of travelers, given the current planning OD. In other words, assuming that the planning OD reflects the actual load on the network, this procedure arrives at an equilibrium between the demand and the supply components of the system and establishes travelers' choices which include route, mode and departure time choice. The method to obtain the equilibrium travel times is explained in greater detail in Section 3.3.1.

The next step, is to update the OD matrix to match the observed sensor counts, given the equilibrium travel times so far. Hence during Step 2 in the flowchart, OD estimation is performed based on available sensor counts, the current estimate of the planning OD matrix and the equilibrium travel times recently computed in Step 1. Specifically, these equilibrium travel times are necessary, since these affect traveler's route choice decisions, which in turn have a significant bearing on the simulated sensor counts. Details of this procedure are outlined in Section 3.3.2.

It is important to understand the need for several iterations of steps 1 and 2, in the above methodology. The equilibrium travel times are computed assuming an OD matrix (the planning OD) in Step 1, but this matrix is updated as a result of Step 2. Therefore the set of equilibrium travel times is inconsistent with the estimated OD matrix and hence a fresh computation of these times has to be performed. Further Step 2 has to be performed again since the travel times have changed again. In short, the current problem is a fixed point problem and thus repeated iterations are necessary to establish the equilibrium conditions. The convergence criterion usually depends on the available data and should be based on quantities that are exogenous to the system. For example the convergence criterion could be based on the difference between the simulated sensor counts and the field sensor counts. Further, if additional data such as speeds or occupancies is available, it could be incorporated.

If the convergence criterion is not met, the planning OD matrix is updated based on the estimated OD matrix just computed. There are several ways that one could perform such an update, based on the judgment of the quality of data available. Usually, a linear combination of the previous planning OD and the latest estimated OD obtained from Step 2 can be performed. Further, the weights can be varied so that the latest estimates are closer to the actual value.

Finally on convergence, the planning OD accurately reflects the actual loads on the network and the equilibrium travel times reflect the current performance and level-of-service attributes of the network, resulting from travelers' habitual choices. The following sections illustrate in greater detail steps 1 and 2 of the overall process described in Figure 3-2.

3.3.1 Equilibrium Travel Times Computation

This section focuses on Step 1 (in Figure 3-2) during the process of establishing the day-to-day behavior. Figure 3-3 outlines the procedure used to compute a set of equilibrium travel times, given an input planning OD.

As is evident from Figure 3-3, the process to compute the equilibrium travel times is an iterative one, involving multiple demand-supply interactions which are linked

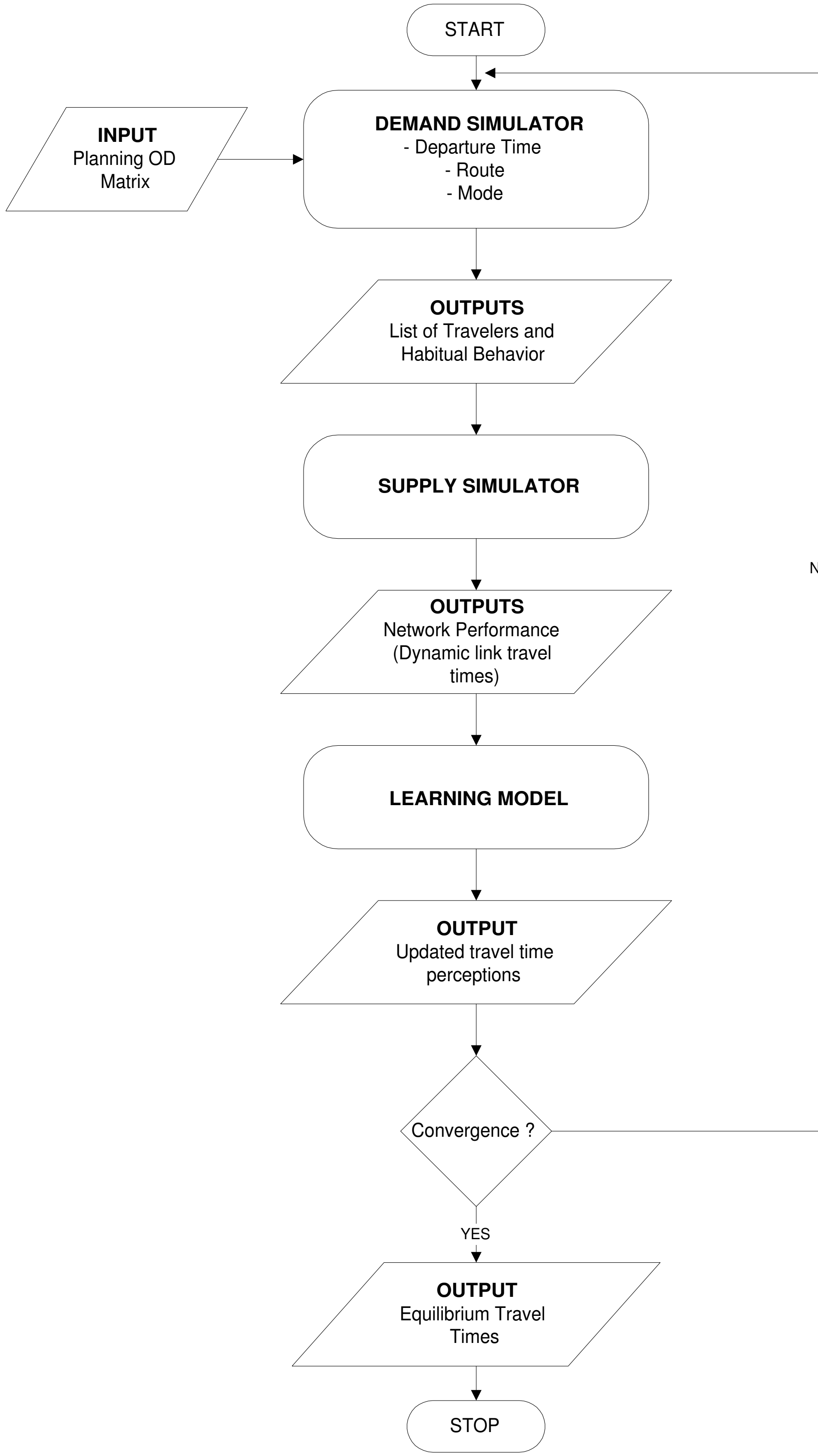

Figure 3-3: Computation of equilibrium travel times (Step 1).

together by the learning models.

The first step in the process, is to obtain the list of travelers that will be used in the supply simulator. This process of disaggregating the input planning OD matrix and generating a set of actual travelers is performed by the demand simulator. The input OD flows are disaggregated into individual travelers who are assigned socio-economic characteristics such as trip purpose, information source and value of time. Further departure time, mode choice and route choices for the travelers are performed to provide the travelers with habitual travel behavior. It is critical to note that travel times used as explanatory variables by the various travel behavior models are based on the previous best estimate of the equilibrium travel times. For the first iteration in Figure 3-2 the best estimate of equilibrium travel times is the input historical travel times. In the absence of historical travel times, free flow travel time estimates may be assumed. However, several iterations may be required to establish equilibrium conditions, for a given OD matrix.

Once travelers have been disaggregated and supplied with habitual paths, the list of actual travelers is loaded onto the supply simulator which models the movement of the vehicles in the network for the planning horizon. The supply produces level of service characteristics of the performance of the network such as link-travel times, speeds, queues, densities etc. The results from the run of the supply simulator can be conceptually thought of network conditions resulting from travelers' behavior on a particular day. Using the same analogy, the first iteration in this process of computing the equilibrium travel times, may be thought as the first day during which travelers base their choices on their previous best estimate of link travel times (the historical travel times). Travelers' perceptions of travel times will change based on their experienced vis-a-vis expected travel times. Based on the level of service characteristics on the network, travelers will make adjustments to their choices. This is captured by the learning models, which model travelers' learning process. Thus, assuming that the similar conditions hold the next day, travelers will make decisions based on their new perceptions of travel times. These perceptions may be altered based on their experiences on the second day and so on. The equilibrium travel times are established by this iterative procedure, until the travelers' expected travel times (i.e the previous estimate of the equilibrium travel times) match their experienced travel times (generated by the supply simulator). This may take several days (or several iterations in Figure 3-3). At the end of each day (or every iteration), the equilibrium travel times are updated to reflect travelers' latest experience and expectations (from the supply simulator). It is also obvious from the above description as to why this behavior of travelers is referred to as the day-to-day behavior.

The convergence criterion follows naturally from the description above and is based on the similarity between the previous equilibrium travel times and the latest travel times obtained from the supply simulator. If the convergence criterion is satisfied, a set of equilibrium travel times has been formed for the assumed planning OD. Otherwise further demand-supply and learning model iterations are performed after updating the equilibrium travel times.

The next step, after computing the equilibrium travel times is Step 2, involves updating the planning OD matrix to reflect the latest observation of traffic loads.

3.3.2 OD Estimation

The aim of this step is to update the planning OD to reflect the field sensor counts. Typically, the inputs to the OD estimation problem include a seed OD matrix, recent observation of link counts and an assignment matrix which maps OD flows to sensor counts (Ashok [6]). In this framework, the seed OD matrix is the best estimate of the planning OD, the historical travel times are the computed equilibrium travel times from Step 1. The assignment matrix, consists of the fraction of every OD pair has been counted on each sensor by time period. The assignment matrix is usually not available and has to be generated internally through the supply simulator. Hence the problem of estimating an OD matrix is a fixed point problem. The solution is an iterative process between two components, the OD estimation algorithm and the supply simulator, linked by the assignment matrix. The process involving these iterations is depicted in Figure 3-4.

A process of OD estimation and demand disaggregation is the first step in the

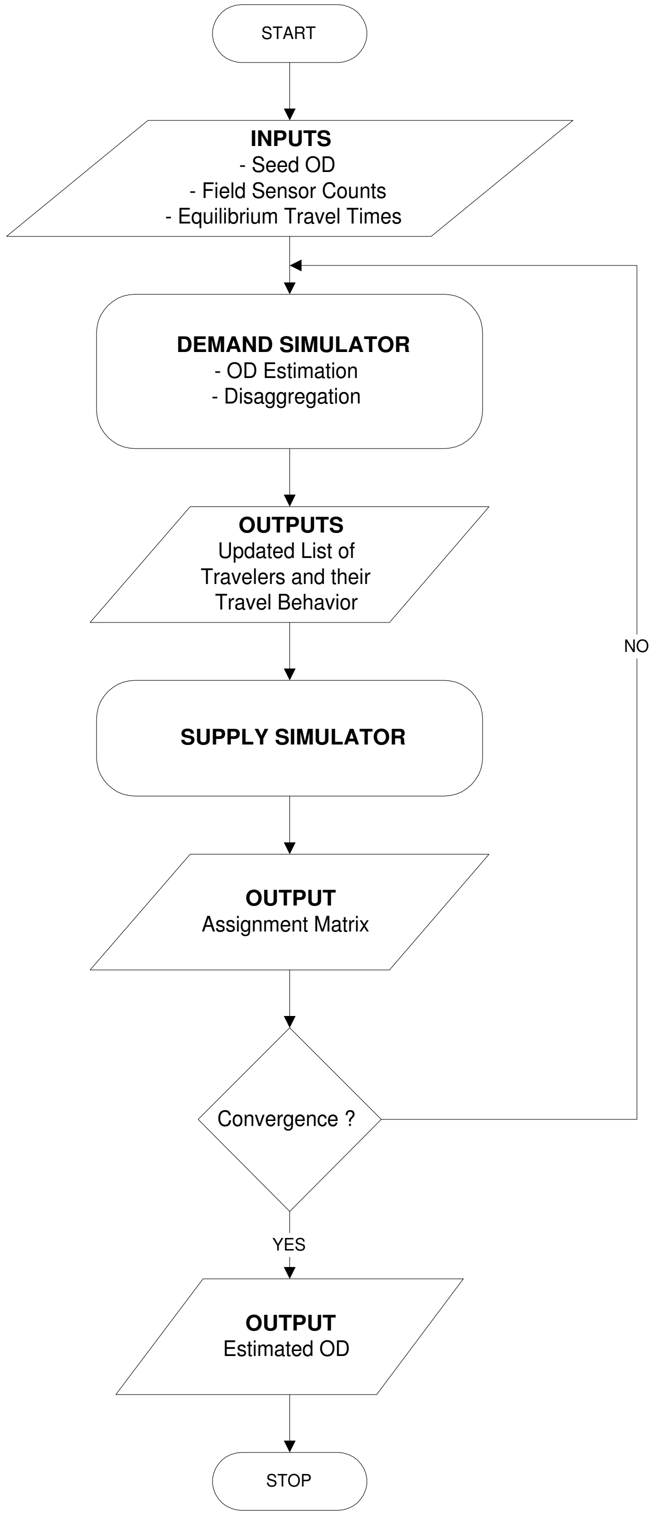

Figure 3-4: Estimation of the planning OD (Step 2).

process. During the first iteration of the current loop, there is no assignment matrix available and hence no OD estimation is performed; thereby the estimatedOD is equal to the planning OD. In subsequent iterations, an assignment matrix will be available and an estimated OD is obtained using the OD estimation algorithm. The estimated OD is disaggregated to create the list of travelers, as described in the previous section.

Once an estimated OD is available, the list of travelers loaded into the supply has to be modified to reflect the new matrix. Therefore additional vehicles may have to be generated or some vehicles may have to be removed. Further, new packets are assigned paths according to the travel behavior models and the equilibrium travel times. The new list of travelers is then loaded into the supply simulator. The output from the supply simulator usually contains information regarding vehicles that passed through a particular sensor and an associated time-stamp. Based on this information, a time-dependent assignment matrix is generated.

Iterations of the above steps may be necessary, since the assignment matrix is internally generated and depends on the OD matrix assumed initially. After each iteration, the convergence criterion is examined. The convergence to be examined ideally in this case is the convergence of the assignment matrix. However, successive OD matrix estimates may also be used for this purpose.

At the end of this procedure (Step 2) we have a set of equilibrium travel times computed from Step 1 and the final estimated OD obtained as a result of Step 2. The planning OD is updated based on the discussion earlier and further iterations of Steps 1 and 2 are repeated until the overall convergence criterion is satisfied, in accordance with Figure 3-2.

3.4 Modeling Within-Day Behavior

This section focuses on modeling the within-day dynamics. The within-day behavior is modeled only after the base-case or the day-to-day behavior has been established. It is assumed that the habitual patters of travelers are not affected greatly by travelers' within-day decisions. For a particular situation (scenario) the within-day behavior is established using the following inputs:

- Planning OD matrix (from the day-to-day analysis)
- Equilibrium travel times (from the day-to-day analysis)
- Stochastic events which form the basis of the scenario (sampled from a database)
- Characteristics of the ATIS/ATMS strategy being evaluated etc.

Within-day behavior is analyzed by simply performing iterations between the demand and the supply components of the system in response to the stochastic events/special events. Further details of using the within-day model is discussed in the following sections.

3.5 Applications of the Planning Framework

Typically, transportation short-term planning concerns itself with evaluating the existing conditions in the network and the conditions in the presence of special events or disturbing events. Further, evaluating the impact of proposed strategies such as ATIS, ATMS and demand management strategies is another important aspect of transportation planning. In typical applications, the planning framework can be applied for the analysis of the base-case and scenarios which include the changes to the system to be evaluated.

3.5.1 Base-Case

This analysis tries to capture the existing conditions of the network and tries to establish travelers' habitual decisions. The base-case is evaluated using the planning framework primarily by the use of the day-to-day behavior model. The use of the day-to-day model captures the network conditions on "standard" days.

However, there are several days that are "non-standard" and occur less frequently such as a major sport day or a holiday. Analyzing the network conditions under such circumstances may also be a part of the base-case analysis. However, on these days travelers will differ from their habitual paths and hence their analysis requires the within-day framework. The analysis of such events may require changes both on the demand and the supply side. Certain links may have to be blocked in the network due to parades, police patrol etc. The OD matrix has to be spiked up to reflect the corresponding demand patterns. If actual field counts from similar events are available, the OD estimation algorithm could be used to update the planning OD matrix to match the observed counts. Multi-modal strategies, such as the shift to transit during such special events can be captured through the mode choice models. The performance of the system in the base-case is the weighted average of its performance under normal conditions and special events.

3.5.2 Scenarios

The scenarios to be analyzed can be classified into two broad categories: *Infrastructure-based* scenarios and *Traffic Management-based* scenarios. Especially, traffic management scenarios may include several ATIS/ATMS elements.

- Infrastructure-based scenarios include assessment of network conditions under situations such as lane closures. These are the traditional planning scenarios, which involve changes primarily at the network level. Work-zone management is a typical example of such a scenario.

- Traffic management-based scenarios fall under the techniques of managing the existing traffic conditions without the addition of major infrastructure. Traffic management scenarios for example, consist of evaluating network impacts due to converting a normal lane into HOV/HOT lane. Traffic management scenarios also consist of evaluating the network performance as a result of traveler behavior under ATIS/ATMS strategies. Further, ATIS scenarios modeled in this planning framework are in-vehicle or VMS information and they could be based either on instantaneous or predictive information.

Furthermore, since ATIS and traffic management related strategies are important during non-recurrent congestion events, a combination of various scenarios can occur, such as evaluating the effect of a VMS message due a lane closure resulting from an accident.

It is however critical to note that based on the planning framework outlined and based on the application, certain scenarios can be analyzed using the day-to-day behavior model, whereas some scenarios place more emphasis on the within-day dynamics component for analysis. The following sections illustrate the application of the planning framework to evaluate various scenarios in more detail:

1. Infrastructure-Based Scenarios

Infrastructure-based scenarios cause changes to either the supply characteristics, the demand characteristics or both. These scenarios can be evaluated using the day-to-day behavior model. The effects of these scenarios can be captured by updating the supply characteristics or the demand characteristics (through the inputs) and evaluating the network performance under the modified inputs. Additional demand/supply iterations may be required to capture travelers' adjustment to the infrastructure change.

A typical example is lane closure and its effects for a temporary period (e.g construction). In this case, the capacity of the corresponding segment/link is reduced to account for the lane closure. The habitual list of travelers with their habitual routes (obtained from the base-case) are then loaded into the supply and the effects of the network under this lane closure are measured.

Another example could be the case of work-zone management. In this case, it is typically required to analyze the state of the network under various work-zone configurations. Again, appropriate reductions in capacities of the corresponding segments are performed on the supply side. No changes are required on the demand side. In this case, demand-supply interactions through the learning models may be required since travelers may change their travel patterns based on their knowledge of the work-zone in the following days.

2. Traffic Management-Based Scenarios

Various traffic management scenarios include demand-management strategies such as HOV/HOT lanes and ITS strategies such as ATMS/ATIS deployments.

A. HOV Scenarios

The traffic management scenarios to be addressed using this planning tool are demand management strategies involving HOV lanes as discussed in Chapter 1. Further, these strategies can include assessing the impacts of currently functioning HOV lanes or assessing the impacts of a new HOV lane construction (e.g. converting a normal flow lane into an HOV lane).

To evaluate these strategies appropriate models and representation are required both on the supply side and the demand side. On the supply side, changes in the network are required to represent the HOV lanes. Changes in the demand side may however depend on the scenario being analyzed. For instance, the mode choice model is critical in the case of the scenario involving converting a normal flow lane into an HOV lane, but is not as critical if the impact of existing HOV lanes is being analyzed. In the latter case, instead of using behavioral disaggregate models of mode (HOV) choice, a separate HOV matrix may be estimated (at the aggregate level), using data collected by sensors on HOV lanes. The above observations will be made clear during the discussion of the implementation of HOV lane scenarios in Chapter 4. It is important to note that the day-to-day model is required for the analysis of HOV lane strategies because travelers will make changes to their travel choices in the short-term as they experience the network conditions as a result of the HOV lane.

B. ATMS Scenarios

ATMS strategies are modeled in the supply simulator through their impact on link capacities. Based on the ATMS strategy, this is achieved by dynamically updating the capacities of various segments/links in the supply simulator. Modeling the capacities according to various ATMS strategies (e.g adaptive traffic control system) is beyond the scope of this thesis and has been dealt with by Tian, [51].

