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# A Simulation-based Framework for the Analysis of Traffic Networks Operating with Real-time Information

Partners in Advanced Transit and Highways (PATH), CALTRANS
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Final Report

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## PATH Goal Statement

The research reported herein is a part of the Program on Advanced Technology for the Highway, PATH, within the Institute of Transportation Studies, at the University of California. PATH aims to increase the capacity of the most used highways, to decrease traffic congestion, and to improve safety and air quality. It is evolutionary and voluntary. It is a cooperative venture of automakers, electronic companies, local, state and federal governments, and universities.

## Disclaimer Statement

The contents of this report reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the STATE OF CALIFORNIA or the FEDERAL HIGHWAY ADMINISTRATION. This report does not constitute a standard, specification, or regulation.

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# Chapter 1
# PROJECT DESCRIPTION

## 1.1 Introduction

As traffic conditions continue to worsen at an alarming rate in many of the urban areas around the world, traffic and transportation engineers are becoming increasingly aware of the relatively limited impact of conventional and mostly local approaches to tackle the problem. Potential solutions could be based on 1) augmenting the network capacity by constructing more roadways, 2) implementing travel demand management, which would manage traffic growth by developing policies to reduce the number of vehicles on the roadways during peak travel times, and 3) increasing the efficiency of the existing transportation system by incorporating operational improvements. The first solution is often economically infeasible, and the second solution has often proved difficult to implement. The focus of this research project is the third alternative, namely the modelling of operational improvements that incorporate rapidly developing communication and computing technologies into the vehicle-highway infrastructure. This application of advanced technologies to the vehicle-highway system is formally termed as Intelligent Vehicle Highway Systems (IVHS) in the United States. There four categories under IVHS are : Advanced Traveler Information Systems (ATIS), Advanced Traffic Management Systems (ATMS), Commercial Vehicle Operation (CVO) and Advanced Vehicle Control Systems (AVCS). Thus, two critical issues arise; the first one focuses on the evaluation of the performance of traffic systems in ATIS/ATMS context, and the second upon the drivers response to the provided information.

The performance of traffic networks under ATIS/ATMS is the result of complex interactions between and within several elements. User decisions, made in real-time as well as from day-to-day, determine the time-dependent distribution of flows on the various components of the network. Nonlinear interactions in the traffic stream on the network links, and at the nodes, determine the associated trip times, delays, and quality of traffic service experienced by the tripmakers. The dynamic interaction among user decisions, traffic conditions, controller actions, and information governs the overall performance of the system.

Some functional requirements of a suitable model for the evaluation of ATIS/ATMS are:

1. Ability to model the route choice behavior of drivers with and without access to ATIS information.
2. Responsiveness to dynamic O-D information available to the controller as reported by the ATIS and other sources.
3. Ability to track the route and location of the drivers who receive the route advice from the control center.
4. Ability to predict time-dependent impedance (travel time) based on the assignment results, and provide feedback to the control center that may be used in the assignment of vehicles.

In-vehicle information supply strategies differ in terms of their characteristics along several important dimensions, such as the nature of the information displayed, being descriptive or prescriptive. Four principal generic types of information strategies classified by Mahmassani and Jayakrishnan (1991) are :

1. Descriptive, stored information: " static map" that displays only stored information on time-dependent trip times on the various links.
2. Descriptive, real-time information: display of network (or portions thereof) with indications of prevailing congestion on the various links.
3. Descriptive, real-time information with individual optimization: the link-level information is processed either on board or centrally to compute the current shortest path from present position to desired destination of given driver.
4. Controlled guidance : the instructions given to users reflect a central controller's system level objectives, subject to certain constraints to prevent unreasonable penalties to any individual tripmakers.

It is probable that user response will be governed by different behavioral mechanisms and heuristics under each type of information supply strategy. Unfortunately, the literature on the early research on travel behavior under IVHS information has not yet provided an adequate basis for modelling user response and evaluating the above strategies.

Existing methodologies for network assignment and traffic systems analysis do not adequately capture the complex interactions described earlier. Traffic simulation models typically require known time-varying input flows on links and known movements from one link to another. Virtually none of the models used in practice consider the behavioral processes that determine the formation of these flows on the paths in the network. On the other hand, available network equilibrium assignment models are aimed at static steady-state conditions, and as such are used primarily meant for transportation planning applications rather than traffic operations analysis. This was the primary motivation behind this research project to develop a new simulation framework for analyzing traffic networks with ATIS and/or ATMS. This research report describes the development of DYNASMART (Dynamic Network Assignment-Simulation Model for Advanced Road Telematics), which grew out of an early prototype ***program*** developed at the University of Texas at Austin.