The day-to-day model is required because travelers' habitual decisions (for e.g. route choice) may be influenced by the ATMS system in place. However, sometimes we may want to analyze the performance of an ATMS strategy on a special event day. In this case, we require the within-day analysis framework. Thus, in order to evaluate ATMS, we may require day-to-day analysis or within-day analysis depending on the application.

C. ATIS Scenarios

ATIS strategies are typically employed due to various stochastic events (such as incidents) and in order to evaluate them, the within-day dynamics component is critical. To evaluate such strategies, the planning tool should be capable of handling ATIS at various levels of sophistication. For example, an ATIS may provide instantaneous information or it may provide predicted information. Further, the tool must incorporate design parameters such as the frequency updating of the information etc. The method to both generate instantaneous/predictive travel times and also use it to evaluate the network performance is illustrated below:

ATIS with Instantaneous Information

Figure 3-5 represents the procedure to model an ATIS system with instantaneous travel times. The frequency with which the information is updated is a design parameter and is an input.

The planning OD matrix is disaggregated to produce a list of travelers. Based on the information available about the percentage of unguided and guided travelers, the list of travelers is divided into two driver classes: informed and uninformed drivers. The habitual paths of both the classes of drivers' is obtained by the standard route choice model using the equilibrium travel times. Uninformed travelers are loaded into the supply with the habitual paths and do not make en-route decisions unless they encounter a VMS message. Informed vehicles on the other hand may change their routes dynamically based on the both

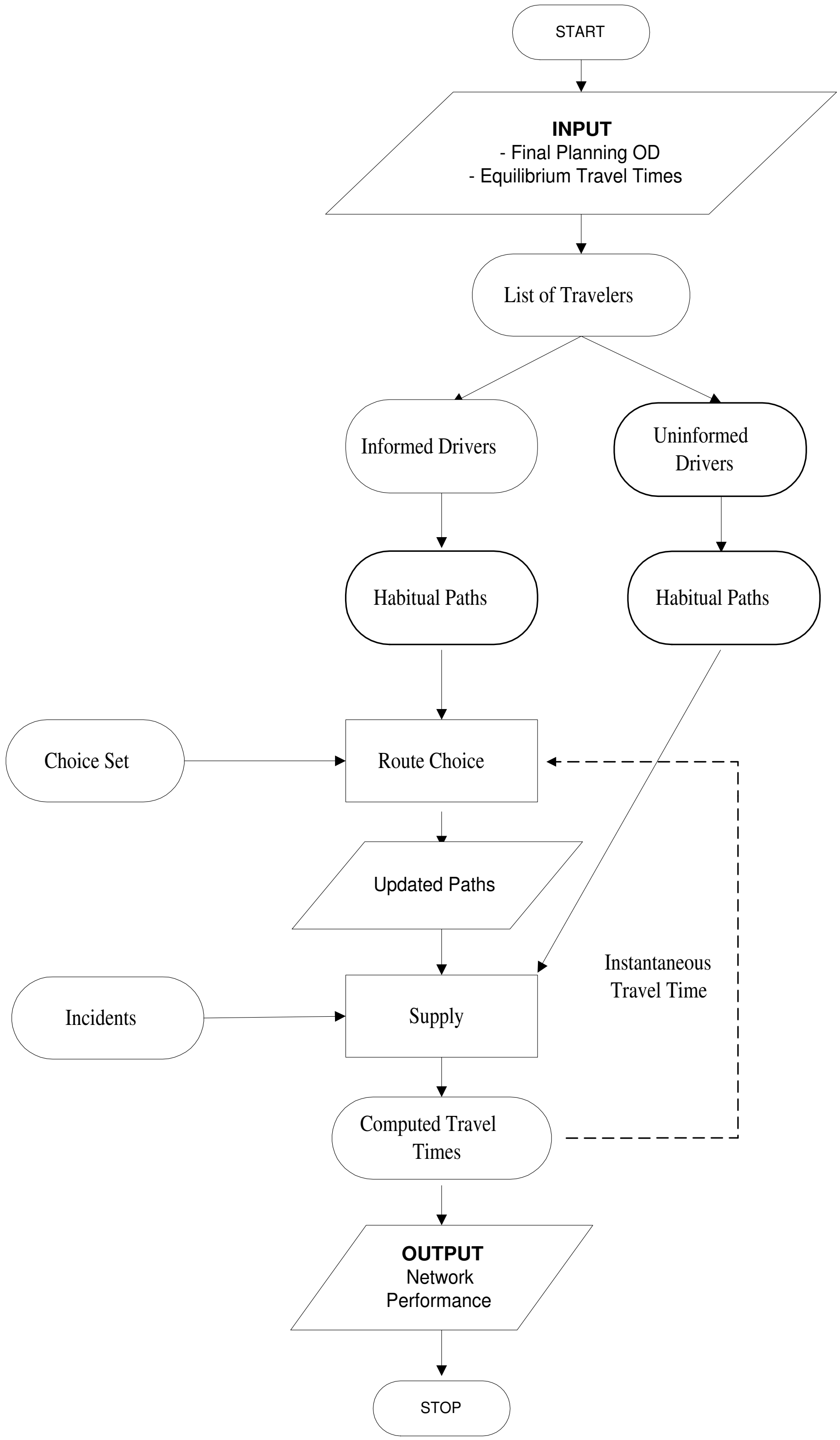

Figure 3-5: Modeling instantaneous ATIS scenarios.

in-vehicle and VMS information.

The instantaneous information is obtained by aggregating travel time information from the supply, after every information-update period. For example, if the frequency of the information updating is 5 minutes, every 5 minutes the travel times provided by the supply simulator are broadcast to informed drivers. These informed drivers then make en-route choices depending on the travel times supplied to them, using appropriate compliance and en-route choice models. The travel times provided to drivers can be on certain links, or on certain paths depending on the characteristics of the ATIS. This mechanism is shown by the dotted lines in Figure 3-5.

In the case of a VMS message, information could either be prescriptive (recommended routes) or descriptive (with information regarding travel times/delays on certain links or paths). During the supply simulation, whenever any vehicle passes over a link which has a VMS message, a driver may respond to VMS with certain probabilities. In this case, traveler behavior models in the demand component are invoked to perform en-route choice. Typically, a compliance model, (e.g a simple binary logit model) can be used to update the path in the case of prescriptive information. In the case of descriptive information, the utilities for the en-route choice models is computed based on the travel times provided by the VMS (for the specific links or paths) and equilibrium travel times for all the other links. A nested logit model could also be used for this purpose, where the first decision level is to decide whether to comply with the VMS message or not and the second level of decision making is to update the current path.

ATIS with Predictive Information

The important aspect of traffic prediction is the concept of consistency. Based on the guidance provided, travelers' response to the guidance will influence network conditions and hence the guidance strategy. Hence, the problem of obtaining a consistent guidance is a fixed point problem. Thus any ATIS based on predictive guidance has to iterate so that the outcome of the guidance strategy matches the network conditions after travelers' reactions to the guidance. Based on this concept, evaluating a predictive ATIS scenario is based on the algorithm outlined in Figure 3-6.

An initial set of predicted travel times is assumed (typically this is the equilibrium travel times) and network conditions are simulated. Based on the simulated travel times, algorithms are used to obtain a new prediction of travel times and which are used for guidance generation. The new set of predicted travel times is provided either through in-vehicle or VMS information and travelers update their paths. If the resulting travel times do not match the predictive travel times provided to travelers, then consistency has not been achieved and more iterations are necessary as indicated by the solid line in Figure 3-6. On convergence, a guidance strategy that is consistent is obtained.

The guidance generating algorithm generates the new set of travel times by a linear combination of the previous guidance and the latest simulated travel times. The framework for this algorithm is the method of successive averages (MSA) and is referred to as the time-smoothing (for more details see Bottom, [17]).

3.6 Summary

This chapter developed a framework for modeling short-term planning applications and described in detail the methodology to capture the day-to-day and within-day behavior in simulation-based DTA systems. The establishment of the day-to-day be-

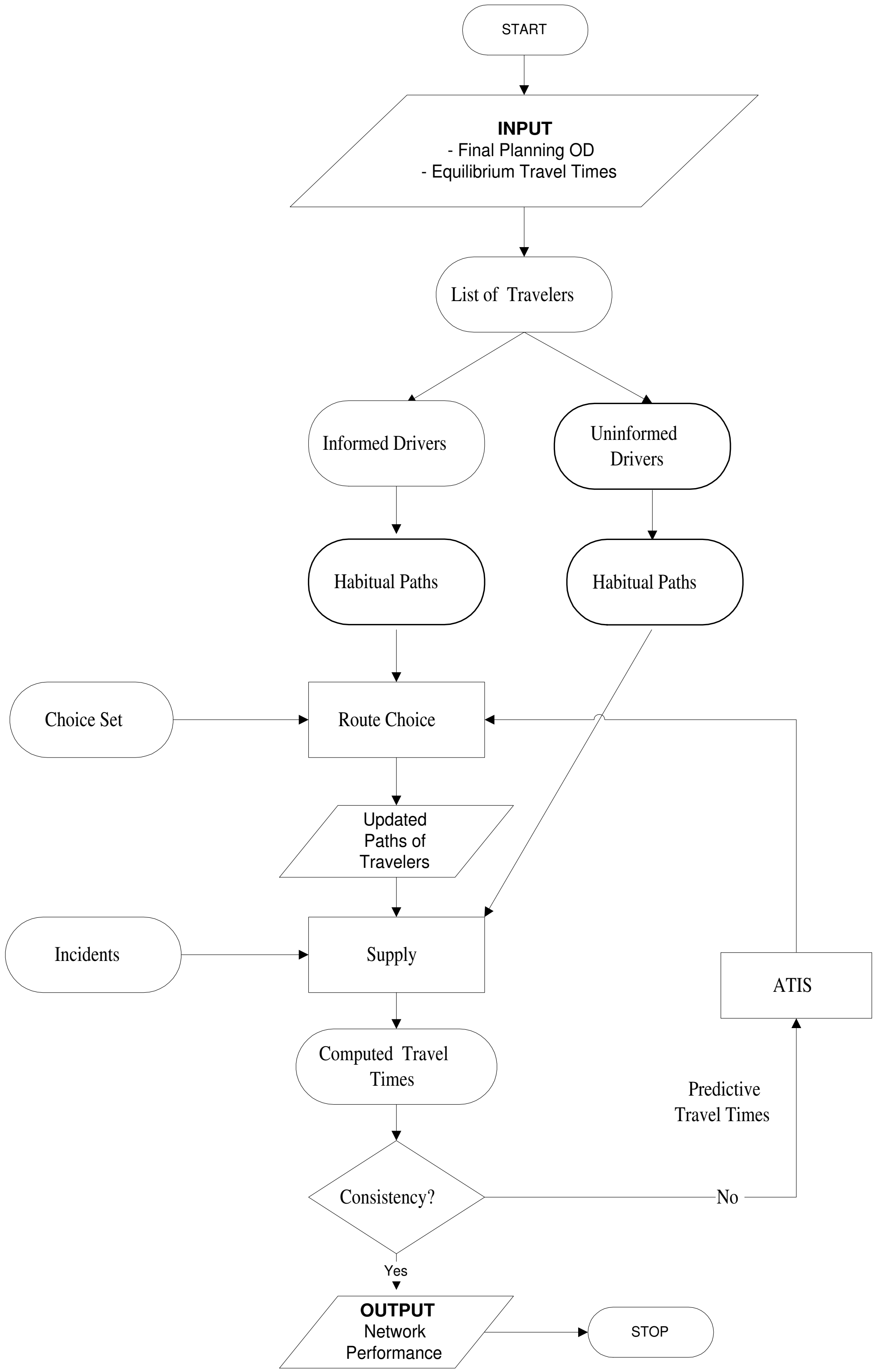

Figure 3-6: Modeling predictive ATIS scenarios.

havior involved the application of two steps, computing the equilibrium travel times for a given OD matrix and OD estimation, in an iterative framework. Details regarding each of the above steps were mentioned.

Further, application of the framework for the analysis of the base-case and scenarios (infrastructure-based and management-based) were discussed. Particularly, the ATIS instantaneous and the ATIS predictive scenario were developed in detail. The next chapter implements this framework in a real-time simulation-based DTA system, DynaMIT.

Chapter 4

Implementation of the Planning Framework

This chapter focuses on implementing the framework developed in Chapter 3 to develop a planning tool (DynaMIT-P) for short-term planning applications. The planning framework is implemented in DynaMIT (Dynamic Network Assignment for Management to Information to Travelers), a simulation-based DTA system that was described briefly in Chapter 2. A detailed overview of DynaMIT is presented in this chapter followed by a description of the basic components of DynaMIT-P. Details regarding the implementation of day-to-day, within-day dynamics and the representation of the base-case and scenarios in DynaMIT-P are then provided.

4.1 A Brief Overview of DynaMIT

DynaMIT is a state-of-the-art real-time computer system for traffic estimation and prediction, and the generation of traveler information and route guidance. DynaMIT's main functionality is to combine historical databases with real-time inputs from the surveillance system to perform estimation of current network conditions and perform rolling horizon predictions of network conditions. To sustain users' acceptance and achieve reliable predictions and credible guidance, DynaMIT incorporates *unbiasedness* and *consistency* into its guidance generation methodology. Unbiasedness guarantees that the information provided to travelers is based on the best available knowledge of current and anticipated network conditions. Consistency ensures that DynaMIT's predictions of expected network conditions match what drivers would experience on the network.

DynaMIT has the ability to trade-off level of detail (or resolution) and computational performance, without compromising the integrity of its output. Its main features include:

- Estimation and prediction of origin-destination flows.
- Optimal use of historical, surveillance and OD data to generate reliable OD estimates in real-time. The system records the results from previous OD estimations to update OD databases.
- Iteration between predicted network state, driver response to information and the resulting network state, towards the generation of a consistent information strategy.
- Generation of information/guidance that is consistent and unbiased to maintain drivers' confidence in the system.
- Generation of information/guidance that avoids to incident congestion.
- Demand simulation using a micro-simulator, which generates individual travelers and simulates their pre-trip and en-route decisions (choice of departure time and route) in response to information provided by the ATIS.
- Simulation of driver behavior.
- Capability to distinguish between informed and uninformed drivers.
- Supply simulation using a mesoscopic traffic simulator that explicitly captures traffic dynamics related to the development and dissipation of queues, spillbacks, and congestion.

- Capability to handle real time scenarios such as incidents, special events, weather conditions, highway construction activities, fluctuations in demand, etc.

- Integration with the MITSIMLab microscopic traffic simulator for off-line evaluation and calibration.

- Deployment over a computer network, using its flexible and internally distributed CORBA architecture.

DynaMIT was used as the DTA system to implement the planning framework developed in Chapter 3, because of its rich features and functionality.

4.2 Basic Components of DynaMIT-P

The basic components of DynaMIT-P (and DynaMIT) consist of the demand simulator, the supply simulator and the learning models to capture the demand-supply interactions.

4.2.1 Demand Simulator

The demand simulator in DynaMIT-P is a microscopic simulator of travel behavior. In addition, the demand simulator includes an OD estimation algorithm. The models in the demand simulator are:

- OD Estimation

- Demand Disaggregation

- Travel Choice Models

OD Estimation

The demand simulator in DynaMIT-P includes an OD estimation algorithm. The OD estimation problem may be viewed as combining and reconciling information from diverse sources and with various error characteristics. The external inputs to the model include link counts and the historical database of OD flows. The historical matrices in DynaMIT-P are time dependent in order to capture varying levels of traffic demand during the day. The key inputs generated internally in DynaMIT-P that are required for OD estimation are the time-dependent assignment matrices generated by the supply simulator.

The input OD flows are coupled with the concept of flow deviations in order to effectively capture the information contained in the past estimates. The current version of DynaMIT-P employs a GLS-based OD estimation algorithm. Though DynaMIT-P is an off-line tool and a simultaneous estimation for OD matrices of all the time intervals can be performed, a sequential procedure is adopted for computational efficiency. The OD estimation problem addressed in DynaMIT-P is based on the equation below:

$$\begin{aligned}\hat{\mathbf{x}}_h = argmin[(\mathbf{x}_h - \mathbf{x}_h^a)'\mathbf{W}_h^{-1}(\mathbf{x}_h - \mathbf{x}_h^a) \\ +(\mathbf{y}_h - \sum_{p=h-p'}^{h-1} \mathbf{a}_h^p \hat{\mathbf{x}}_p - \mathbf{a}_h^h \mathbf{x}_h)'\mathbf{V}_h^{-1}(\mathbf{y}_h - \sum_{p=h-p'}^{h-1} \mathbf{a}_h^p \mathbf{x}_p - \mathbf{a}_h^h \mathbf{x}_h)]\end{aligned} \tag{4.1}$$

where:

$\hat{\mathbf{x}}_h$ is the estimated flows for interval h,

$\mathbf{x}_h^a$ are the target OD flows (a priori flows),

$\mathbf{W}_h$ is the error covariance matrix associated with OD flow measurements,

$\mathbf{y}_h$ is the counts that are measured by the surveillance for time interval h,

$\mathbf{a}_h$ is the assignment matrix mapping flows from a departure interval p to the current interval h,

$\mathbf{V}_h$ is the error covariance matrix associated with the link counts and

p' is the length (in number of intervals) of the longest trip.

The constraints imposed on the OD flows are that they must be nonnegative.

Demand Disaggregation

The role of the disaggregation component is to generate a population of drivers from the OD matrices. Origin, destination, departure time interval and mode are assigned to the travelers using information from the OD matrices. The origin and the destination come from the particular OD pair for which the driver is generated, the departure time interval is the interval to which the OD matrix corresponds and the mode is the car by default (since it is assumed that the OD matrices contain only car trips). The disaggregation procedure also generates paths for travelers from their origin to their destination and provides travelers with a preferred route using the travel choice models. A number of socio-economic characteristics (such as value of time, information source) and trip characteristics (such as trip purpose) are generated and assigned to each traveler.

Travel Choice Models

Travel choice models are very critical to be able to capture traveler behavior. The primary travel choice models in DynaMIT-P are models to generate path choice sets for travelers and and models to assign departure time, route and mode for travelers. Further, these travel choice models capture response to ATIS information.

- **Path choice set generation:**

  The choice set generation step involves the computation of a good set of feasible paths connecting every OD pair of interest. The importance of this step cannot be underestimated in demand simulation. While the set of shortest paths between every OD pair might capture driver behavior, changing traffic patterns can increase the attractiveness of other paths. Incidents, for example can block the shortest route and force drivers onto less attractive paths. A good set of paths for each OD pair is therefore essential in planning applications.

  DynaMIT-P employs three steps in its path generation algorithm. The main steps involved in the path generation algorithm are:

– The **shortest path computation** step generates the shortest paths connecting each link in the network to all defined destination nodes.

– A **link elimination step** augments the paths from the shortest path set with alternative paths. This step involves the elimination of each link in the network and the subsequent re-computation of the shortest path, and ensures that an incident on any link will still leave alternative paths open for every OD pair.

– A **random perturbation** step is performed in order to obtain a richer path set. The impedances of the links are perturbed randomly to simulate varying travel times. Another set of shortest paths are now computed, and appended to the existing set. The number of random perturbations performed can be controlled by the user.

The algorithm also screens the final path set for uniqueness, and eliminates unreasonably long paths.

- **Route Choice:**

  Once a set of feasible paths has been obtained, the preferred path for a particular traveler is obtained by means of a **route choice** model based on discrete choice analysis and the concept of utilities. A Path-Size logit model is used to obtain probabilities for each of the choices. Stated mathematically the PS-Logit is as follows.

$$P_n(i) = \frac{e^{V_i + lnPS_i}}{\sum_{j \in C_n} e^{V_j + lnPS_j}} \tag{4.2}$$

  where $P_n(i)$ is the probability of individual n choosing alternative i, V_i is the utility of alternative i, PS_i is the size of path i, and C_n denotes the choice set for individual n. The size of a path is defined as (Exponential Path-Size formulation, Ramming [47]):

$$PS_{in} = \sum_{a \in \Gamma_i} \left(\frac{l_a}{L_i} \right) \frac{1}{\sum\limits_{j \in C_n} \frac{L_i^\gamma}{L_j^\gamma} \delta_{aj}} \tag{4.3}$$

where l_a is the length of link a, L_i is the length of path i and δ_{aj} takes the value 1 if link a is a part of path j (and is zero otherwise). The inner summation is computed over all paths in choice set C_n, while the outer summation is over all links a in path Γ_i. γ is a parameter to be calibrated.