## 1.2 Literature Review

Extensive development of traffic simulation models over the past twenty years has produced several effective programs (TRANSYT, NETSIM, INTRAS, TEXAS and PASSER, to name a few; see TRB special report 194) to study conventional traffic networks. However, the technological advances and concepts underlying ATIS/ATMS in urban networks were not envisioned when these models were developed. For this reason, those simulation models are not directly applicable towards networks with ATIS or ATMS. The two primary deficiencies of the existing simulation models are 1) the lack of modelling of path-based traffic dynamics and 2) the lack of explicit representation of user decisions such as route-choice under information.

During the mid and late 80's, research efforts in Europe to develop analysis tools specifically for this purpose led to further development of assignment based models such as CONTRAM (Leonard et al, 1989) and SATURN (Van Vuren and Watling, 1991). While both these models have been used with reasonable results for the above purpose, they are limited in their ability to capture the dynamic performance of traffic networks under real-time information. It is not clear whether the time-dependent user equilibrium that these models attempt to find is a meaningful or realistic construct to evaluate real-time information systems, especially under non-recurrent congestion. These models have a limited behavioral basis, and little or no ability to incorporate realistic behavioral rules for the response of the drivers to information/guidance.

Further limitations arise from the inadequacy of link cost functions in capturing the dynamics of traffic flow in networks. For instance, the cost functions are usually required to be convex and monotonically increasing, which implies a low cost at small flows; however, it is well known that links in heavily congested networks generally exhibit very high trip time costs at stop-and-go speeds and small flows.

Similar limitations apply to the recent body of work presenting mathematical formulations for the time-dependent user optimum assignment problems (Ran, Boyce and Leblanc, 1993). No efficient algorithms for general networks are presently available for these types of problems and the proposed algorithms appear to be inapplicable to networks of realistic sizes, especially for a reasonable number of time periods.

There have been recent efforts to develop simulation models for studying networks under information. Among the better-known examples is INTEGRATION developed at the Queens University (Van Aerde and Yagar, 1988a&b). This model has been under development at the same time as DYNASMART and appears to share some of its features, especially in terms of the general approach to traffic flow simulation. It is difficult to ascertain the exact features of the INTEGRATION model as these have not been fully described in the literature due to the proprietary nature of this commercial program. DYNASMART was developed as a flexible research tool at the University of Texas and we discuss its features below.

There is increasing interest in the assignment of time-dependent network flows, as reflected in the published literature. However, most studies have assumed the time-varying demand pattern to be given, and have solved for the link flows, as a function of time, given the OD trips rates (as a function of time), and the physical and operational characteristics of the transportation network. Early contributions in this area include the work of Yager (1976) on numerical techniques for the dynamic traffic assignment problem; a proposal to extend this approach to include some sensitivity to route guidance strategies has been presented by Van Aerde and Yager ( 1988a and 1988b), though the behavioral aspects of user response to information appear to be limited. A special case of the traffic assignment problem has been addresses by Sheffi, Mahmassani and Powell ( 1981) in the context of estimating network clearing times during emergency evacuations. A mathematical programming formulation and solution procedure was presented by Merchant and Nemhauser (1978) for system-optimal assignment of a discretized time-varying demand pattern for multiple origins to a single destination. The formulation was recently expanded by Carey (1987). A pure network formulation of the problem of determining the system optimal joint scheduling and routing of trips in an urban corridor with a single destination was recently given by Chang, Mahmassani, and Engquist (1988).

A dynamic simulation and assignment framework was developed by Mahmassani, Chang, and Herman to investigate the day-to-day dynamics of traffic in a single-destination commuting corridor ( Mahmassani and Chang, 1986; Chang et al., 1985). It consists of (1) a special-purpose macroparticle traffic simulator ( MPSM), which simulates vehicular movement on freeways and arterials given time-dependent input functions, and (2) a user decision component, which determines the time dependent departure functions resulting from individual departure functions resulting from individual departure time and route choice decisions of commuters in response to experienced congestion in the system and available exogenous information. A more general framework was proposed by Mahmassani and Jayakrishnan (1991) for investigating the effect of different parameters on the performance of a congested urban traffic system under real-time information. The model that Jayakrishnan developed during his doctoral study (1992) underwent modifications under the project described herein, and is now named DYNASMART ( DYnamic Network Assignment Simulation Model for Advanced Road Telematics). As part of this project several traffic control strategies, such as pretimed and actuated signal control, are combined into DYNASMART in order to capture the real traffic system. In this report, the structure, capabilities and principal modelling features of DYNASMART, as well as numerical results from simulation experiments are examined.

## 1.3 Overview of the Report

The next chapter discusses the simulation approach of DYNASMART and explains the traffic control features incorporated in it during the research on MOU-39. Chapter 3 discusses the simulations performed with a trial network with ATMS controls. Chapter 4 concentrates on the ATIS simulations on the Anaheim network. Results from the simulations of traffic management for special-events traffic from the Anaheim stadium are presented in Chapter 5. This is followed by a brief chapter with conclusions.

# Chapter 2
# MODELLING FRAMEWORK

DYNASMART (Dynamic Network Assignment-Simulation Model for Advanced Road Telematics) uses an assignment-simulation modelling framework designed to assign time-varying traffic demands and model the corresponding traffic patterns and evaluate overall network performance of an Advanced Traveler Information System (ATIS) and/or an Advanced Traffic Management System (ATMS). In its present form, DYNASMART is primarily a descriptive analysis tool for the evaluation of information supply strategies, traffic control measures and route assignment rules at the network level. However, it is evolving towards a model that may be executed on-line in quasi real-time to support the functions of the system controller in the ATIS/ATMS. DYNASMART moves vehicles individually according to macroscopic traffic relations and microscopic driver behavior rules.

## 2.1 DYNASMART Model Structure

Several approaches have been applied to evaluate traffic systems under ATIS/ATMS, including analytical methods, assignment-based models and simulation-based models. Because of the complexity of the problem and the issues involved, a model for evaluating system performance for ATIS/ATMS with adequate realism needs to combine the concepts and features of simulation and assignment methodologies. In light of the limitations of existing traffic simulation models, as well as those of network assignment models, for ATIS/ATMS applications, four possible development strategies are identified:

1. Interface existing traffic simulation models and network assignment models.
2. Add network path processing and route choice capabilities to an existing traffic simulation package.
3. Add dynamic traffic flow simulation capability to an existing network assignment package.
4. Configure a simulation-assignment model structure to best fit the functional requirements of the ATIS/ATMS context.

DYNASMART is based on the fourth strategy. Its overall structure is shown in Figure 2.1. The approach adopted in DYNASMART integrates traffic flow models, path processing methodologies, behavioral rules and information supply strategies into a single simulation-assignment framework. The input data include time-dependent OD matrices and network data. All components of DYNASMART are examined in the following section.