The utility V_i of each path could be specified as a function of several explanatory variables. Typically, the explanatory variables and their co-efficients in the route choice models are identified during the process of model estimation, primarily by means of surveys. The default utility specification used in DynaMIT-P is given by:

$$V_i = \beta_1 tt_{Ai} + (\beta_2 \beta_1) tt_{Fi} \tag{4.4}$$

where tt_{Ai} and tt_{Fi} are the arterial and freeway components of the travel time along path i, β_1 is the coefficient of arterial travel time, and β_2 is the freeway bias.

En-route choice models are employed to capture travelers' response to in-vehicle information and VMS information. The structure of these models depends on the nature of the information system in place (e.g. prescriptive/descriptive).

- **Departure Time Choice:** During demand disaggregation, each traveler is assigned a departure time interval during which he/she departs. Based on a uniform distribution, the traveler is assigned a specific departure time in the departure interval. In the current implementation, no departure time choice model is used.

- **Mode Choice:** The default mode in DynaMIT-P is assumed to be the car. However, DynaMIT-P also supports alternative modes such as HOV vehicles.

4.2.2 Supply Simulator

The supply simulator is a mesoscopic traffic simulator. For a given set of travelers and control strategies, it predicts the performance of the network in terms of time-dependent travel times, queue lengths, etc. The simulator is designed to operate at different levels of granularity, depending on the requirements of the application. The flexibility in the design facilitates its use in a wide range of applications.

The complexity of the flows on the network is captured by integrating the classes of models summarized below:

- Capacities associated with roadway features. The movement of vehicles from one segment to the next is governed by a host of capacity calculations. The primary quantities of interest are the input and output capacities of the various segments. These capacities are compared with the available physical space on the downstream segments before allowing vehicles to cross segment boundaries. A constraint on either capacity or space would cause vehicles to queue.

- Incidents and intersection controls achieved through capacity controls.

- Deterministic queuing reflecting the effect of bottlenecks.

- Macroscopic speed-density relationships representing uninterrupted flow. Each segment contains a moving part (with vehicles moving at certain speeds), and a queuing part. The movement of vehicles in the moving part are governed by macroscopic speed-density relationships that take the following form:

$$v = Max(v_{min}, v_{max}\left[1 - \left(\frac{k - k_{min}}{k_{jam}}\right)^{\beta}\right]^{\alpha}) \tag{4.5}$$

  where v is the speed of the vehicle (in mph), v_{max} is the speed on the segment under free-flow traffic conditions, k is the current segment density (in vehicles/mile/lane), k_{min} is the minimum density beyond which free-flow conditions begin to break down, k_{jam} is the jam density, and α and β are segment-specific coefficients. v_{min} is the minimum speed of a moving vehicle that is determined by the network and vehicle attributes. These speed-density parameters are obtained by a process of supply calibration for a particular network.

The supply simulator obtains aggregate measures of network performance by simulating the movement of drivers on the road network. Detailed mesoscopic models capture traffic dynamics and accurately model the build-up and dissipation of lane-specific queues and spill-backs. The links in the network are subdivided into segments to capture changing section geometries. Further, the lanes within each segment are grouped into lane groups to account for turning-movement-specific capacities at diversion and merge points and intersections.

The simulation of the traffic operations proceeds in two phases: the update phase and the advance phase. During the update phase the most time consuming calculations are performed, where the traffic dynamics parameters (e.g. densities and speeds) used in the simulation are updated. During the advance phase the vehicles are advanced to their new positions. The advance phase has a higher frequency than the update phase. The exact time discretization, for both the phases depend on specific the application and are selected to obtain the best compromise between accuracy of results with respect to network performance (e.g. travel times) and computational performance.

Various ATMS strategies can be simulated through their impact on intersection capacities. For example, traffic actuated and adaptive control are modeled through capacities that are determined dynamically as a function of the prevailing flows (Tian, [51]).

4.2.3 Learning Models

The learning model in DynaMIT-P is used to update the average expected time of travelers' based on their experienced travel times. The average expected travel time is computed by using the following filter:

$$\bar{T}_k^t = \lambda T_k^{t-1} + (1-\lambda)\bar{T}_k^{t-1} \tag{4.6}$$

where $\bar{T}_k^t$ is the expected time-dependent travel time along path k on day t, and T_k^t is the time-dependent travel time experienced along path k on day t. λ captures the learning rate, and may vary across market segments. The value of λ lies between 0 and 1, and is affected by the use of ATIS.

4.3 Implementation of Day-to-Day Behavior in DynaMIT–P

1. Inputs:

The inputs required for the day-to-day behavior were described in Chapter 3. The specific nature of inputs employed in DynaMIT-P are:

- *Time Dependent Historical OD Matrices.*
- *Time Dependent Historical Link Travel Times:* In DynaMIT-P, link travel times for each of the links are stored based on the time of entry into the link. Thus the travel time stored for a particular link and time interval, is the average travel time that a vehicle will experience if it enters the link during that time interval. This time interval is an user controlled parameter and can be varied depending on how sensitive the travel times of links are to the entry time on the link. However, as was discussed earlier in Chapter 3, this input is not necessary to be provided and free flow estimates of travel times can be input instead.
- *Field Sensor Counts:* Field sensor counts received by actual surveillance sources are used as inputs to the OD estimation algorithm.
- *Socio-economic Characteristics:* The socio-economic characteristics of potential travelers (trip purpose, information source, value of time).

2. Outputs

The outputs from DynaMIT-P, after establishing the day-to-day behavior are:

- *Equilibrium Travel Times:*
- *Planning OD Matrices:*

3. Implementation

The implementation of the day-to-day behavior is based on the framework described in Figure 3-2. However, some particular details are mentioned below:

- **Convergence Criterion:**

  The convergence criterion used in DynaMIT-P is given by:

$$\sqrt{\frac{\sum_{t=1}^{T}\sum_{s=1}^{S}\left(\mathcal{SC}_s^t - \mathcal{FC}_s^t\right)^2}{\mathcal{N}_t.\mathcal{N}_s}} < \epsilon \tag{4.7}$$

  where $\mathcal{SC}_s^t$ is the simulated sensor count on sensor s in time interval t, $\mathcal{FC}_s^t$ is the corresponding field sensor count, $\mathcal{N}_s$ is the number of sensors reporting counts in the network, $\mathcal{N}_t$ is the number of time intervals and ϵ is the threshold, which is a user defined parameter.

  In the presence of other data available such as speeds and densities, the convergence criterion can be expanded to include these observations. Also from an implementation standpoint, the process terminates either when the the stopping criterion in Equation 4.7 is met or when a maximum number of iterations has been performed.

- **Updating the Planning OD:**

  In the current version of DynaMIT-P, the estimated OD obtained in Step 2 (in Figure 3-2) is used as the planning OD for the next iteration.

Specific details regarding the computation of equilibrium travel times and OD estimation are provided next:

4.3.1 Equilibrium Travel Times Computation in DynaMIT-P

Figure 4-1 shows the computation of the equilibrium travel times in DynaMIT-P. The procedure to compute the equilibrium travel times for a particular planning OD is based on the algorithm described in Chapter 3.

- Step 1:

  Generate a list of travelers for the planning OD matrix and traveler path choices based on their current perceptions of travel times in the network. During the

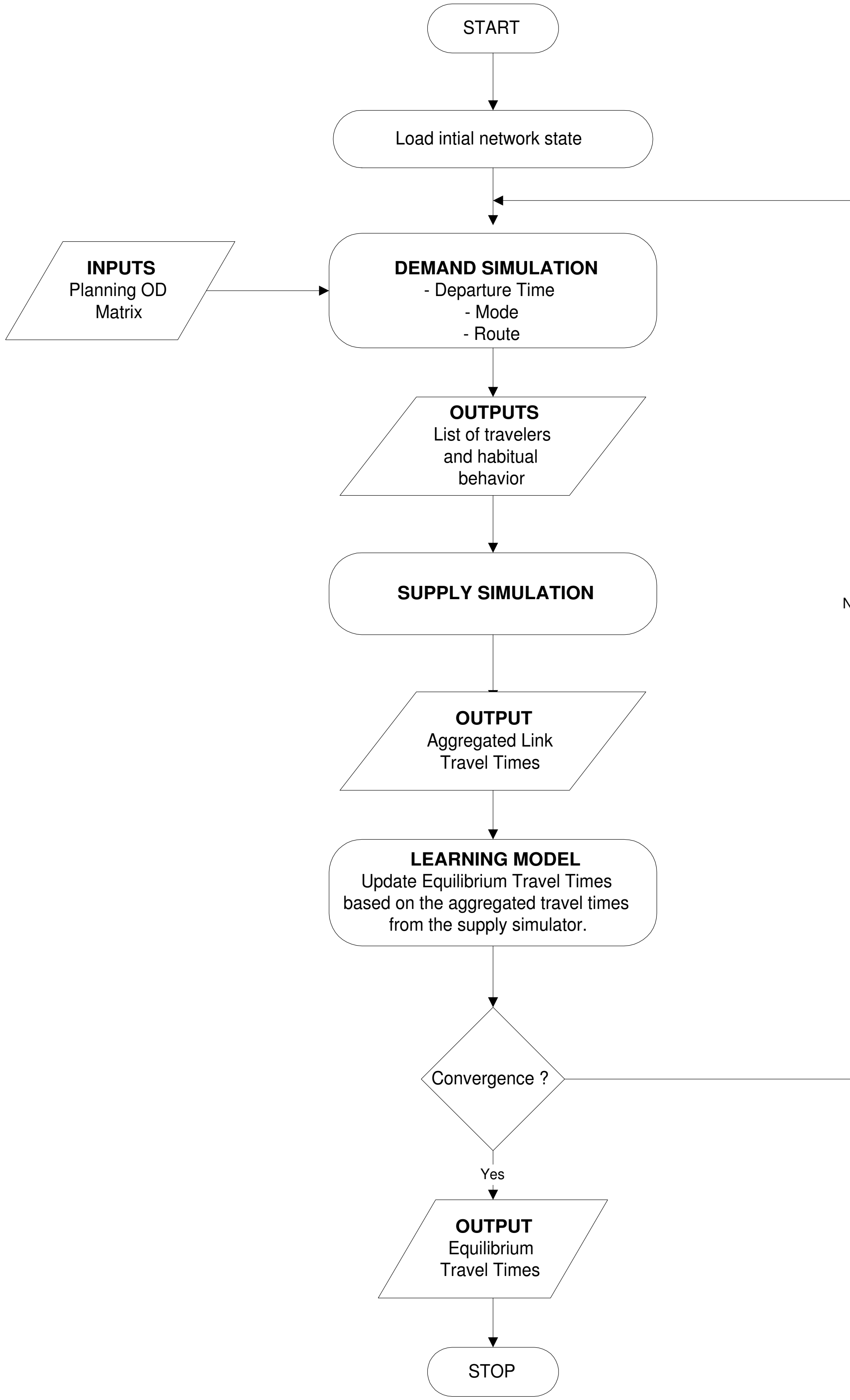

Figure 4-1: Computation of equilibrium travel times in DynaMIT-P.

first iteration of the outer loop, travelers' best perceptions of travel times are the initial historical travel times. This process of providing a list of travelers and their behavior based on the current perceptions of the travel times is performed by demand disaggregation as outlined in Section 4.2.1

- Step 2:

  Run the supply simulator for the entire planning horizon to provide aggregate link travel times that are experienced by the travelers based on their travel decisions obtained in Step 1.

- Step 3:

  Update the perceptions of the travelers' expected travel times (equilibrium travel times) based on their recent experiences that were simulated by the supply. The learning model described in Equation 4.6 is used for this purpose.

- Step 4:

  Check for convergence based on the equation below to determine if the expected travel times of travelers matches their experienced travel times:

$$\sqrt{\frac{\sum_{l=1}^{L}\sum_{t=1}^{T}\left(\mathcal{EQ}_i^{l,t}-\mathcal{EQ}_{i-1}^{l,t}\right)^2}{\mathcal{N}_l.\mathcal{N}_t}} < \epsilon \tag{4.8}$$

  where $\mathcal{EQ}_i^{l,t}$ is the equilibrium link travel time (or the expected link travel time) in the current iteration i, on link l, for a vehicle that enters the link in time interval t, $\mathcal{EQ}_{i-1}^{l,t}$ is the corresponding link travel time in the previous iteration $i-1$, $\mathcal{N}_l$ is the number of links in the network, $\mathcal{N}_t$ is the number of time intervals with which the travel times are represented and ϵ is the threshold, which is a user defined parameter. Further, there is also the provision of specifying a maximum number of iterations to be performed.

  If the convergence criterion is satisfied, then travelers' latest perceptions of travel times based on their most recent network experience matches their previous expectations. Thus under this scenario, travelers have established their "equilibrium decisions" and the expected travel times are hence the final equilibrium travel times for the input planning OD. If however, there is a discrepancy in travelers' expected vis-a-vis their experienced times, then Steps 1, 2 and 3 are repeated until convergence is achieved.

A few extensions to the basic idea are also mentioned in Figure 4-1. One of them is to allow for the process described above to start from a loaded network. This is achieved in DynaMIT-P by creating a list of travelers based on an input file that describes the state of the network in terms of the travelers path, location, origin, destination and so on. This input file for instance may be generated by running DynaMIT-P from a start time at which the network is relatively empty until the start of the planning horizon and utilizing functions in DynaMIT-P to dump the required network characteristics. It is critical to note however that the habitual paths of these travelers is not updated in each iteration and these travelers are assumed to have already made their habitual travel choices.

4.3.2 OD Estimation in DynaMIT-P

The inputs to this procedure consist of the previous estimate of the planning OD matrix and the latest set of equilibrium travel times.

The OD estimation procedure in DynaMIT-P is performed sequentially, for computational reasons for each time period. Thus, an estimated OD matrix is generated for each time period based on the previous estimate of the planning OD and the observed sensor flows for that time interval. This sequential procedure is illustrated by the outer loop in Figure 4-2.

Before the start of the sequential procedure, the network state corresponding to the start of the planning horizon is loaded in a manner similar to that described in the previous section.

The steps to estimate an OD matrix for a particular time interval is an iterative procedure as and is described by the following steps:

- Step 1:

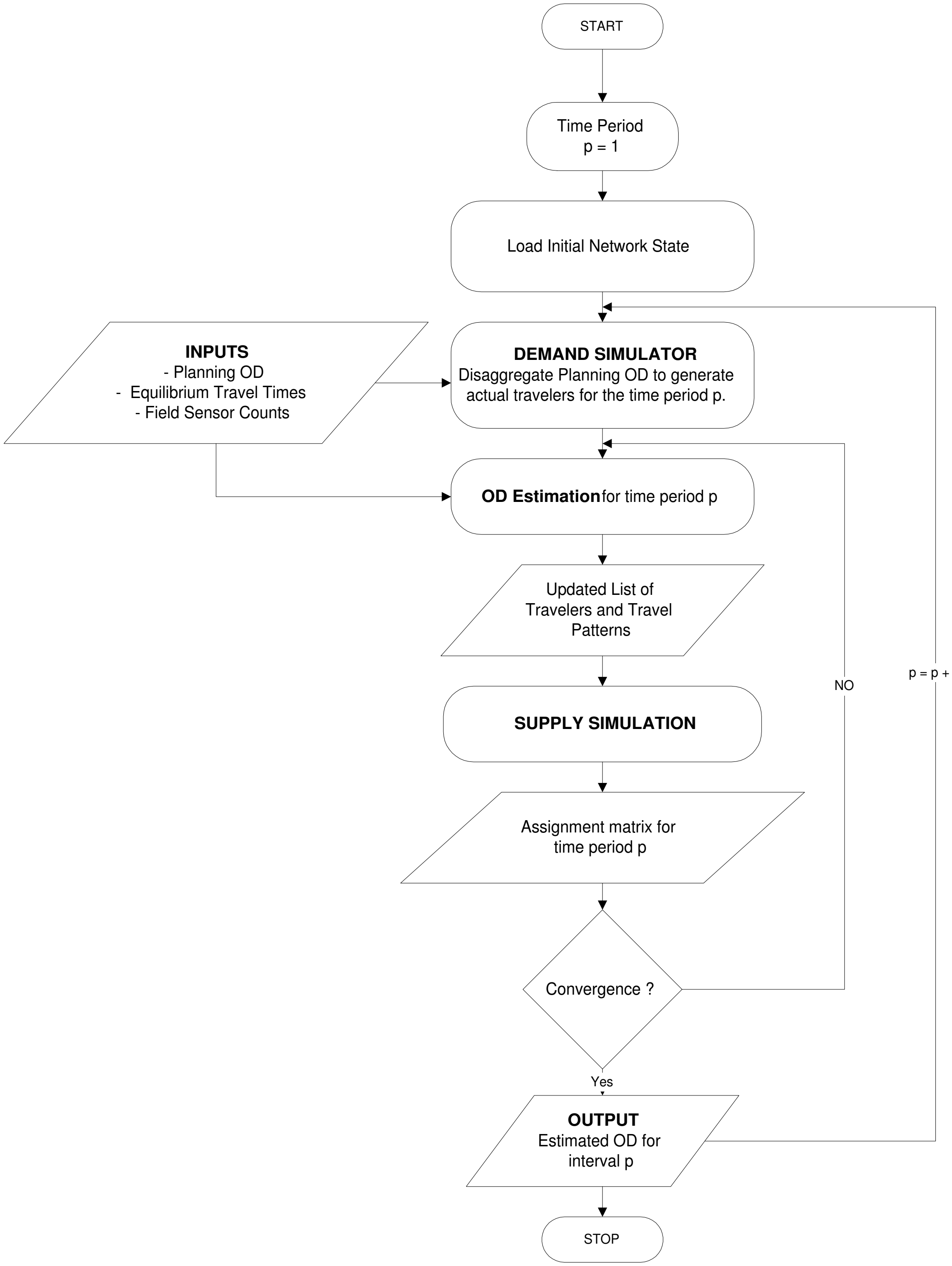

Figure 4-2: OD estimation in DynaMIT-P.

The planning OD matrix is disaggregated for the time interval is disaggregated to produce an initial list of travelers using the same procedure described in the previous section.

- Step 2:

  The OD estimation algorithm is then used to provide a new estimate of the OD for the time interval. In addition to the seed OD matrix and the field counts for the corresponding time interval, an assignment matrix is required for the OD estimation module described in Section 4.2.1. If no assignment matrix is available the estimated OD matrix is equal to the seed OD matrix (such as in the first iteration).

- Step 3:

  Based on the updated OD matrix, the initial list of travelers (obtained in Step 1) is updated by a process of kill and clone. Additional travelers if required for any OD pair are disaggregated in the usual manner by the clone process. Travelers for a particular OD pair are removed from the list at random by the kill process.

- Step 4:

  The updated list of travelers is then loaded into the supply simulator. The main purpose of the supply simulation is to generate the assignment matrix. This matrix is generated based on the information obtained during the supply regarding the time at which every vehicle crossed a traffic sensor. Based on this data, the assignment matrix for the particular time interval is computed.

- Step 5:

  The OD estimation algorithm in Step 2, requires an assignment matrix, which however was obtained only in Step 4. Further, the assignment matrix depends on the OD matrix, which is updated by the OD estimation algorithm. Thus the establishment of the estimated OD is a fixed point problem. Several iterations of steps 2, 3 and 4 may be required to establish the convergence of the algorithm (i.e. convergence of the assignment matrices in successive iterations. However, in DynaMIT-P, the convergence criterion is based on successive OD estimates generated for the particular time interval and is given by:

$$\sqrt{\frac{\sum_{n=1}^{N_{od}} \left(\mathcal{F}_i^{o,d,p} - \mathcal{F}_{i-1}^{o,d,p}\right)^2}{\mathcal{N}_{od}}} < \epsilon \tag{4.9}$$

where $\mathcal{F}_i^{o,d,p}$ is the OD flow in the current iteration i, from origin o to destination d in time interval p, $\mathcal{F}_{i-1}^{o,d,p}$ is the corresponding OD flow in the previous iteration $i-1$, $\mathcal{N}_{od}$ is the number of OD pairs and ϵ is the threshold, which is a user defined parameter. The inner summation is carried out for all the OD pairs. There is again a maximum number of iterations parameter, which can be supplied by the user to terminate the iterations beforehand.