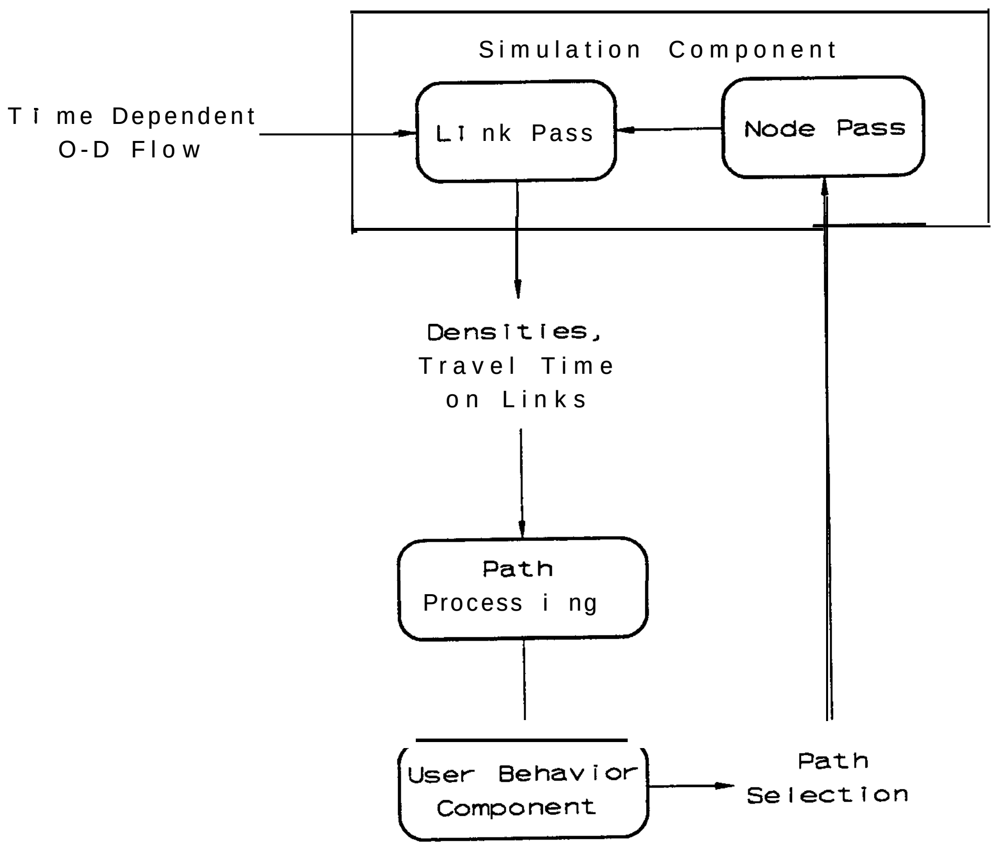


Figure 2.1. DYNASMART Model: Conceptual Structure

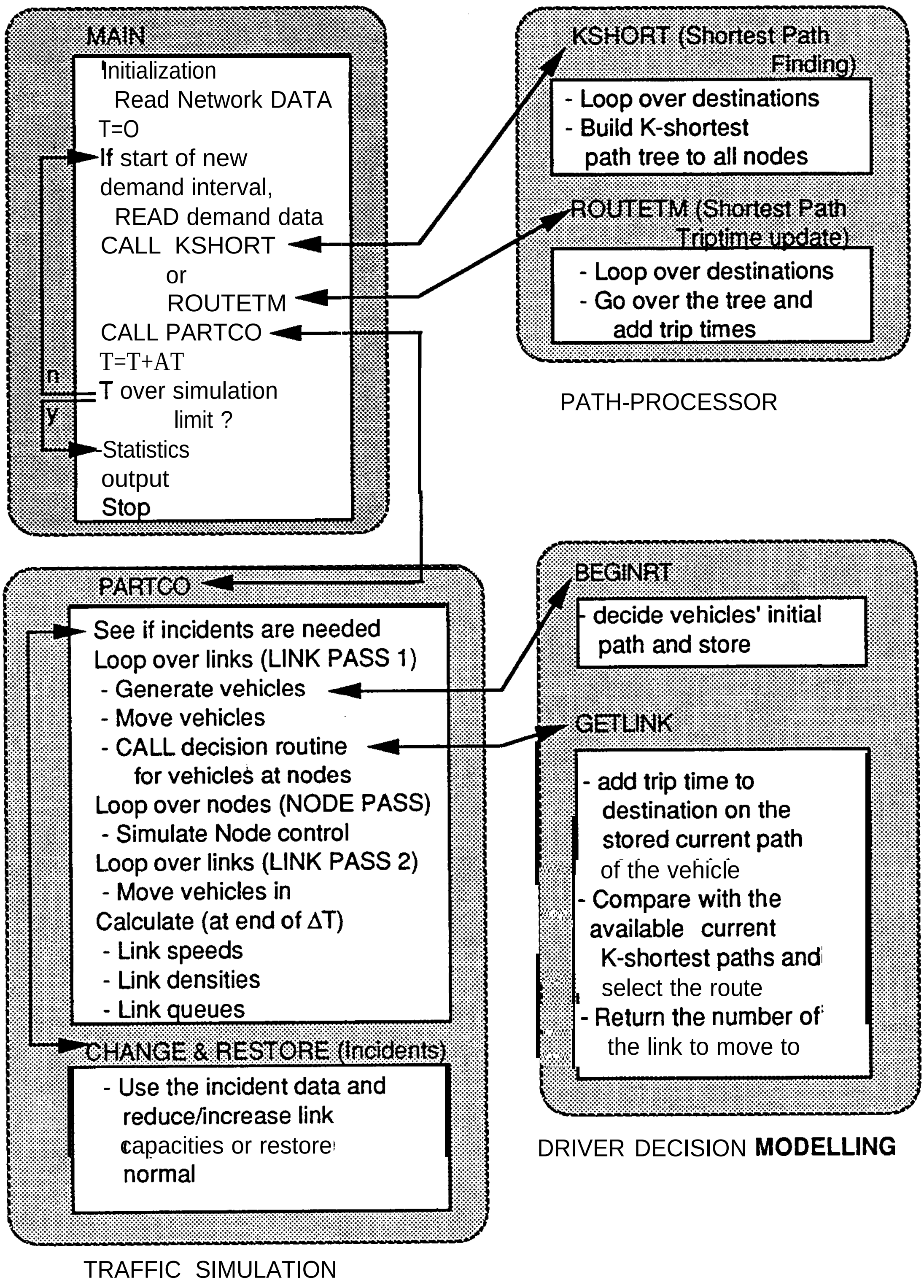


**Fig.** 2.2 Program Flow and Communication between the Conceptual Modules.

The various conceptual modules of DYNASMART are depicted in Figure 2.2. The simulation is deterministic, and follows constant time increments. Vehicles are generated according to specified dynamic Origin-Destination zonal demands, and moved in the network. After every simulation time step, the path database is updated, based on the traffic conditions. The information supply system is assumed to use this database for information/guidance to drivers reaching route decision points (i.e., network nodes) during the simulation time step. Based on the modelling of driver response to this information and the nodal flow constraints, the modelling of vehicle movements into various network links are modelled, which in turn determines the ensuing traffic flow conditions in the network and the simulation proceeds. Incidents are to modelled with link capacity reductions, with their locations, time periods and capacity reduction factors externally specified. The details of the various components are discussed in the following sections.

The information center (ATIS computer) is assumed to provide route information using current information only. This means that future conditions are not predicted while the routes are displayed to the driver. The framework does not include a traffic prediction algorithm (such as used by, say, ALI-SCOUT in Germany, See Von Tomkewitsch, 1987). Once reliable prediction algorithms become available, such capabilities may be added to the framework.

## 2.2 Simulation Component

The traffic simulation approach in DYNASMART is an extension of the macroparticle simulation model (MPSM) [Chang et al. 1985], initially developed as a special-purpose code for experimental studies of commuter behavior dynamics in congested traffic corridors.

Macroscopic simulation models use traffic stream relations to describe traffic interactions (see Drew, 1968; Gerlough and Huber, 1971; May 1990). In general, this approach is based on a continuum representation of traffic, described in terms of the continuity equation:

$$\frac{\partial q}{\partial x} + \frac{\partial k}{\partial t} = g(x,t) \tag{1}$$

where,

$q$ = Flow ( vehicles/ hour ),

$k$ = Concentration ( vehicles/mile ), and

$g$ = Net generation at source / sink.