The iterative procedure just described is shown by the inner solid loop in Figure 4-2.

4.4 Implementation of Within-Day Behavior in DynaMIT-P

The inputs to the within-day behavior are the equilibrium travel times and the planning OD matrix obtained from the day-to-day analysis. Various stochastic conditions and characteristics of any particular ATMS/ATIS strategy are input. Further, in order to implement within-day dynamics changes in both the supply and the demand side may be required. Changes in the supply side are effected through the link-capacities that DynaMIT-P uses and changes in the demand side are reflected through the planning OD matrix or through the travel choice models.

Thus to implement the within-day analysis, these modified inputs are incorporated, the state of the network at the start of the planning horizon is loaded and the demand and the supply simulators are used to obtain the resulting network conditions.

4.5 Representation of the Base-Case in DynaMIT-P

As was outlined in Chapter 3, establishing the base-case may require the day-to-day model (for "standard" days) and within-day model (for "non-standard" days). In DynaMIT-P, the day-to-day and within day framework described in the previous sections are used with the relevant inputs in order to establish the base-case.

4.6 Representation of Scenarios in DynaMIT-P

Infrastructure-based and *Traffic management-based* scenarios are implemented in DynaMIT-P in accordance with the framework developed in Chapter 3. The inputs to the scenario evaluation consist of the equilibrium travel times and the planning OD obtained from the base-case analysis. The analysis of these scenarios is described in detail below.

4.6.1 Infrastructure-Based Scenarios

These scenarios are captured by modifying the relevant inputs used for establishing the base line scenario that are specific to the scenario being analyzed and then evaluating the network performance. The day-to-day model is used for this purpose.

Any changes to the demand side are performed on the planning OD matrix. Such changes would be necessary to capture spikes in demand due to events such as sports, special events etc. Changes on the supply side are made primarily on the segment capacities that DynaMIT-P uses. Lane closures and work-zone configurations are captured by appropriate capacity reductions.

Once the inputs have been modified to suit the particular scenario, the scenario is evaluated by disaggregating the appropriate OD matrix using the equilibrium travel times to evaluate travelers' choices. As before, the initial network corresponding to the start of the planning horizon is loaded. The supply simulation is then performed for the planning horizon on the list of travelers to yield the network conditions. Iterations of the demand and supply may be required to account for travelers' adjustments made in response to network conditions. The impact of the scenarios is analyzed by comparing the baseline network state with the obtained network state through outputs produced by DynaMIT-P.

4.6.2 Traffic Management-Based Scenarios

Analysis of the impact of HOV/HOT lanes is the primary topic studied under traffic-management strategies.

A. HOV Scenarios

The changes that are required to model such scenarios in DynaMIT-P involve the following. As discussed briefly in Chapter 3, scenarios involving HOV lanes include evaluation of existing HOV lane facilities or evaluation of proposed new HOV lane strategies. The analysis of HOV lanes can be done either through a statistical approach (focusing on aggregate statistics such as OD flows) or through a behavioral approach (focusing on disaggregate decisions such as mode choice). Based on the scenario being analyzed and on the data available either one of the above approaches can be adopted. If the scenario being analyzed involves existing HOV facilities and the OD matrix specific to the HOV lanes is known, an aggregate approach may suffice. On the other hand, if the scenario being analyzed involves the conversion of a normal flow traffic lane into a HOV lane, behavioral models that capture travelers' mode choice decisions are required. Some of the changes required in the system to incorporate HOV strategies are described below:

- Changes to the supply side:

  The network has to be modified to represent the conversion of the normal lane into a HOV lane. This is achieved by removing the lane (that is to be converted) from the existing link and adding a separate link to represent the HOV lane.

- Changes to the demand side:

The changes required on the demand front can further be categorized below:

- The path choice set is regenerated based on the network changes resulting from the supply. Further, the HOV paths are identified during this process and are present in the choice set of HOV vehicles only. While HOV travelers have access to all paths, non-HOV vehicles are restricted to non-HOV paths.

- Mode choice models are enhanced to model the transition of travelers between HOV and non-HOV modes. This is relevant only for scenarios which require the behavioral approach.

- For scenarios which require the aggregate approach, a separate HOV OD table is used. OD pairs for which the HOV flows exist are modeled as two separate OD pairs (by adding a dummy origin or a destination). One of these OD pairs is devoted exclusively for non-HOV vehicles and the other to HOV vehicles only. The usual process of OD estimation in the day-to-day behavior, will yield flow for both the OD pairs. This change is required for scenarios such as evaluating the network conditions under existing HOV infrastructure in the presence of counts on HOV lanes.

B. ATMS Scenarios

ATMS scenarios, such as evaluation of ramp metering strategies, are also captured by means of capacity modifications of the relevant facilities. Further DynaMIT-P has algorithms that dynamically modify the capacities of various segments to model for instance actuated signal controls. For more details regarding ATMS representation, the reader is referred to Tian, [51]. However, the analysis of the ATMS systems can be performed either by the day-to-day analysis or the within-day analysis depending on the application.

C. ATIS Scenarios

In order to deal with ATIS-related scenarios, travelers in DynaMIT-P are divided into two classes: guided and unguided. This distinction is indicated in the socio-economic characteristics assigned to each vehicle during disaggregation. While guided drivers update their paths and make en-route decisions based on information broadcast to them through in-vehicle units, unguided drivers make en-route decisions only in the presence of a VMS message. The information provided by ATIS and VMS, as currently implemented in DynaMIT-P is descriptive.

In order to correctly represent the various travel times, the following impedance tables are employed in DynaMIT-P:

- *Equilibrium Travel Times:* These are the travel times obtained from the day-to-day behavior analysis.

- *Current Guidance Travel Times:* These are the travel times used by guided travelers and by unguided travelers in the presence of VMS messages (for the selected links covered by the VMS's) to make en-route choice decisions. The methodology to generate these travel times depends on the sophistication of the system (instantaneous, predictive) and will be discussed shortly.

- *Supply Simulator Travel Times:* These are travel times generated by the supply simulator and represent the expected network performance for a given OD matrix and assigned travel behavior.

The impedance tables described above store the travel times for every link in the network and are time-dependent.

A brief description of in-vehicle and VMS representation in DynaMIT-P is presented next, followed by method used for the generation of instantaneous and predictive information.

In-Vehicle Information:

Guided travelers who receive in-vehicle information continuously update their paths using the en-route choice models in DynaMIT-P. The frequency with which they update their paths depends upon the nature of information and the frequency with which this information is updated. As mentioned earlier, guided travelers use the current guidance impedance tables to make en-route decisions. Currently, in DynaMIT-P, in-vehicle travelers receive descriptive information.

VMS Information:

DynaMIT-P models two types of VMS:

- *Path-VMS* that displays information on specific paths or sub-paths
- *Link-VMS* that displays information on individual links

Both guided and unguided drivers may respond to the VMS messages and perform en-route decisions based on the VMS message. The implemented behavior is captured by Figure 4-3, in which guided travelers respond to the VMS signs with probability $p1$ and ignore with probability 1 - $p1$. Unguided travelers respond with probability $p2$. The values of $p1$ and $p2$ are inputs to the model and can be determined through calibration.

The path travel times for travelers making en-route decisions in the presence of a VMS are computed based on the following rules:

1. In the case of a link-VMS, the latest travel times for the links provided by the VMS are substituted for the habitual travel times. These latest times are stored in the current guidance table. Thus, for example in Figure 4-4, assuming that the VMS is located on link 6 and that it provides information about link 2, then for the path represented by a sequence of links $6-4-2-5-8$, the travel time on link 2 is obtained from the current guidance table and the travel times of all other links are obtained from the habitual travel time table.

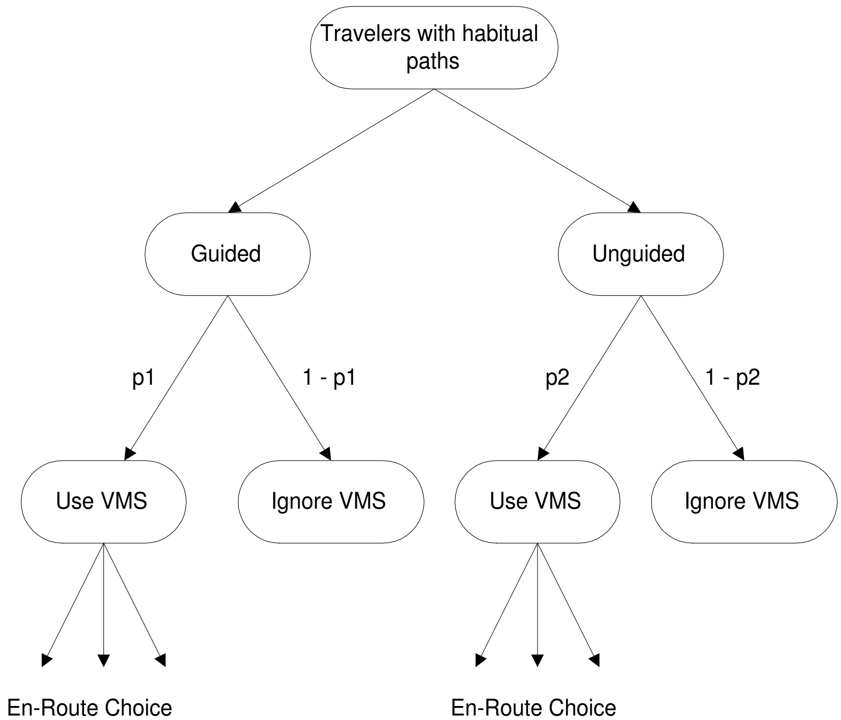

Figure 4-3: Travelers response to VMS.

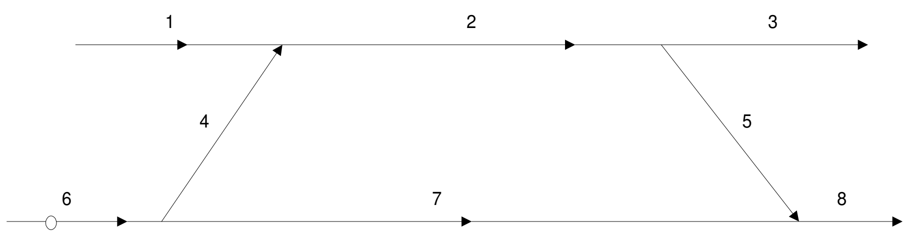

Figure 4-4: Example to illustrate link-VMS and path-VMS.

2. In the case of a path-VMS, while computing path travel times for a particular path, it is checked whether sub-paths for which the VMS provides guidance is a subset of the current path. If it does, then for all the links in the sub-path the guidance provided by the VMS is employed to get the link travel times. Otherwise the habitual travel times are used for the entire paths. Thus, with reference to Figure 4-4, assuming that the VMS located on link 6, gives path guidance for path $4-2-5$, then for vehicles following the path $6-4-2-5-8$ use the current guidance table for links 4, 2 and 5 and the habitual travel times for all the other links. However, if for example a vehicle is using the path $4-2-3$, then it uses habitual travel times for all the links on this path, since path $6-4-2-3$ does not contain the sub-path $4-2-5$.

ATIS scenarios that can be analyzed using DynaMIT-P may be based either on instantaneous or predictive information. The details of these scenarios are provided next:

ATIS with Instantaneous Travel Times:

The implementation in DynaMIT-P to capture the instantaneous ATIS scenario is illustrated in Figure 4-5. The network state corresponding to the start of the planning horizon is loaded, followed by the disaggregation of the planning OD (using the equilibrium travel times) to produce the list of habitual travelers.

The supply simulator is then run for the time intervals p in succession. The width of each interval is determined by the frequency with which information is updated. It is critical to note that while running the supply simulator, travelers make en-route decisions based on the latest information and according to the rules specified earlier in this section. At the end of the current interval p, the link travel times are calculated for that time interval. These travel times represent the latest instantaneous information that is used by the VMS. For the next interval (i.e. until the next VMS update travelers that view the VMS), the travelers update their paths according to the displayed information (using

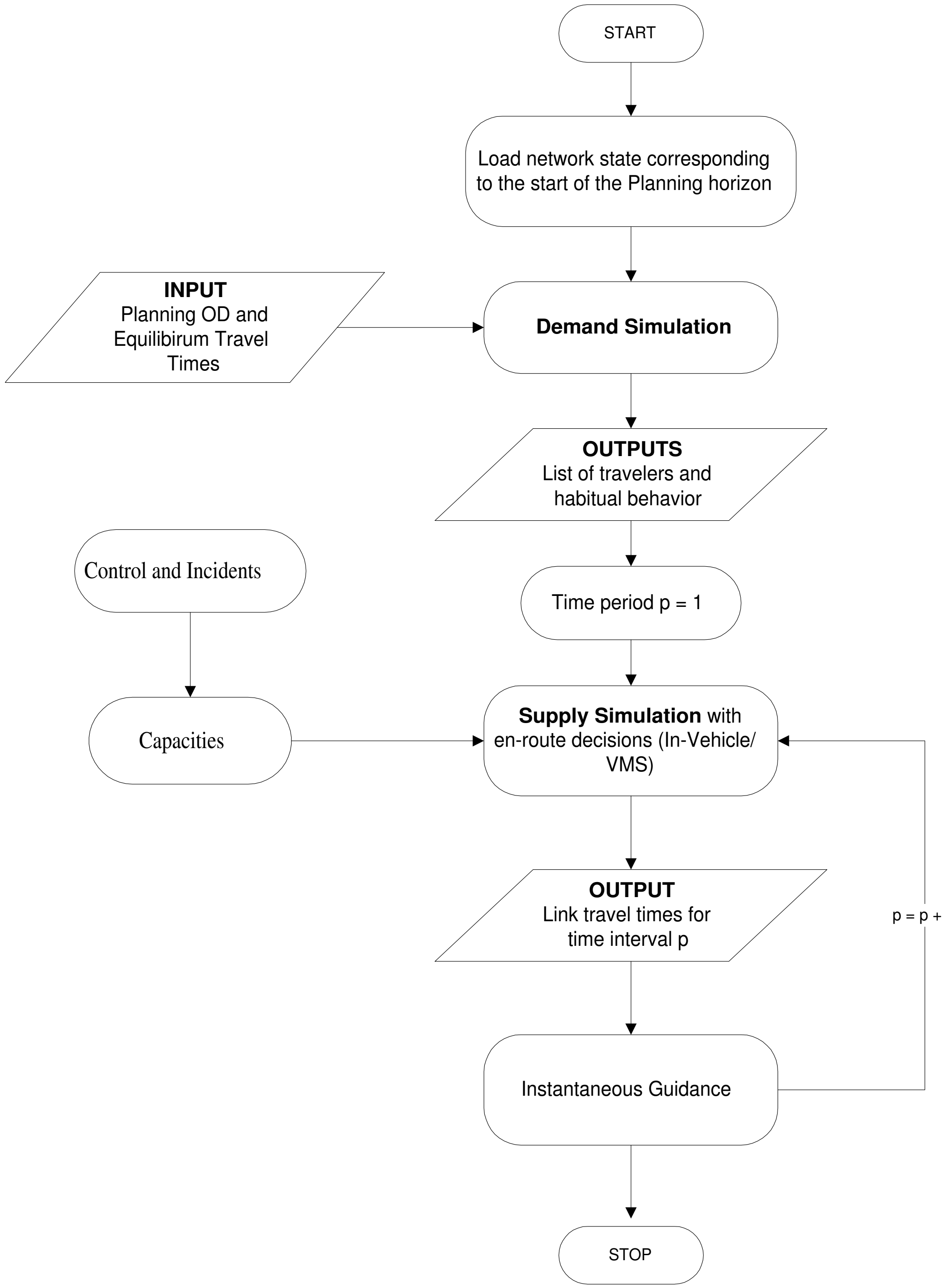

Figure 4-5: ATIS instantaneous scenario in DynaMIT-P.

the process described next). These steps are repeated in succession for each of the time intervals p. For example if the planning horizon is from 7:00 AM to 8:00 AM and the frequency of information update is every 5 minutes, then the above steps are repeated in succession for 7:00 to 7:05, 7:05 to 7:10 and so on.

The issue that needs to be discussed is the way travelers update their information based on instantaneous information. To illustrate travelers' behavior, as implemented in DynaMIT-P, consider a traveler who looks at a VMS message displaying a message that the travel time on link l is $\mathcal{T}$ minutes. If this link is the travelers' next link or very close to the VMS message, then the traveler would probably assume the information as accurate and would base his route choice based on the information. However, suppose that the traveler will reach link l only 30 minutes later. In this case he/she would probably not consider the travel time as reported by the VMS as accurate but will make a judgment on the travel time based on when he/she would get to that link. Due to lack of rigorous route choice model that capture the above behavior, the model based in Figure 4-6 is employed to represent travelers' perceptions of link travel times.

Assume that T_0 is the current time, and a traveler is located on the link for which the information is being supplied. Under such a scenario, a traveler will use the instantaneous information and this is represented by the value of λ of 1.0. However, suppose that the traveler will get to the link only much later than the time of the broadcast information, then the traveler would probably ignore the information. This scenario is represented by a λ value of 0 and hence travelers will only base their choices based on the historical or the equilibrium travel times. In between the two extreme cases, the value of λ is a decreasing function as shown in the figure. It may be noted that λ reflects the importance of the instantaneous information and hence decreases with time. The resulting travel times based on the above implementation are stored in the current guidance table as indicated in the figure and this table is used by the travelers to make route choices (for the corresponding link or paths). Thus, the guidance is based

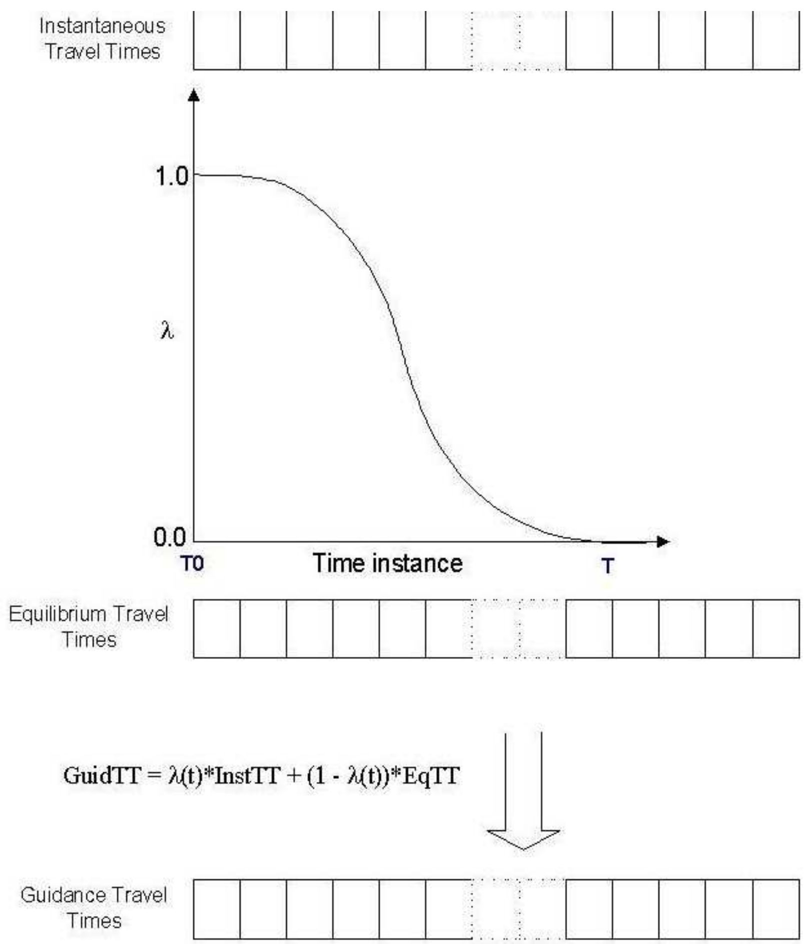

Figure 4-6: Guidance generation in the presence of instantaneous information.

on:

$$GTT_l^t = \lambda(t).InstTT_l + (1 - \lambda(t)).EqTT_l^t \qquad (4.10)$$

where GTT_l^t is the link travel time in the guidance table for link l for an entry time interval t, $EqTT_l^t$ is the corresponding link travel time in the equilibrium travel times table and $InstTT_l$ is the instantaneous travel time for link l.

ATIS with Predictive Travel Times:

Scenarios with predictive ATIS are implemented based on Figure 4-7.

As usual, the first step in the process consists of loading the initial network state and disaggregating the planning OD to produce a list of travelers. The current guidance table is initialized to be the same as the equilibrium travel time tables. Incidents are reflected in the capacities input to the supply simulator.

An iterative procedure is employed to achieve a consistent guidance is illustrated by the following steps:

- Step 1:

  The list of travelers is loaded into the supply simulator, which is used for the entire planning horizon to predict the state of the network. During the supply simulation, if travelers encounter a VMS, they update their paths based on en-route choice models. Guided travelers on the other hand continually update their paths. These travelers perform route choice based on the current guidance table.

- Step 2:

  The next step involves updating the guidance based on the aggregated link travel times from the supply simulator. A linear combination of the previous current guidance and the latest aggregated travel time tables from the supply is used as the guidance generating algorithm for this purpose (this is similar to the learning model for the day-to-day behavior).

- Step 3:

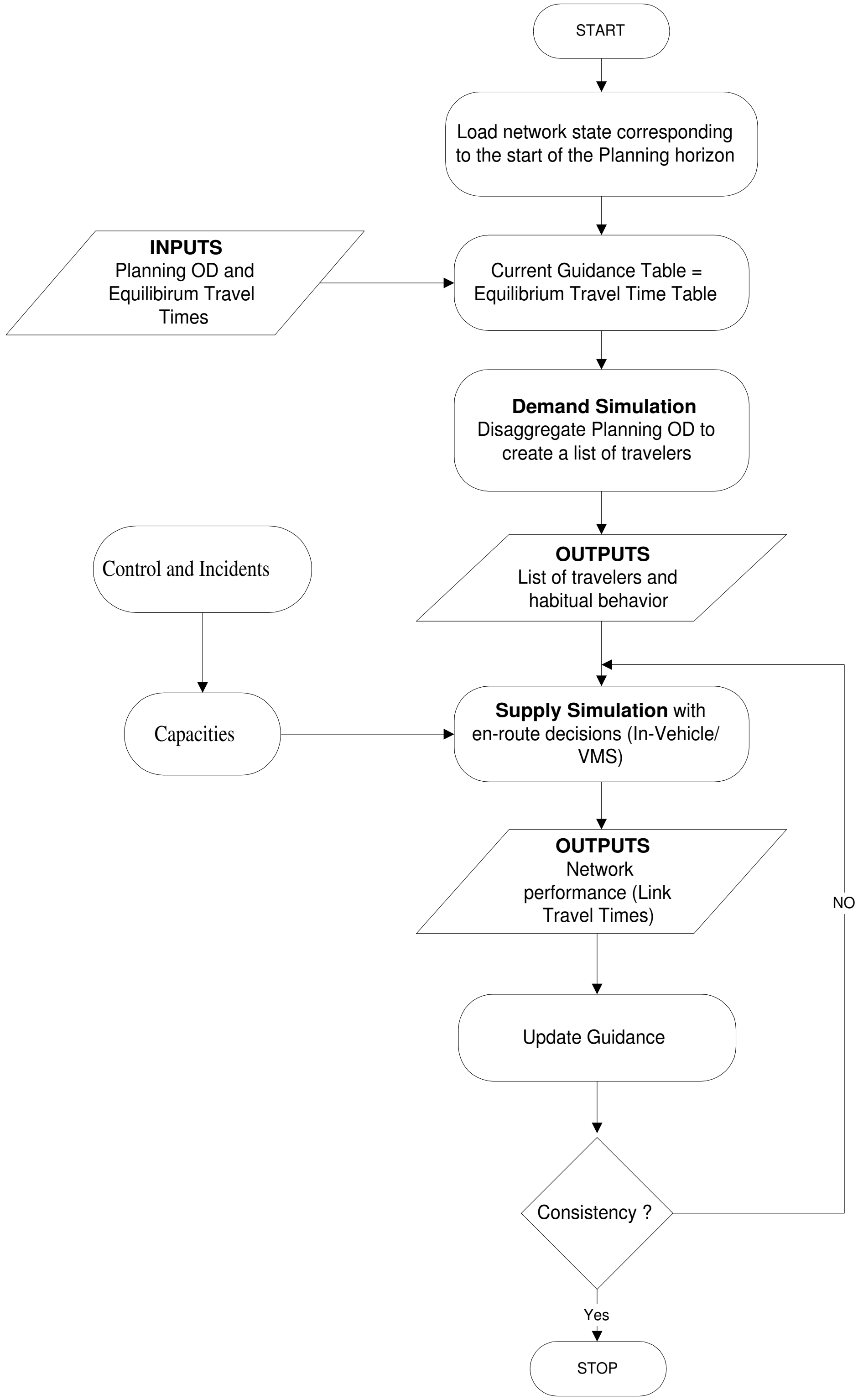

Figure 4-7: ATIS predictive scenario in DynaMIT-P.

It was mentioned that consistency was a key concept in the case of predictive information. Under consistency, the guidance provided to travelers must take into account travelers' reaction to the guidance. Thus, a consistency check is made based on the following equation:

$$\sqrt{\frac{\sum_{l=1}^{L} \sum_{t=1}^{T} \left(\mathcal{G}_i^{l,t} - \mathcal{G}_{i-1}^{l,t} \right)^2}{\mathcal{N}_l . \mathcal{N}_t}} < \epsilon \tag{4.11}$$

where $\mathcal{G}_i^{l,t}$ is the link travel time from the guidance table in the current iteration i, on link l, for a vehicle with time of entry into the link t minutes after the start of the planning horizon, $\mathcal{G}_{i-1}^{l,t}$ is the corresponding link travel time from the guidance table in the previous iteration $i-1$, $\mathcal{N}_l$ is the number of links in the network, $\mathcal{N}_t$ is the number of time intervals corresponding to that of the impedance tables in DynaMIT-P and ϵ is the threshold, which is a user defined parameter.

If the convergence criterion is not satisfied, then more iterations are performed as indicated by the loop in Figure 4-7 and Steps 1 and 2 are repeated in sequence.

4.7 Summary

This chapter focused on implementing the planning framework outlined in Chapter 3. A brief overview of a DTA system DynaMIT was presented followed by the basic components of DynaMIT-P (the planning tool being developed). The specific details of implementing the day-to-day behavior and within-day dynamics was illustrated in DynaMIT-P. Further, the use of the day-to-day and within-day model for the analysis of the base-case and the scenarios were discussed. The next chapter discusses some of the applications of DynaMIT-P to a network in Irvine, California.

Chapter 5

Case Study

This chapter demonstrates some of the functionalities of DynaMIT-P, the tool that was developed in the previous chapter for short-term planning applications. The case study used to demonstrate the capabilities of DynaMIT-P is based on an actual large-scale network in Irvine, California. A brief description of the Irvine network is first provided and the data obtained from various sources are summarized, followed by a brief review of input files required for DynaMIT-P. Critical tasks that are to be performed before the use of DynaMIT-P such as calibration are briefly mentioned. Base-case results are provided and the impact of a VMS displaying instantaneous and predictive travel times during a hypothetical incident is analyzed.

5.1 Description of the Irvine Network

The data used in this research was collected from a network at Irvine in Orange County, California, USA. The main features of this network and the surveillance data recorded for this network are discussed in this section.

5.1.1 Network Description

The study network (Figure 5-1) is comprised of three major freeways and a dense network of arterial segments. The I-5 and I-405 Interstates, along with State Route

133, define a wedge that is criss-crossed by several major arterials. It lies along the heavily traveled corridor connecting Los Angeles and San Diego. It is a major commercial and business center, and has an important regional airport.

Figure 5-1: The Irvine network.

The network is represented as a set of 298 nodes connected by 618 directed links. These links represent the physical links on the network, and are further subdivided into 1373 segments to model changing link characteristics. Almost all of the 80 intersections within the study area are signalized, and are controlled by vehicle-actuated signal logic. A high fraction of the signals along the primary arterials (Barranca Parkway, Alton Parkway and Irvine Center Drive) are co-ordinated to minimize the number of stops.

5.1.2 Data Description and Preliminary Analysis

The available data was derived primarily from four sources:

- Network geometric characteristics files
- OD flows from OCTAM planning study
- Time-dependent detector data
- Signal timing and coordination plans

The network files included descriptions of network geometry, link and lane connectivity, sensor locations and signal phase timing plans. The OCTAM planning study generated a static matrix of OD flows from 61 zones covering the morning peak period. Time-varying freeway and arterial detector data recorded over 5 working days was available from California Department of Transportation (Caltrans). This data consisted of counts and occupancies. The freeway detectors reported data every 30 seconds and the arterial detectors reported data every 5 minutes. Signal timing and coordination charts from the city of Irvine specified the details regarding signal phasing, timing, actuation and co-ordination.

The input files required for DynaMIT-P are included in Appendix A.

5.2 Calibration

Before DynaMIT-P is employed, a critical task is the calibration of the system. Calibration in DynaMIT-P involves:

1. Calibration of the Demand Simulator: The various items to be calibrated in the demand component are:
    - Parameters in the utility models for route choice, departure time choice etc.
    - Autoregressive and Covariance matrices that are used in the OD estimation algorithm

- Historical OD Flows

2. Calibration of the Supply Simulator: The parameters that need to be calibrated for the supply simulator are:

    - Various speed-density relationship parameters such as the jam density, the parameters in the speed-density equations such as α, β etc.
    - The capacities of the lane-groups in each segment

A joint calibration of the demand and the supply components is usually performed to account for the strong interaction between the two components. Calibration usually involves obtaining parameter estimates in order to match observed data such as flows and speeds. For a detailed description of the calibration methodology, the reader is referred to Balakrishna [8] for calibration of the demand simulator and Kunde [36] for calibration of the supply simulator.

5.3 Base-Case

For the purpose of the case study, a peak demand period lasting from 7:15 AM to 8:15 AM was chosen. In order to establish the base-case for this period, we need to obtain a set of equilibrium travel times and the planning OD matrix for that period. The demand calibration exercise (Balakrishna, [8]) established the base-case. Some of the key results are presented below and the reader is referred to Balakrishna [8] for a comprehensive review of the results obtained during calibration.

5.3.1 Equilibrium Travel Times

The computation of the equilibrium travel times and the results obtained are illustrated with respect to an important OD pair for the Irvine network. Figure 5-2 illustrates this OD pair $(1-2)$ along with a sample of paths in the path choice set. The flow for this OD pair comprises of about 8000 vehicles per hour.

Figure 5-2: Example of paths for the OD pair $1 - 2$.

The procedure to establish the equilibrium travel times is identical to the procedure described in Section 4.3.1. Figures 5-3 to 5-6 illustrate the process by which equilibrium was achieved. These figures represent travelers' experienced travel times as a function of their departure times. As can be seen, in Figure 5-3, the first iteration (using free flow travel times) resulted in a wide range of experienced travel times. The reason for the wide distribution in travel times is attributed to the fact that, based on the free flow path travel times, travelers were distributed on all the paths. Travelers who chose arterial paths experienced significant delays (due to lower capacities, signalized intersections etc.), while travelers who chose the freeway path arrived at their destination earlier. However, during subsequent iterations, the learning model captures travelers' experiences and updates their travel time perceptions. Based on these new sets of travel times, fewer vehicles chose the arterial paths. Thus by this process, the travel times on the freeway paths increase, but the travel times on arterial paths decrease. By the fourth iteration, the travel times on the paths start converging.

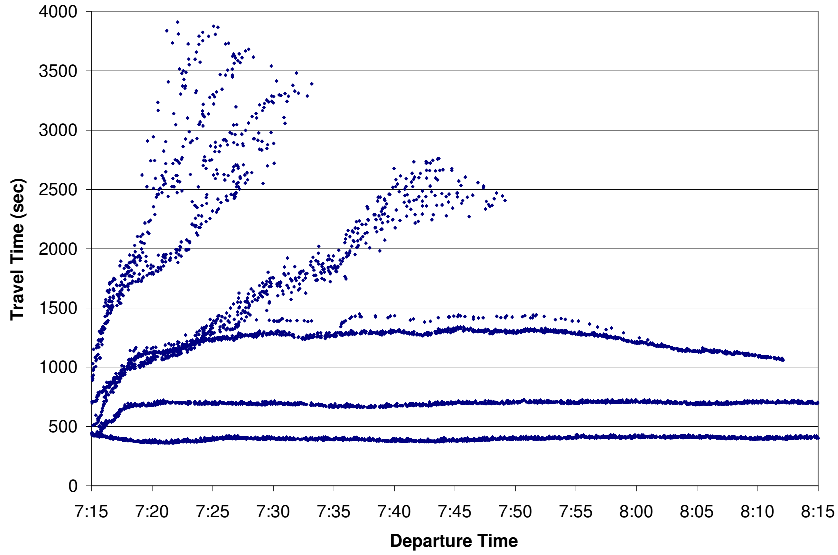

Figure 5-3: Travelers' experienced travel times (Iteration 1).

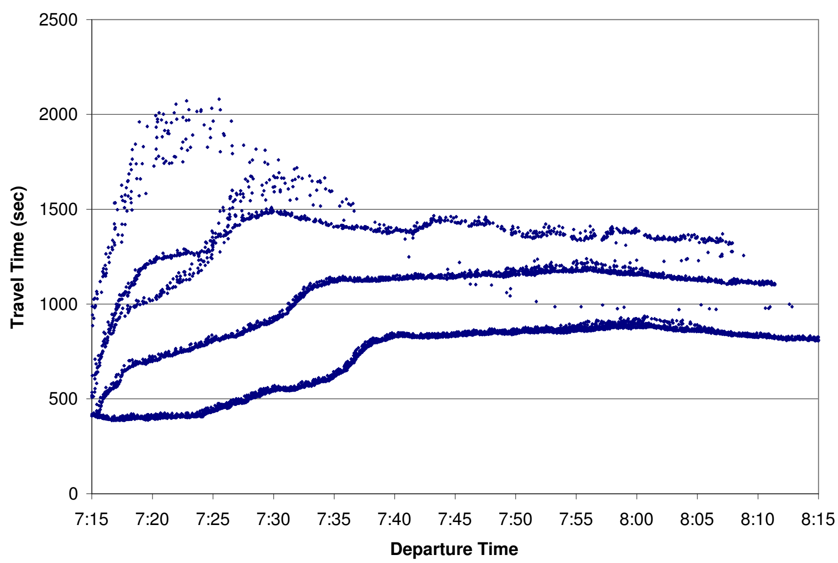

Figure 5-4: Travelers' experienced travel times (Iteration 2).

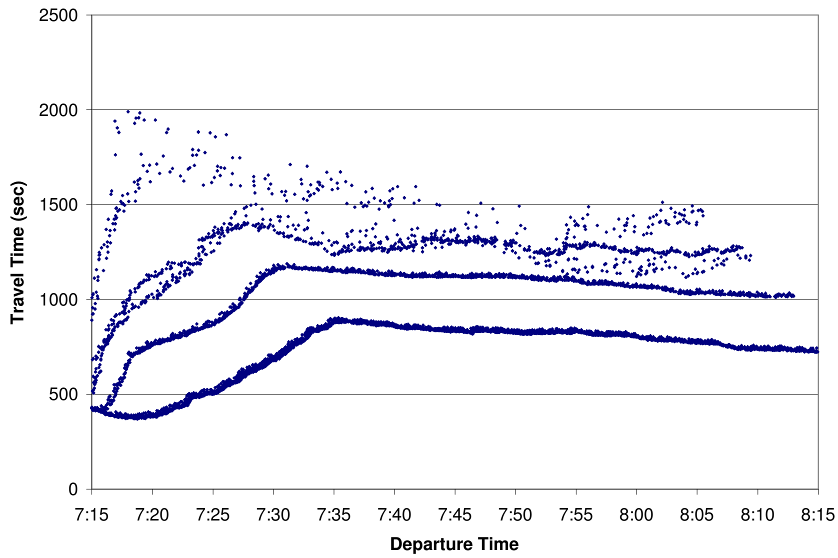

Figure 5-5: Travelers' experienced travel times (Iteration 3).

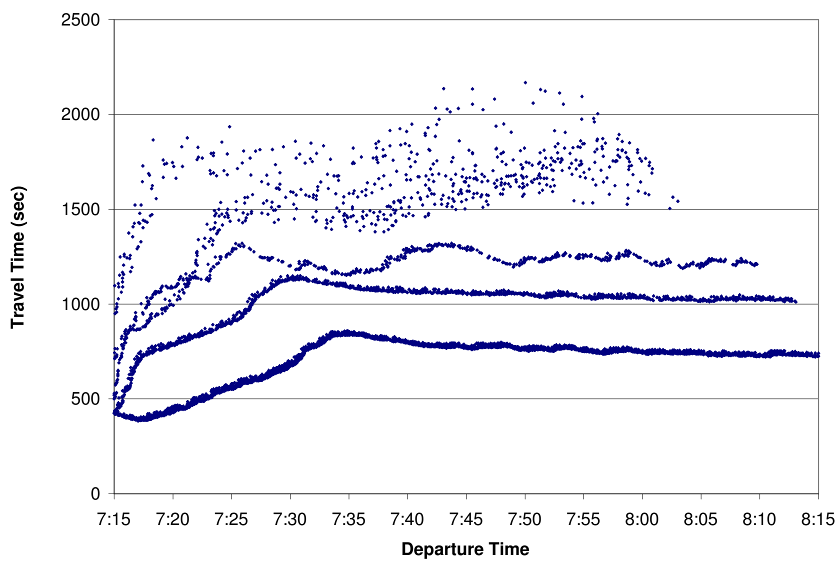

Figure 5-6: Travelers' experienced travel times (Iteration 4).

Finally after 10 iterations, convergence was achieved and the experienced travel times of travelers are shown in Figure 5-7. The average travel time for these travelers who departed in the interval 7:15 AM to 8:15 AM is 961 seconds and the number of completed trips in the interval is 6891. Further, Figure 5-8 illustrates the frequency of experienced travel times. As can be seen from this figure a significant number of travelers experienced travel times between $1000 - 1500$ seconds. However, a few travelers experienced low travel times ($500 - 1000$ seconds) and some of the experienced high travel times (greater than 2000) seconds. The relative number of travelers who experienced these travel times are in accordance with the probabilities associated with choosing the corresponding paths (computed from the utility models based on path travel times).

Further evidence of convergence can be obtained by comparing the input path travel times for this OD pair, (from the previous estimate of the equilibrium travel times, Figure 5-9) and their latest experienced path travel times (Figure 5-10), during the last iteration. The similarity between the input and output path travel times suggests that travelers have made their "equilibrium" decisions and that convergence has been achieved.

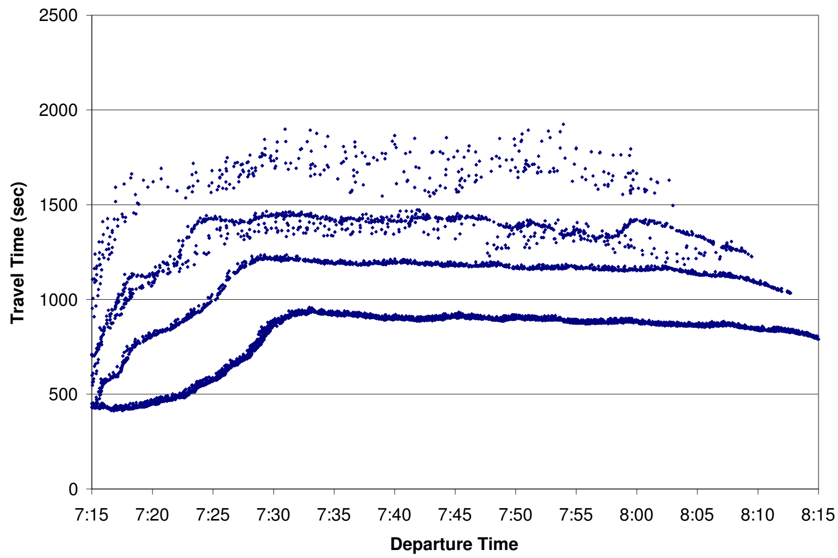

Figure 5-7: Travelers' experienced travel times (after convergence).