The above equation is usually coupled with a speed-concentration relation. In addition, macroscopic simulation models typically use the identity $q = k\ v$ (where v is the average speed). The continuity equation, expressed in finite difference form, can be solved numerically using discrete time steps. However, for links of finite lengths, moving vehicles according to the $q = k\ v$ identity may lead to physically unrealistic speeds, as discussed in Chang et al. (1985). For this reason, the original MPSM model moved vehicles in discrete bunches or macroparticles, at the prevailing local speeds determined from the speed-density relations. The macroparticle concept is adapted from plasma physics (Leboeuf, 1979) which exhibits similar properties in this regard. In its current implementation, DYNASMART uses macroparticles of one vehicle, which means that it tracks the movement and locations of individual vehicles. However, it does not keep track of the microscopic details of individual traffic maneuvers. Furthermore, it models the individual route choice decisions of users at nodes microscopically. The traffic simulation consists of two primary steps: the link pass and the node pass, as described next.

### 2.2.1 The Link Pass

The link pass is a process for moving vehicles on the network links during every simulation time step, a scanning time interval in the simulation (5 to 10 seconds is results in reasonable computational efficiency). Note that the network's links can be subdivided into smaller sections or segments for traffic simulation purposes. The vehicle concentration prevailing on a section over a simulation time step is calculated using the finite difference form of the continuity equation (equation 1), given the concentration as well as the inflows and outflows over the previous time-step. Using the concentration at the end of the previous time step, the corresponding section speeds for are calculated according to a speed-density relationship:

$$V_i^t = ( V_f - V_0 ) ( 1 - K_i^t / K_0 )^{\alpha} + V_0 \qquad (2)$$

where,

$V_i^t$, $K_i^t$ = Mean speed and concentration in section i during the $t^{th}$ time step,

$V_f$, $V_0$ = Mean free speed and the minimum speed, respectively,

$K_0$ = Jam concentration (say, 140 vehicles per lane mile), and

a = Parameter used to capture the sensitivity of speed to the concentration.

The minimum speed used is effectively the average speed at the worst stop-and-go traffic, and can be assumed to be between 5 and 10 miles per hour. The above speed-density relationship is effectively a non-linear version of the well-known Greenshield's model.