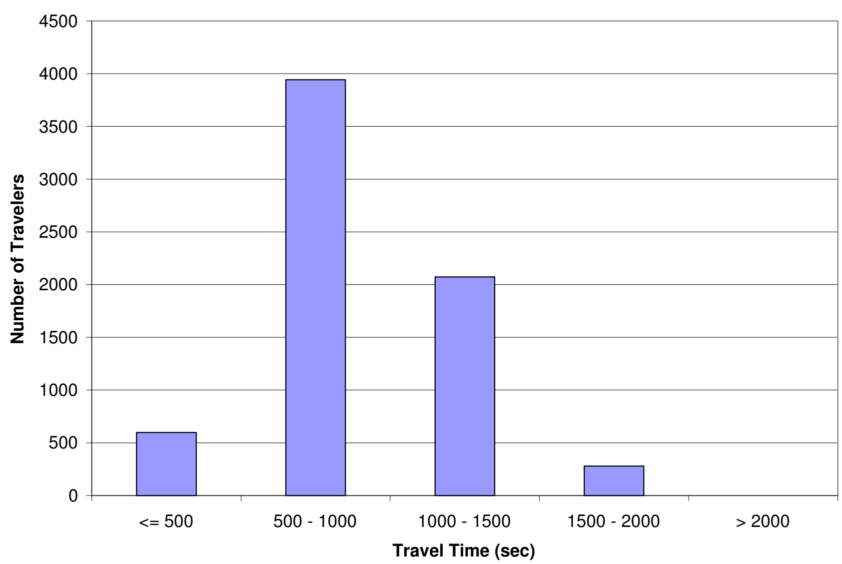

Figure 5-8: Frequency of experienced travel times.

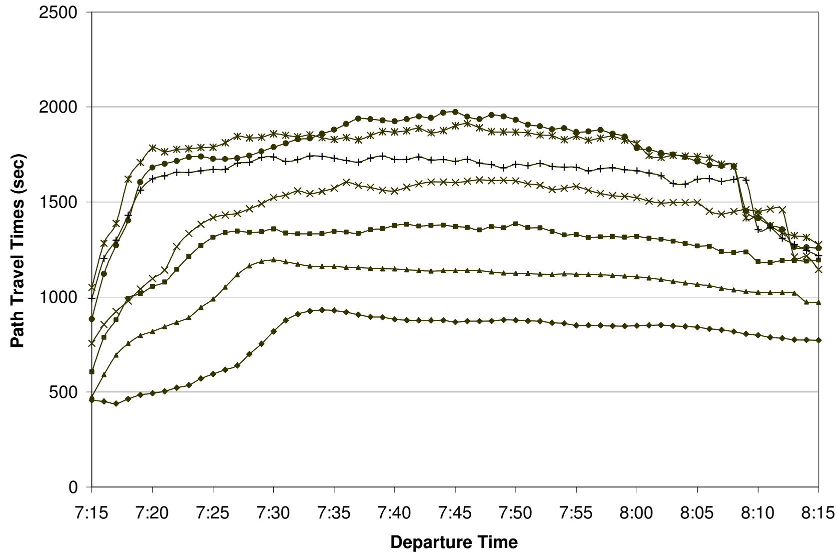

Figure 5-9: Convergence. Input travel times.

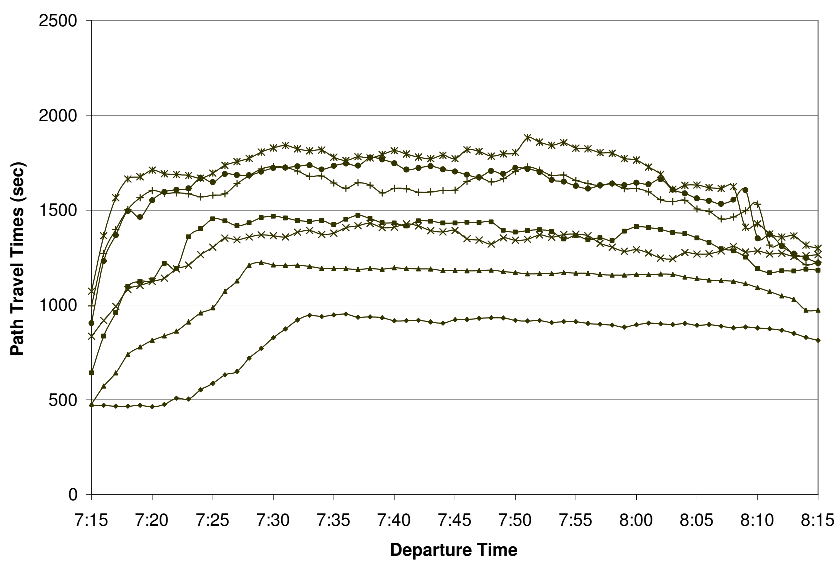

Figure 5-10: Convergence. Output travel times.

5.3.2 Estimation of the Planning OD

The planning OD matrix was established during the process of calibration and the details are not discussed in this thesis. The reader is referred to Balakrishna, [8] for further details.

5.4 VMS Scenario

This section presents the impact of an incident on the network. The impact of VMS based on instantaneous and predictive travel time is then evaluated.

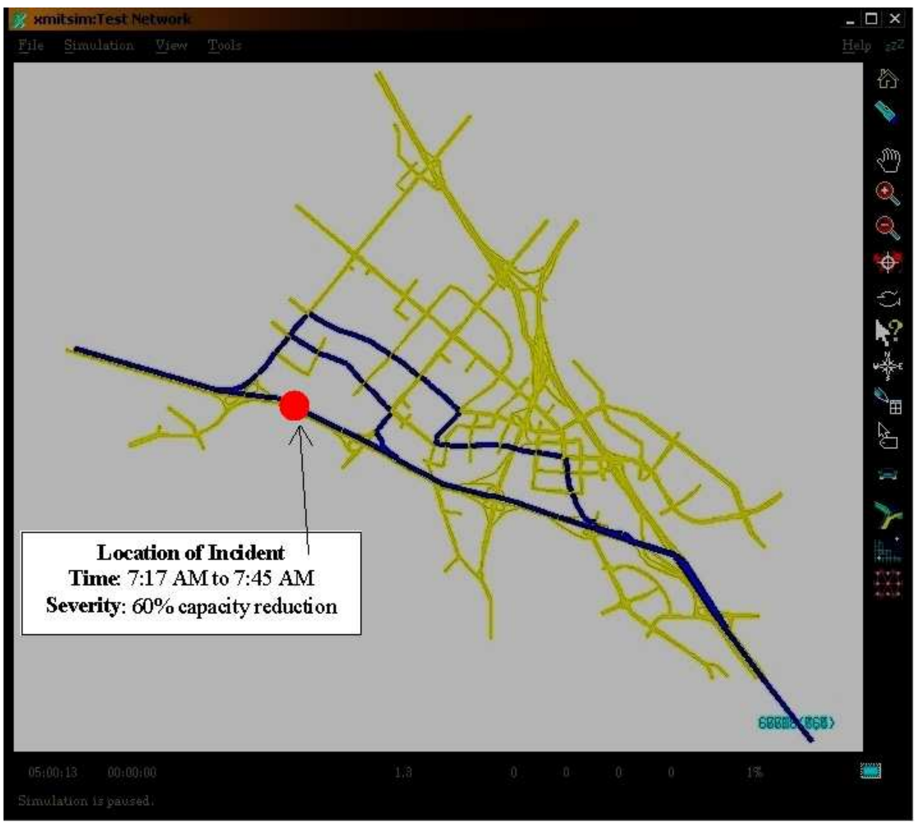

Figure 5-11: Location of the incident.

The planning OD and the equilibrium travel times obtained from the base-case during the time period 7:15 AM to 8:30 AM were used as inputs for the scenario evaluation. The scenarios that are discussed in this section are based on the impact of predictive and instantaneous VMS on the network performance, during a hypothetical incident. An incident is introduced into the system at the location shown in Figure 5-11. The time of the incident is from 7:17 AM to 7:40 AM and sixty percent of the segment capacity is unavailable during the incident.

The analysis focuses on OD pair $1-2$ which is the primary OD pair affected by the incident. The demand for this OD pair is as follows:

Time	**OD Flow (veh/hr)**
7:15 - 7:30	8600
7:30 - 7:45	7000
7:45 - 8:00	7000
8:00 - 8:15	5600

Table 5.1: OD flow for pair $1-2$.

5.4.1 Impact of the Incident

To illustrate the impact of the incident alone, the incident was introduced into the system, without the VMS sign and the network performance was analyzed assuming that travelers follow their habitual paths (established by the equilibrium process). The resulting plot of the travel times experienced by the travelers based on their departure time is shown in Figure 5-12. Figure 5-13 shows the frequency of experienced travel times.

In order to illustrate the impact of the incident and as a reference for future comparisons, the frequency of experienced travel times is further analyzed based on the departure time. (i.e. the diagram such as the one in Figure 5-13 is repeated for the 15 minute time intervals starting from 7:15 AM. These results are presented in Figures 5-14 to 5-16.

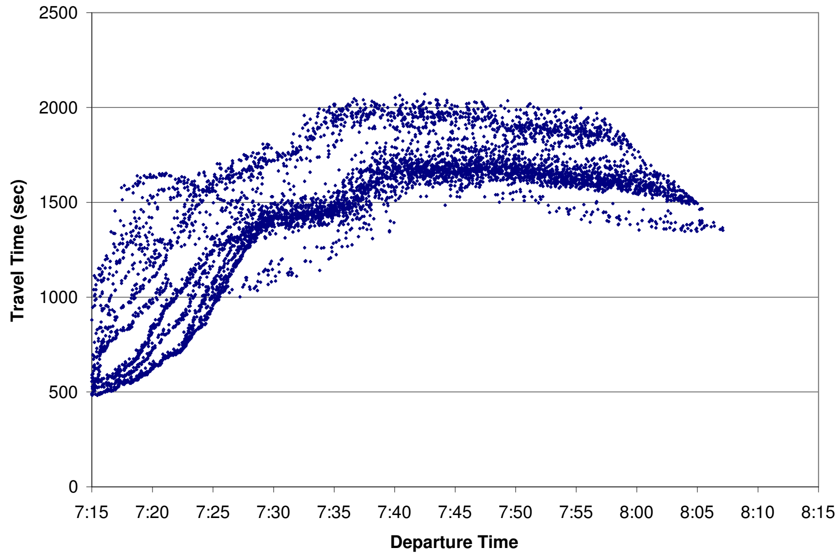

Figure 5-12: Base-case with incident. Travelers' experienced travel times.

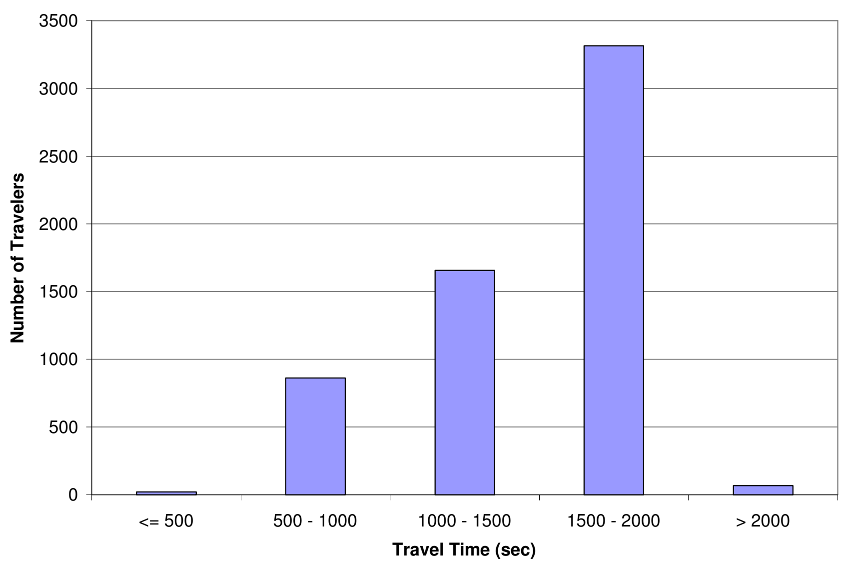

Figure 5-13: Base-case with incident. Frequency of experienced travel times.

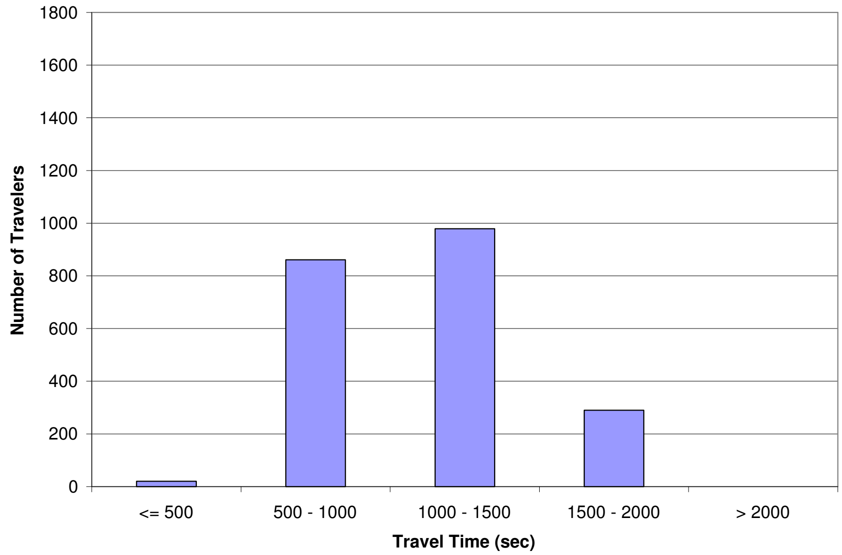

Figure 5-14: Base-case with incident. Frequency of experienced travel times for departure time interval 7:15 AM - 7:30 AM.

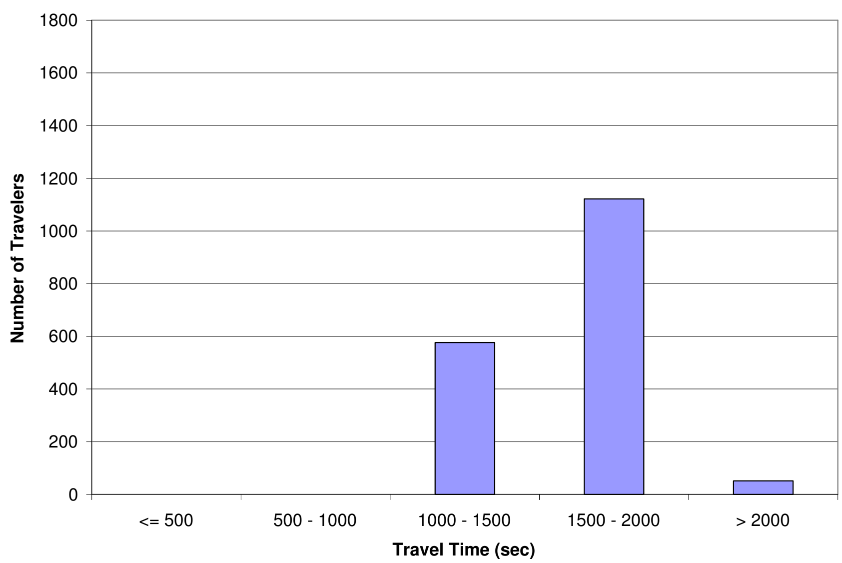

Figure 5-15: Base-case with incident. Frequency of experienced travel times for departure time interval 7:30 AM - 7:45 AM.

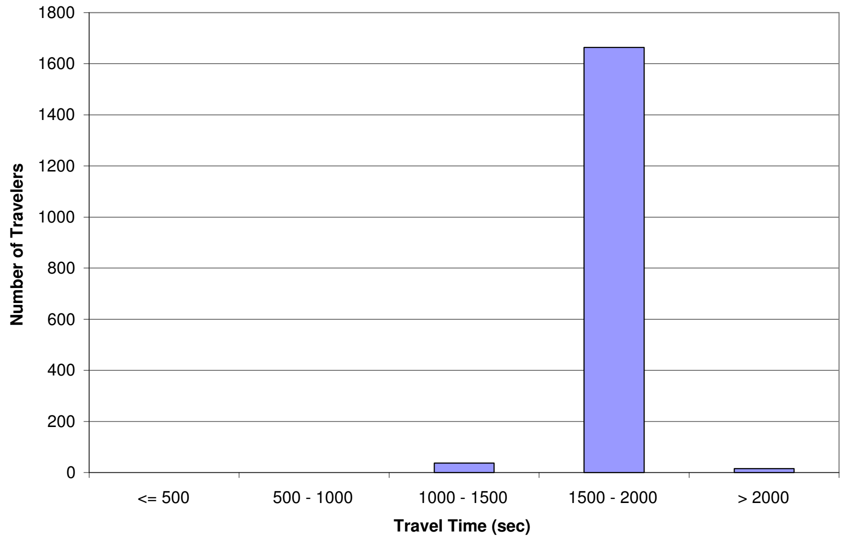

Figure 5-16: Base-case with incident. Frequency of experienced travel times for departure time interval 7:45 AM - 8:00 AM.

Some important statistics regarding the OD pair $1-2$ in the presence of the incident are:

- 5919 packets completed their trips
- The average travel time for these travelers who departed in the interval 7:15 AM to 8:15 AM is 1455 seconds
- The average travel times and numbers of completed trips based on the departure time intervals are shown in Table 5.2:

Departure Time Interval	Average Travel Time (s)
7:15 - 7:30	1088
7:30 - 7:45	1637
7:45 - 8:00	1717
8:00 - 8:15	1538
7:15 - 8:15	1455

Table 5.2: Base-case with incident. Average travel times based on departure time interval.

A comparison with the equilibrium conditions presented in Section 5.3.1, yields the following:

- As a result of the incident, 972 less travelers completed their trips
- The travel time for the OD pair has increased by 494 seconds. This is also evident from Figure 5-8 and Figure 5-13. The majority of travelers experienced travel times is in the range of $1500 - 2000$ seconds as opposed to $1000 - 1500$ seconds under incident-free conditions.

5.4.2 VMS with Instantaneous Information

This section analyzes the impact due to a VMS display instantaneous information for a frequency of information updating of 5 and 10 minutes respectively.

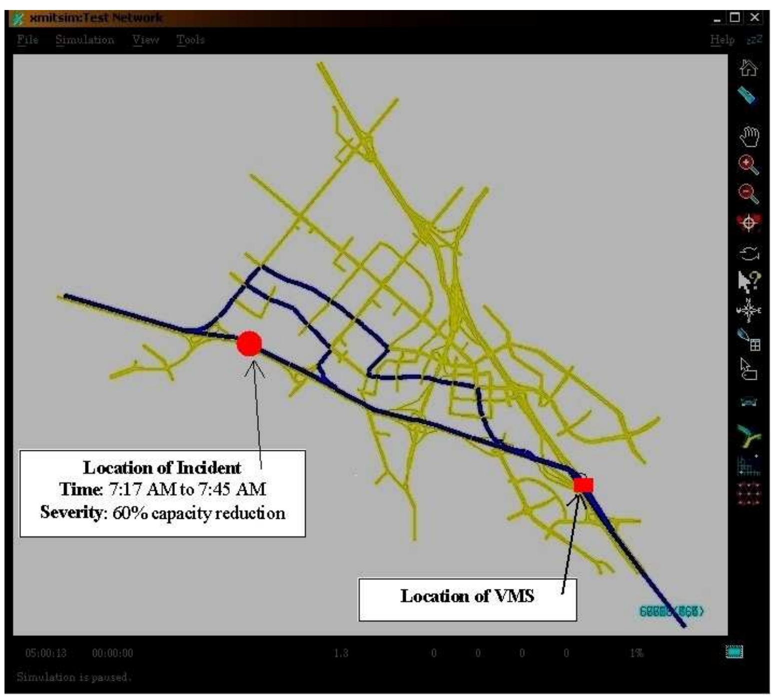

Figure 5-17: Location of VMS message.

The VMS message is located as shown in Figure 5-17. The VMS message sign is placed strategically so that travelers on the OD pair 1−2, which is most affected by the incident can divert in response to the VMS message. The VMS chosen for this purpose is a path-VMS (Chapter 4), that gives information on the travel times of alternative paths. The path VMS is further assumed to provide guidance for the freeway paths and for the arterial paths. Link-VMS in this case would have very little impact, since travelers may divert in response to the link-VMS which completely ignores travel times on the arterials. In this case a degradation of network performance may even occur (due to high congestion on the arterials).

Instantaneous VMS: 10-Minute Information Update Frequency

The experienced travel times of travelers plotted as a function of their departure times is shown in Figure 5-18. The frequency of experienced travel times is shown in Figure 5-19.

Further, as was done for the base-case with incident, the frequency of experienced travel times for various intervals is shown in Figures 5-20 to 5-22.

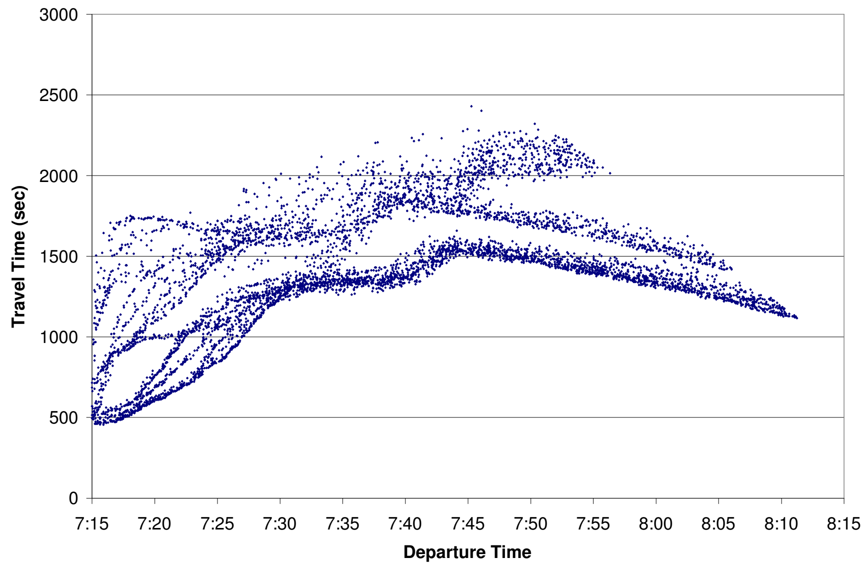

Figure 5-18: Instantaneous VMS (10-minute update). Travelers' experienced travel times.

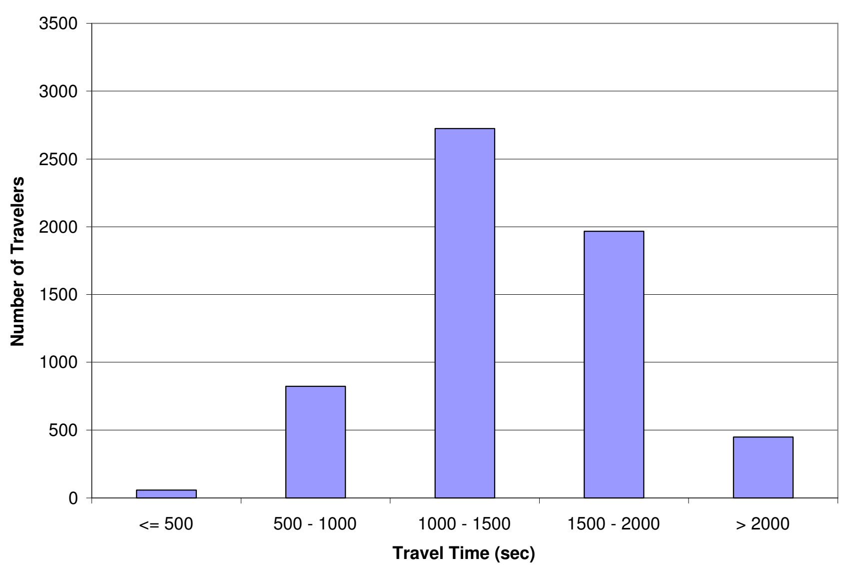

Figure 5-19: Instantaneous VMS (10-minute update). Frequency of experienced travel times.

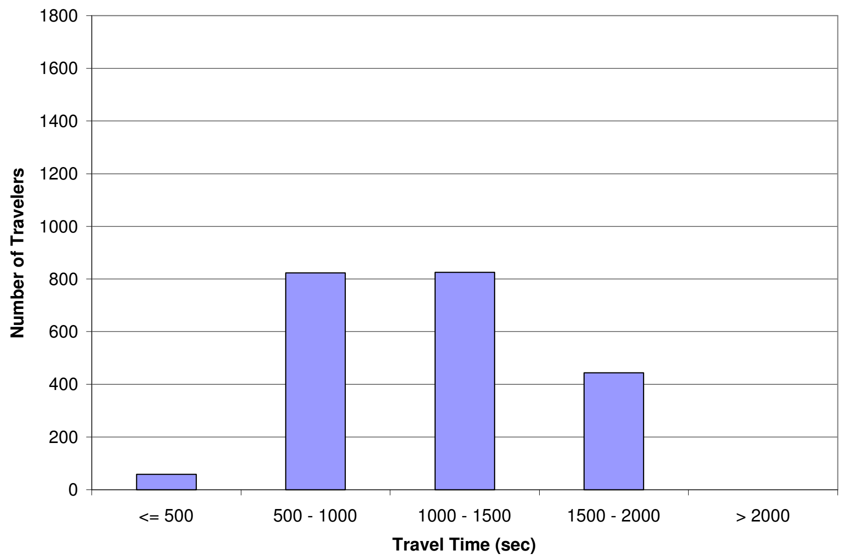

Figure 5-20: Instantaneous VMS (10-minute update). Frequency of experienced travel times for departure time interval 7:15 AM - 7:30 AM.

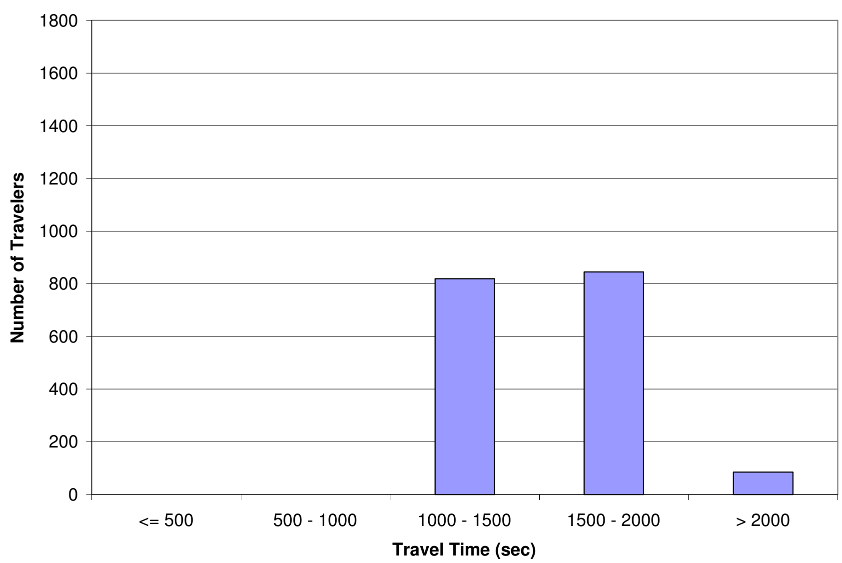

Figure 5-21: Instantaneous VMS (10-minute update). Frequency of experienced travel times for departure time interval 7:30 AM - 7:45 AM.

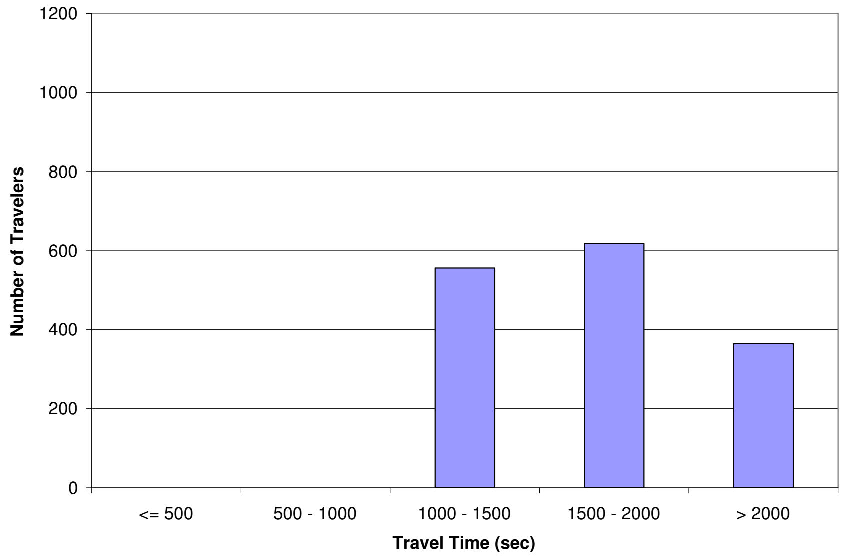

Figure 5-22: Instantaneous VMS (10-minute update). Frequency of experienced travel times for departure time interval 7:45 AM - 8:00 AM.

Again, some important statistics regarding the OD pair $1-2$ under this scenario are illustrated below:

- 6021 packets completed their trips
- The average travel time for these travelers who departed in the interval 7:15 AM to 8:15 AM is 1410 seconds
- The average travel times based on the departure time intervals are shown in Table 5.3:

Departure Time Interval	Average Travel Time (s)
7:15 - 7:30	1102
7:30 - 7:45	1584
7:45 - 8:00	1679
8:00 - 8:15	1310
7:15 - 8:15	1410

Table 5.3: Instantaneous VMS (10-minute update). Average travel times based on departure time interval.

A comparison of the results obtained with the other scenarios is made finally in Section 5.5.

Instantaneous VMS: 5-Minute Update Frequency

The experienced travel times of all the travelers is presented in Figure 5-23. Figure 5-24 shows the bar graph illustrating the frequency of experienced travel times. Finally, Figures 5-25 to 5-27 further show the frequency of experienced travel times on a departure time interval basis.

Some important statistics regarding the OD pair $1 - 2$ are:

- 6047 packets completed their trips
- The average travel time for these travelers who departed in the interval 7:15 AM to 8:15 AM is 1404 seconds
- The average travel times based on the departure time intervals are shown in Table 5.4:

Departure Time Interval	**Average Travel Time (s)**
7:15 - 7:30	1110
7:30 - 7:45	1602
7:45 - 8:00	1640
8:00 - 8:15	1278
7:15 - 8:15	1404

Table 5.4: Instantaneous VMS (5-minute update). Average travel times based on departure time interval.

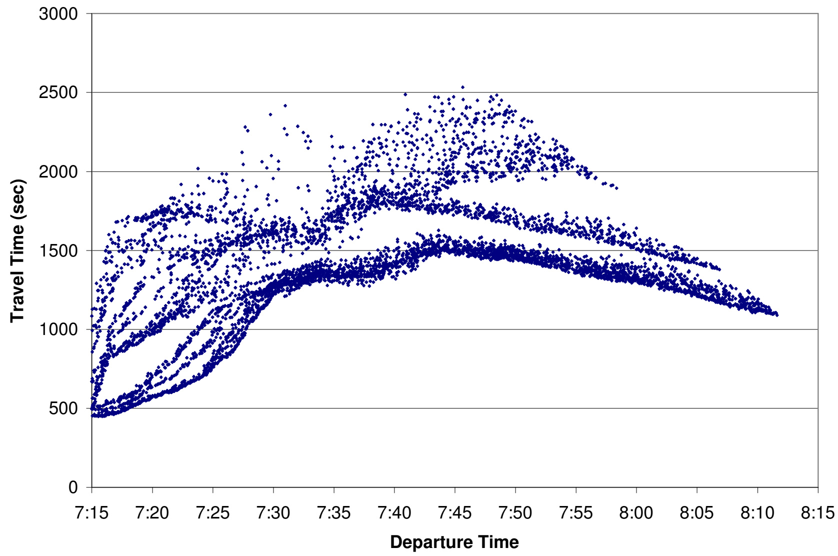

Figure 5-23: Instantaneous VMS (5-minute update). Travelers' experienced travel times.

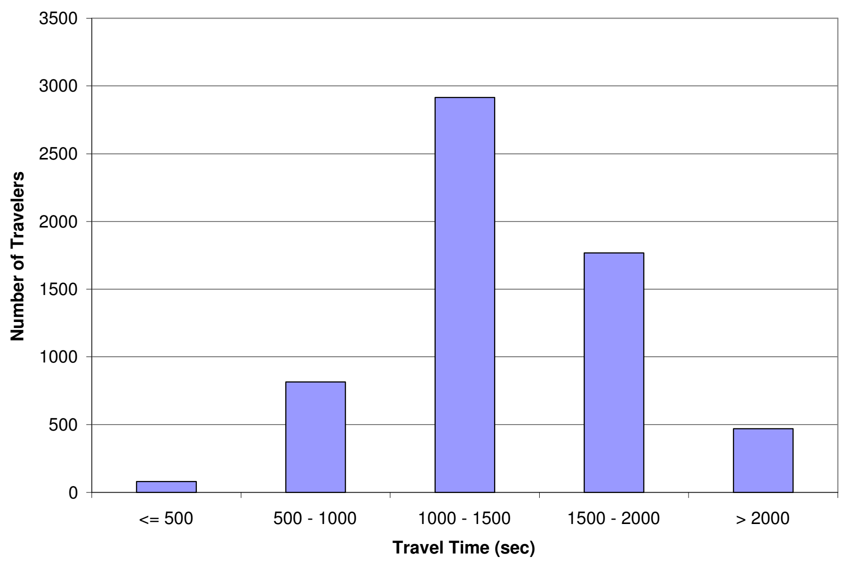

Figure 5-24: Instantaneous VMS (5-minute update). Frequency of experienced travel times.

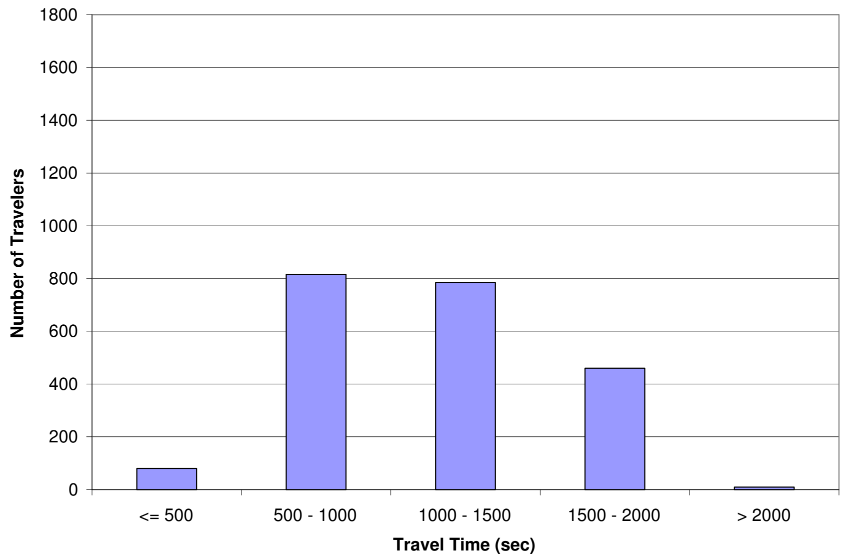

Figure 5-25: Instantaneous VMS (5-minute update). Frequency of experienced travel times for departure time interval 7:15 AM - 7:30 AM.

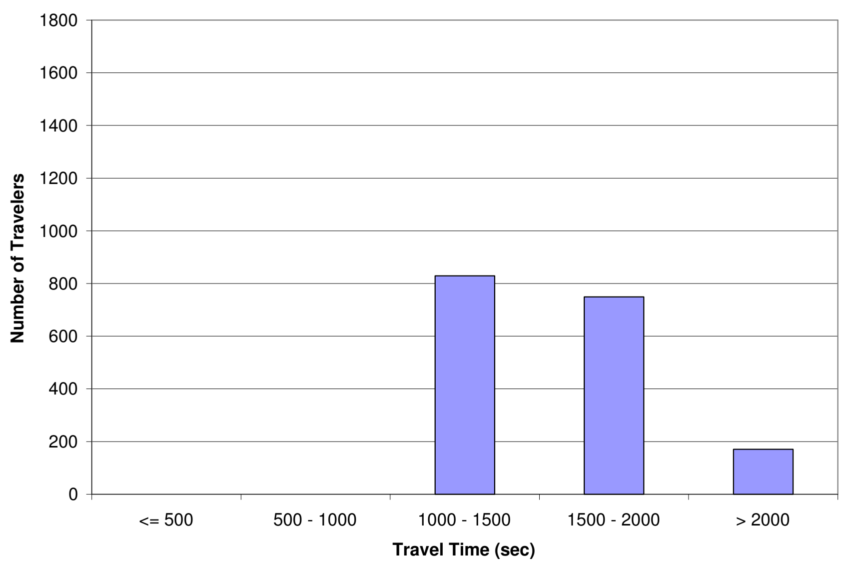

Figure 5-26: Instantaneous VMS (5-minute update). Frequency of experienced travel times for departure time interval 7:30 AM - 7:45 AM.

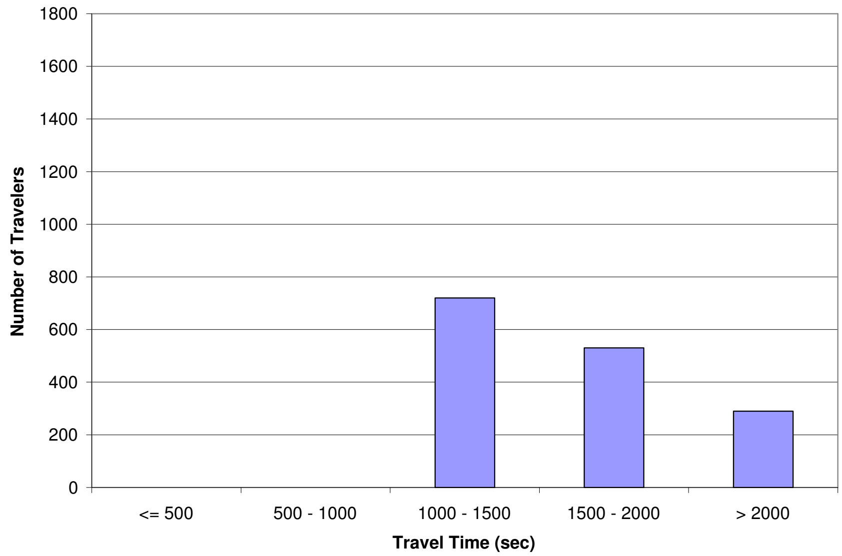

Figure 5-27: Instantaneous VMS (5-minute update). Frequency of experienced travel times for departure time interval 7:45 AM - 8:00 AM.

5.4.3 VMS with Predictive Information

Finally, under the same setting as before, a predictive VMS scenario is analyzed. Several iterations were performed to achieve consistency in the prediction and the best guidance was chosen based on criteria such as the number of finished trips, the average travel time during the planning horizon and the distribution of the travel times experienced by travelers. Figure 5-28 shows the travel times experienced by the travelers. Figure 5-29 shows the frequency of experienced travel times. Further, the frequency of experienced travel times is shown on a departure time interval basis in Figures 5-30 to 5-32.