The vehicles occupy specific positions within the link, the positions being updated during every time step. All the vehicles in a link move at the same speed during a given time step, which is the speed calculated from the above equation (2). No individual maneuvers of the vehicles such as lane-changing or car-following is modelled. The number of lanes on a link is reflected in the number of cars that can occupy the link at jam density.

The link pass is called twice during each time step. First to move all the vehicles in each link, and then to move the vehicles that reach the link end on the new link that it moves to. The second pass is done after the node control is simulated and after the drivers' link-choice behavior is simulated. During the second pass on each link, the vehicles are moved in from each upstream link from which the movement is permitted (according to the current node control). The vehicle with the earliest arrival time at the node moves in first. If a link reaches its jam density, no more vehicles can move in from the upstream link, and those cars will be left in a link-end queue. Those cars which move in to each link is moved in the link according to the link speed, for a period equal to the remaining fractional time step after it reached the previous link's end.

### 2.2.2 The Node Pass

The node pass performs the link-to-link or section-to-section transfer of vehicles. For interrupted link flow, the node pass appropriately allocates the right of way according to the control strategy at this intersection. It determines the number of vehicles that are traversing each intersection in the network at each simulation time step as well as the number of vehicles entering and exiting the network. The output of the node pass includes the number of vehicles that remain in queue and the number added to and subtracted from each link section for each simulation time step. Currently, pretimed control, actuated signal control, coordinated control can be modelled by DYNASMART. Further details are provided in section 2.5.

## 2.3 Driver Behavior Component

There are three main behavioral processes that have to be considered: (1) the initial path selection of the drivers, (2) the enroute path selection behavior of the drivers who receive real-time information, and (3) the enroute path-selection behavior (based *on* observed traffic conditions) of the drivers who receive no information. There is ample research literature on the first aspect, though they do not usually address the real-time information availability. The literature on the other two behavioral processes is very primitive at present. DYNASMART at present models the first two cases above, which are discussed in the next two subsections. Modelling of the third aspect under assumed behavioral models is under development now.

### 2.3.1 Initial Path selection

It is assumed that for different alternative designs of an information supply system, the basic information ultimately available *to the* drivers will include termed initial routes. Drivers who are equipped to receive information may change their as early as at the first node during their trips, and the drivers who receive no information assumed to stay on the initial path. Thus the initial path assignment significantly affects drivers without information. Our experience shows that the initial path selection has to be carefully modelled with multiple paths between each O-D pair, without which congestion would develop on the paths that are used by the drivers without real-time information. While there is no universally accepted method of assigning initial routes, some have suggested user equilibrium or stochastic user equilibrium assignment for these initial routes. In the current version of DYNASMART, two options are available for the initial path assignment. The initial routes can be selected randomly from the K-shortest paths calculated at the end of warm-up period (or can be the shortest path itself). The other option is to specify these externally. These external paths can be dynamic equilibrium paths generated using software. However, the external paths need not be provided for all nodes and towards all destination; program will automatically revert to the first option for nodes without external paths.

In the times at which the paths become valid can also be specified in the external data, which that dynamic equilibrium (or optimum) paths can be specified. As an example, we CONTRAM to generate paths for some of the simulations reported here. CONTRAM is multiple time slice user-equilibrium assignment package developed by the Transport and Research Laboratory (TRRL), of the United Kingdom's Department of Transport (Leonard et 1989). In practice, such assignments may be available in the future from historical based on actual measurements.

### 2.3.2 Enroute Path Selection Under Information

It is assumed that for different alternative designs of an information supply system, the basic information ultimately available to the drivers will include travel times on alternate routes (or at least on the 'best' path determined by the controller or navigator). However, it is assumed that it will be impractical to require the drivers to follow the route suggested to them. Thus the behavioral rules governing travelers' route-choice decisions need to be incorporated, with the flexibility to also model the special case in which drivers are required to follow the guidance suggested.

Experimental evidence presented by Mahmassani and Stephan (1988) suggests that commuter route choice behavior exhibits a boundedly-rational character. This means that drivers look for gains only outside a threshold, within which the results are satisfying and sufficing for them. This can be translated to the following route switching model:

$$\delta_j(k) = \begin{cases} 1, & \text{if } TTC_j(k) - TTB_j(k) > \max\{\eta_j * TTC_j(k), \tau_j\} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where, for driver j,

$\delta_j(k)$ = 1, indicates a route switch at node k;

= 0, indicates no switch at node k,

$TTC_j(k)$ = Trip time from node k to the destination on the current path,

$TTB_j(k)$ = Trip time for the best path

$\eta_j$ = Relative indifference threshold, and

$\tau_j$ = Absolute minimum travel time improvement needed for a switch.

This model assumes that the drivers look for certain minimum travel time benefits compared to their current routes's travel time, before making a route-switch, and that this minimum value is a fraction of the current travel route's travel time. This fraction ($\eta_j$) is assumed to be distributed across the drivers modelled. The average value, $\bar{\eta}_j$, for this indifference threshold is externally specified to DYNASMART. A triangular distribution between $0.75 * \bar{\eta}_j$ and 1.25 $* \bar{\eta}_j$ is currently assumed, but this can be easily replaced with other distributions. The absolute minimum threshold ($\tau_j$) is introduced here to ensure that there is no unrealistic switching for very minimum time savings when the drivers are closer to the destination. The sensitivity of simulation results to this model and the parameter values are extensively examined and reported in this report.

Admittedly, this model is very simplified. However, in light of the current lack of knowledge in this important area, the choices were limited. This model, we believe, does incorporate an intuitively acceptable behavioral mechanism. As the state-of-the-art is very primitive, we decided that the best option was to select the most simple model that can still capture the basic behavioral mechanisms that have to be considered. It is easy to alter DYNASMART to model other forms of route choice at a node; for example, a probabilistic discrete choice such as a calibrated logit or probit model. The behavioral modelling routine needs to return a single variable, which is the next link that the driver selects, and hence the user can easily insert a different behavioral model that uses the network-related and driver-related variables from the COMMON storage. (note: models of this form have been developed from laboratory driving simulations as part of the Anaheim ATMS research test bed project funded by CALTRANS at the University of California at Irvine, and a version of DYNASMART incorporating these models is currently under development).

## 2.4 Path Processing

The path processing component of DYNASMART determines the route-level attributes (e.g. travel time), for use in the user behavior component, given the link-level attributes obtained from the simulator. As explained in detail in section 2.3, there are two important ways in which this path information is used: for the initial path assignment of drivers (if equilibrium paths are not externally specified), and for modelling the driver route selection at the nodes. In its present version, only the current trip times are available to drivers; no attempt is made at basing route decisions on predicted traffic conditions. This means that the shortest path algorithm in DYNASMART does not use possible future link travel times while finding a path travel time. It is possible that an ATIS center may have a traffic prediction algorithm that uses historic link travel time profiles along with current conditions before displaying the best paths to the drivers. This would require time-dependent path algorithms that operate on link travel time profiles. Such an algorithm has been recently developed and could be incorporated in the future within DYNASMART.

It is important for a flexible simulation framework to be able to model different behavioral mechanisms such as those based on selecting from multiple paths, as well as different information supply schemes such as those based on displaying multiple paths. for this purpose, a K-shortest path algorithm (i.e., one that finds the second best path, the third best path etc., up to the K best paths) is interfaced with the simulation model to calculate K different paths for every origin-destination pair. However, in order to improve the model's computational performance, the K-shortest paths are not re-calculated every simulation time step, but at pre-specified intervals. In the interim, the travel times on the set of K current paths are updated using the prevailing link travel times at each simulation time step. This approach was adopted because finding the shortest paths is much more computationally intensive than updating the trip times on stored paths. We assume that most of the paths in a particular set of K paths do not drop out of the K-shortest path set during the interim steps, even though their trip times change. For instance, if the simulation time step is 0.1 minute, the path trip times are updated every 0.1 minute, but new sets of K-shortest paths need not be found more frequently than every 1 or 2 minutes. The method used to find the k-shortest paths is explained in section 2.4.1, and techniques for updating the trip times on existing path trees is explained in section 2.4.2.

### 2.4.1 Finding the k-shortest paths

It has been our experience that the path-processing component takes up at least 2/3rds of the computation time for networks of any reasonable size, and for this reason, this component has been very carefully developed and refined in DYNASMART. The k-shortest path algorithm has been implemented using a direct modification of the well-known label-setting algorithm (see Minieka, 1978, for instance) by associating a k-vector label with each node. During each iteration of the algorithm, one label among the label vectors of all the nodes is finalized. The cost labels are stored in a binary heap for efficiency. Heap data structures are also well-known (see Fox, 1978; Tarjan, 1983). A binary heap keeps certain relationships between the values stored at various locations in an array such as,

$$V_{2p},\ V_{2p+1} \geq V_p,\ \ p=1,2\ ,...$$

where,

$V_p$ = Value in the array at location $p$

Thus the first location contains the minimum value, and location $2p$ and $2p+1$ are said to store the 'children' of location $p$. During every iteration of the label-setting algorithm, the minimum is removed from the array, and the heap is rearranged. The rearrangement is performed by moving the smaller value among location 2 and 3 to location 1, then by moving the smaller value among its children to this free location, and so on. We can see that we do not compare all the locations in the array and the algorithm performs with computational efficiency of $O(Nklog_2Nk)$ as opposed to $O(k^2N^2)$. The k-shortest path building is repeated with each destination node as the root.