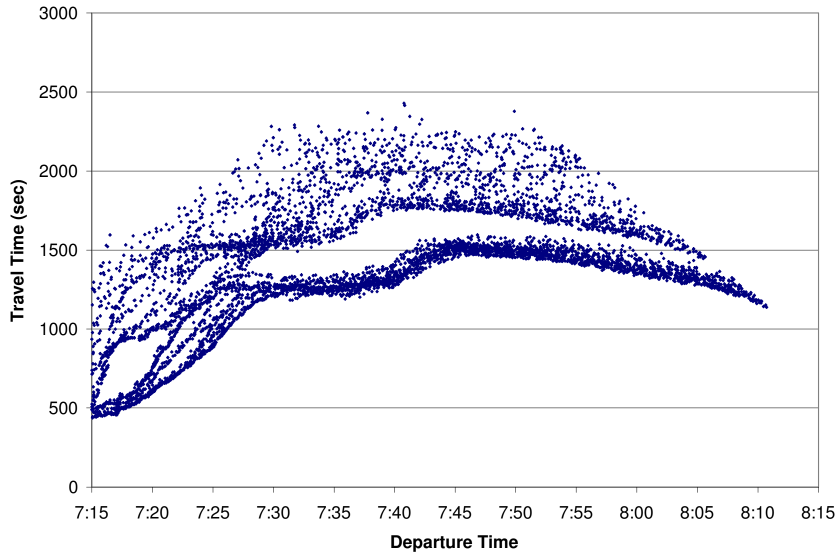

Figure 5-28: Predictive VMS. Travelers' experienced travel times.

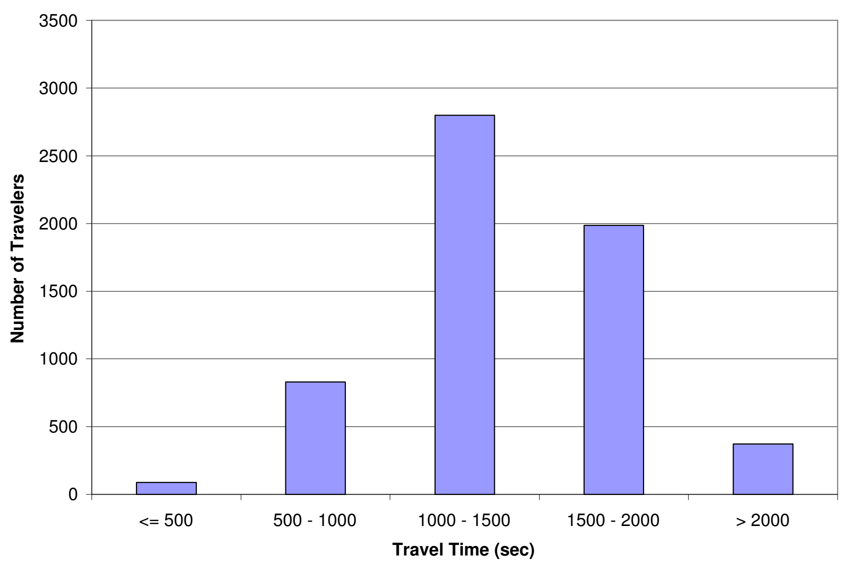

Figure 5-29: Predictive VMS. Frequency of experienced travel times.

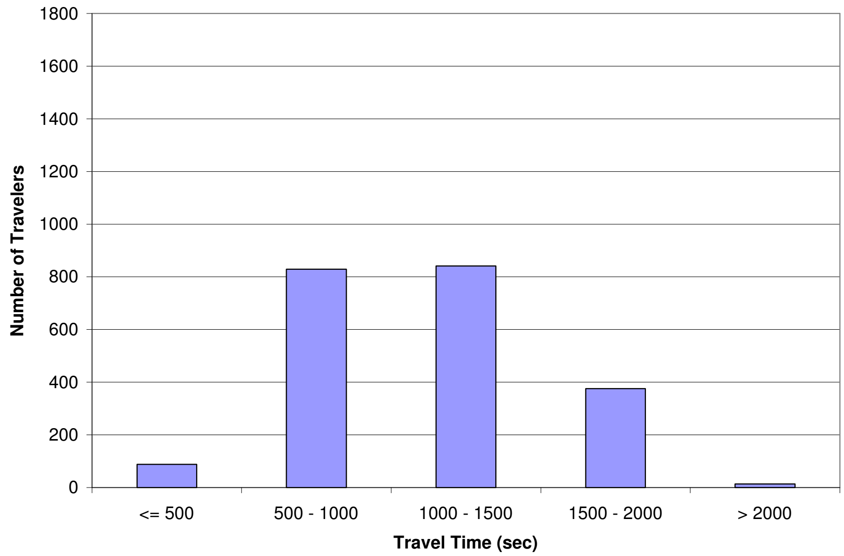

Figure 5-30: Predictive VMS. Frequency of experienced travel times for departure time interval 7:15 AM - 7:30 AM.

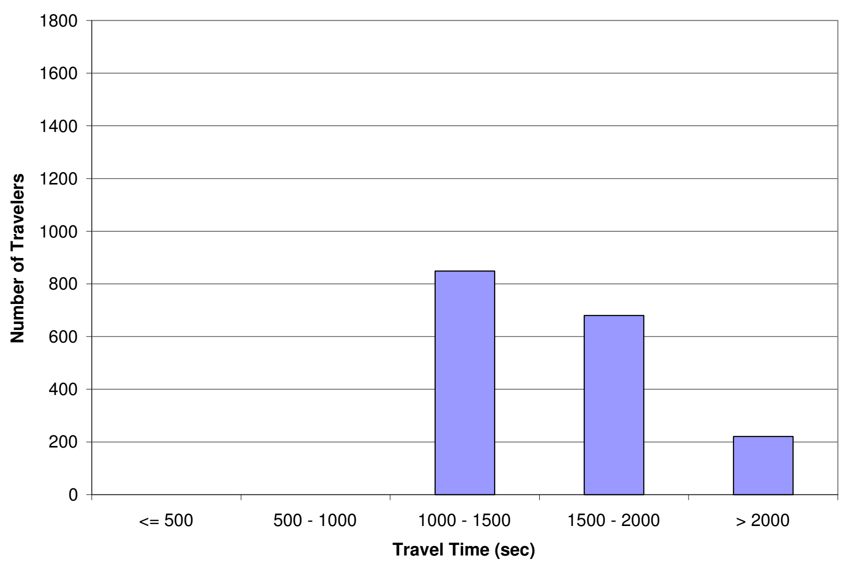

Figure 5-31: Predictive VMS. Frequency of experienced travel times for departure time interval 7:30 AM - 7:45 AM.

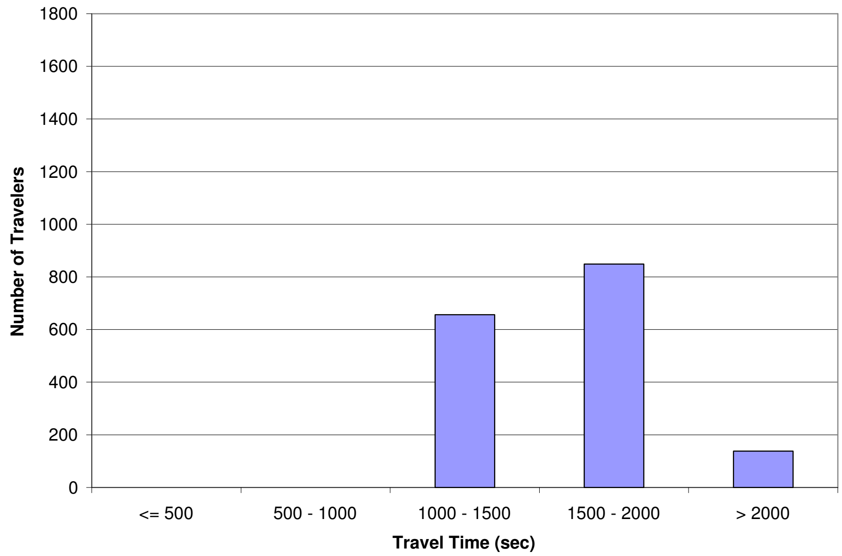

Figure 5-32: Predictive VMS. Frequency of experienced travel times for departure time interval 7:45 AM - 8:00 AM.

The important statistics regarding the OD pair $1 - 2$ are:

- 6075 packets completed their trips
- The average travel time for these travelers who departed in the interval 7:15 AM to 8:15 AM is 1401 seconds
- The average travel times based on the departure time intervals are shown in Table 5.5:

Departure Time Interval	**Average Travel Time (s)**
7:15 - 7:30	1089
7:30 - 7:45	1583
7:45 - 8:00	1628
8:00 - 8:15	1361
7:15 - 8:15	1401

Table 5.5: Predictive VMS. Average travel times based on departure time interval.

5.5 Comparison of VMS Designs

In the discussion that follows, I-VMS denotes the instantaneous VMS and P-VMS denotes the predictive VMS

5.5.1 Comparison Based on Aggregate Statistics

Table 5.6 summarizes the number of completed trips and the average travel times for the various scenarios. Further, the percentage change of the average travel times in indicated in brackets.

	Base-Case	**I-VMS 10-Min**	**I-VMS 5-Min**	**P-VMS**
Completed trips	5919	6021	6046	6075
Avg. TT (s)	1455	1410(-3.1%)	1404(-3.5%)	1401(-3.7%)

Table 5.6: Comparison based on aggregate statistics.

As can be observed from Table 5.6, in the presence of a VMS during the incident some savings in travel times were obtained. However, the savings in travel time were only of the order of 3.1 to 3.7 %. Moreover, from among the various VMS scenarios, the predictive VMS resulted in marginally better savings in travel time (54 seconds as opposed to 45 and 51 seconds for the 10 and 5-minute instantaneous VMS respectively). VMS with instantaneous information updated every 5-minute update was more effective than the one with an update every 10-min. Regarding the number of completed trips in the time interval 7:15 to 8:15, the predictive VMS resulted in 156 more trips being completed and was again marginally superior to both the 10-minute and the 5-minute instantaneous VMS. However, the average travel times after implementing the VMS were still much larger than the average travel times without the incident (961 seconds).

The reasons for the reduced impact of the VMS signs is primarily because of the fact that given the location and the severity of the incident, the primary freeway path that captured a majority of the flow was largely affected. Furthermore, a closer look at the alternative paths which circumvent the incident location revealed that these paths are primarily arterial paths. However, it was not possible in this case, due to capacity constraints on the arterials to divert sufficient number of vehicles so as to cause significant savings in travel time. This fact is made clear by observing the experienced travel times of the travelers with and without a VMS message (for instance by comparing Figures 5-12 and 5-28). Particularly, though the travel times on the freeway reduced significantly after using the predictive VMS (as seen by the lower band in Figure 5-28), some travelers who diverted to arterial paths experienced travel times greater than 2000 seconds. Any further diversion on the arterials would result in travelers experiencing even higher travel times on the arterial paths. The travel times on the freeway however may be reduced significantly as a result of these diversions to arterials. Hence, though an improvement in the average travel times might occur, the resulting guidance would not be consistent. The instantaneous VMS (5 and 10 minute) are not as effective in utilizing the available paths, as evident from Figures 5-18 and 5-23.

The critical question at this point, is whether the use of the VMS is advocated in this scenario. Though the VMS did not yield significant benefits by means of the aggregate statistics, it is nevertheless useful in this case as will be illustrated by more rigorous analysis (discussed next).

5.5.2 Comparison Based on the Frequency of Trip Travel Times

The comparison based on frequency of trips within various ranges of travel times is summarized in the table below.

	Base-Case	**I-VMS 10-Min**	**I-VMS 5-Min**	**P-VMS**
Less than 500 sec	20	58	80	88
500 - 1000 sec	861	823	815	829
1000 - 1500 sec	1657	2724	2915	2799
1500 - 2000 sec	3314	1967	1767	1986
Greater than 2000 sec	67	449	469	373

Table 5.7: Comparison based on the frequency of trip travel times.

The comparison reveals that the number of trips with travel time less than 1000 seconds, do not vary much across the scenarios. The reason for this is that the low travel times are associated with an early departure time in the planning horizon and hence are not largely affected by the incident (given that it takes about 8-10 minutes to reach the incident). However, it can be seen that the VMS has caused a large number of travelers to experience travel times between 1000-1500 seconds as opposed to the base-case with the incident where most of travelers experienced travel time of the order of 1500-2000 seconds. Thus the VMS has been largely beneficial in this regard. However, the use of the VMS has also increased the number of travelers' experiencing travel times greater than 2000 seconds as compared to the base case. This is primarily due to the diversion on capacity constrained arterial paths. When compared to the number of travelers who experienced lower travel times, this shift is not as significant.

Further comparing the alternative VMS strategies, the 5-minute instantaneous VMS scenario succeeded in shifting a large number of travelers to the lower travel time band. However, under this strategy more travelers experience high travel times as compared to the other two VMS strategies. Among the three VMS strategies, the predictive VMS strategy is most effective because it not only causes a large number of travelers to experience lower travel times, it also does it so at the expense of relatively fewer travelers.

5.5.3 Comparison Based on Departure Time Interval

The following table compares the average travel times under each of the scenarios, as a function of the departure-time interval. The percentage change in travel time is also indicated in brackets.

	Base-Case Avg. TT (s)	**I-VMS 10-Min** Avg. TT (s)	**I-VMS 5-Min** Avg. TT (s)	**P-VMS** Avg. TT (s)
7:15-7:30	1088	1102 (+1.3%)	1110 (+2.0%)	1089 (0.0%)
7:30-7:45	1637	1584 (-3.2%)	1602 (-2.1%)	1583 (-3.3%)
7:45-8:00	1717	1679 (-2.2%)	1640 (-4.5%)	1628 (-5.1%)
8:00-8:15	1538	1310 (-14.8%)	1278 (-16.9%)	1361 (-11.5%)

Table 5.8: Comparison based on departure time interval

Interestingly, the average travel times on a departure interval basis holds promise for the use of VMS in this situation. Though marginal benefits were obtained in the average travel time for the second interval, the travel time saving is about 89 seconds for the predictive VMS in the third interval (which is a 5 % improvement) to about 177 seconds (11.5 % improvement in the last interval). The travel time saving in the last interval was even larger for the instantaneous VMS with 5-minute update (about 17 %).

Based on the above comparisons, some conclusions are summarized below:

- Though overall, the average savings in travel times were of the order of 3 to 4 %, the VMS scenarios resulted in a large number of travelers experiencing lower travel times at the expense of relatively fewer travelers. Further, depending on the departure time interval, travel time savings ranged from 3 % to 17 %.

- Based on alternative VMS strategies, the predictive strategy resulted in the best overall network performance, both in terms of the number of travelers who completed their trips and the average travel time. It yielded an overall improvement of 3.7 % in travel time as opposed to 3.1% and 3.5% for the instantaneous scenario. Further, during the planning horizon, 156 additional travelers completed their trips using the predictive guidance (as opposed to 102 and 127, in the case of the 5 and 10-minute instantaneous scenario respectively).

- The instantaneous scenarios may cause travelers to experience longer travel times, since this strategy does not take into account future network conditions and may lead to overreaction. This effect may be avoided by using the predictive VMS scenario with a consistent guidance strategy.

- Instantaneous strategies with the 5-minute information update frequency was found to be better than the strategy with 10-minute update frequency.

- Last but not the least, the potential of VMS to mitigate network conditions during a particular incident depends to a large extent on the incident location, its severity and on the alternative paths that circumvent the incident location.

5.6 Summary

This chapter illustrated the potential of the planning tool in evaluating a VMS case study based on a network in Irvine, California. The base-case was first established based on the calibration exercise. Various scenarios involving a VMS message were then evaluated based on a hypothetical incident on the irvine network. DynaMIT-P was used to evaluate both predictive and instantaneous information through the VMS. Further, in the instantaneous case, the analysis was performed for a frequency of information update of 5 and 10 minutes. The planning tool was found to be extremely useful in analyzing various scenarios and capturing the relevant details critical. The case-study was intended to give a sense of the potential of DynaMIT-P and illustrate the benefits of deploying such planning tools. The next chapter focuses on areas where further research may be employed to improve the functionality of the planning tool.

Chapter 6

Conclusion

This thesis focused on the the development of a DTA planning tool to address short-term planning applications. A framework for short-term planning applications in simulation-based DTA systems was developed. This framework captures the day-to-day and within-day dynamics of travelers. An implementation of the framework DynaMIT (which is a real-time DTA system) to obtain DynaMIT-P was discussed. Case studies on an actual network in California, Irvine demonstrated the potential of the planning tool to address short-term planning applications (especially in evaluating ITS scenarios).

6.1 Research Contribution

The contributions of the research can be identified by the following key points:

- Traditional planning tools for short-term planning applications are static in nature and thus are not adequate to evaluate a whole gamut of planning strategies; especially those that warrant explicit modeling of traffic dynamics and traveler behavior. This research, however used the concept of Dynamic Traffic Assignment and combined it in a simulation environment to develop a planning framework that counters the drawbacks of the traditional planning tools.

- This research modeled a framework to address both day-to-day and within-day behavior of travelers. Such a tool that encompasses both the above aspects of traveler behavior in the DTA context are uncommon.

- The methodology proposed in this research for the establishment of the day-to-day behavior included an OD estimation module that updated the planning OD matrix to reflect recent sensor counts. Thus, the modeling framework presented in this research, establishes not only the equilibrium travel conditions in the network but at the same time provides an OD matrix that best reflects the observed sensor counts. A planning tool with this feature is more effective in addressing short-term planning applications as it captures the baseline scenario more accurately.

- An important feature of the planning framework developed is its capability to model ATIS/ATMS at various levels of sophistication. With recent focus on planning applications shifting from infrastructural enhancements to traffic management and ITS deployments, a planning tool to address a range of traffic management and ITS scenarios is invaluable for traffic planners.

  The use of ATIS strategies to provide information to travelers during non-recurrent conditions such as incidents, has assumed enormous importance in the current transportation environment. Further as mentioned earlier, ATIS strategies can be of various levels of sophistication (e.g. instantaneous or predictive information). A planning tool to evaluate such strategies must be able to generate the information and also model travelers' responses to the information. The planning framework developed as part of this research achieves this objective. For example, the generation of consistent predictive information was implemented in DynaMIT-P for both in-vehicle and VMS information systems. Further, the framework is sensitive to design parameters such as the frequency of the information update etc. and it has a lot of flexibility and potential to include sophisticated traveler behavior models that will capture traveler response in a wide variety of situations.

In a nutshell, the planning framework addresses comprehensively a range of ITS and traffic management scenarios that have not been dealt with successfully in the past.

6.2 Future Research

The research presented in this thesis can be extended in the future in the following directions.

- The planning tool developed in this research focused on short-term planning applications. A natural extension of the tool is to expand it to include long-term planning applications. The planning framework currently assumes that the OD matrix is a given input (though it may be adjusted in the OD estimation procedure). However, the scope of the planning tool can be broadened so as to forecast OD flows based on behavioral models. A step towards achieving this objective will be to integrate an activity schedule model with DynaMIT-P. For a discussion on activity-based disaggregated travel demand model system with activity schedules, the reader is referred to Ben-Akiva and Bowman [10].

- Another important research direction is to enhance the components of the planning tool, specifically with respect to the traveler choice and behavior models. For instance, the mode choice model can be expanded to model changes in mode from car to transit and vice-versa.

- A third important requirement is to understand and model traveler behavior in response to information. Though numerous studies have been conducted in this regard, there is still significant scope for improvement to the existing techniques. Incorporation of traveler behavior models that will closely mimic traveler response to information will enhance the importance of planning tools such as the one developed in this research.

Appendix A

DynaMIT-P Input Files

A brief review the input files required by the DynaMIT-P system are described.

- The **network file** describes the locations of nodes, links, segments and sensors, and defines the connectivity between individual lanes in the network. Changing section geometry within links was modeled by dividing the links into smaller segments.

- The **supply parameter file** contains segment-specific relationships that are used by DynaMIT-P's supply simulator while simulating the movement of vehicles on the network. Specifically, this file contains the parameters of the speed/density function and segment capacities.

- The **OD demand file** specifies the time-varying origin-destination flows for each OD pair.

- DynaMIT-P also requires information regarding driver socio-economic characteristics that are used while generating the population of drivers. These include trip purpose, access to ATIS and value of time, and are defined for each origin-destination pair that appears in the demand file. The **socio-economic** characteristics are used by DynaMIT-P's route choice models.

- A file containing **time-varying traffic sensor counts**.

- DynaMIT-P uses historical estimates of **link travel times** while assigning initial routes to drivers.

- In addition to the inputs discussed above, DynaMIT-P's demand simulator requires **error covariance and autoregressive matrices** that are used during OD Estimation. These matrices result from a process of calibration.

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