It may be noted that label-conecting algorithms (see Minieka, 1978) have been found to perform better than label-setting algorithms for some traffic networks (Van Vliet, 1978), even though their worst case performance is theoretically worse. For this reason, further studies are being conducted with such algorithms, and early results with such an algorithm using a deque (double ended queue) data structure are promising, and modifications may be made in DYNASMART in the future using this.

The current implementation of the shortest path algorithm is not vectorizable, but multiprocessor versions have been developed for building trees rooted at different destinations using different processors. Other algorithms such as the matrix-based Floyd's algorithm, while they are vectorizable, are not applicable to our problem, as they do not find k-shortest paths which are loopless (we have occasionally found multiple paths in the k-path set which differ only by one-block loops). With the label-setting algorithm, we have implemented a loop-check procedure before closing every node (simply backtracking up the tree to a specified number of nodes), but such a procedure is not possible with matrix-based algorithms.

### 2.4.2 Updating the k-shortest paths

The trip times on the network links vary during the simulation and hence the current trip times over the paths have to be found by aggregating the link trip times after each simulation time step (or as specified by the user). Updating the trip times over the paths found earlier using the k-shortest path algorithm can be achieved an order of magnitude faster than finding the paths themselves. As significant stretches are common to numerous paths (which is especially true in the case of k-shortest paths in urban networks), it is important that aggregation of link trip times are not repeated over such stretches. To accomplish this, an efficient path trip time updating technique is used in DYNASMART. Note that the shortest paths from one root node to all other nodes form a tree, the second shortest paths form trees rooted at nodes on the shortest path tree, the third shortest paths form trees are rooted on earlier trees, and so on. So the path trip times are aggregated on successive shortest path trees. For N nodes, there are KN paths towards a given destination and there are several links on each path. However the a shortest path tree rooted at a given destination is made up of only N-l links. Our path updating technique make use of this fact to update the path costs efficiently by making use of the tree connectivity information and avoiding multiple trip time aggregation on common stretches of the paths. As only the successor nodes are stored (i.e., while at a given node, we do not know from which nodes the shortest paths come to it), we require a two-pass procedure that performs two calculations per each arc in the tree. This results in O(N) operations for the shortest path tree rooted at a destination, and fewer operations for the other k-shortest path trees. This updating can be carried out even more efficiently by pre-ordering the tree-traversal, at an additional storage cost. For vector machines such as the CRAY supercomputer, the above technique of path update is not very efficient, as the process is sequential and cannot be vectorized easily. Vectorizable procedures using list storage instead of predecessor-tree storage have been tried, but have not been found better than the pre-ordered tree-traversal procedure.

### 2.4.3 Path Storage

The shortest paths are stored using successor storage. Thus, to trace a given node to a given destination, the successor nodes need to be traced in order. This means that the storage required is (# of nodes)*(# of destinations)*(K). For example, for a network of major arterials and freeways similar to that of Anaheim, if the 3 best paths from each of 400 nodes is stored towards 40 destinations, we need 400*40*3 = 48,000 locations. Comparing this with the separate path-list storage (for, say, a maximum number of nodes in a path equalling 35 for the above network), which requires 400*40*35*30 = 1,680,000 locations, we can easily see the storage efficiency. The key point is that we avoid double-storage of nodes which are part of multiple paths. This is possible because each path is part of a tree rooted at the destination, which means that each node has a unique path connecting it to a given destination in each of the k trees rooted at that destination.

The current path of each driver, however, is stored as separate lists. This is because, the current paths of all drivers going to a given destination, at a given time do not form a tree. To explain this, consider the case of a driver who selected a path at time t = 20 min. This path needs to be stored to be available at, say, time t = 35 when the driver is at a node considering another switch. However, the shortest path trees for the network would have been updated many times by then, and the driver's path may not be in the set any more. Thus, no successor storage is possible for these paths. Thus, these paths do need to be stored as separate lists. For 50,000 drivers in the example network above, if we assume a maximum node-list length of 35, we need 50000*35 = 1,750,000 locations. It is not possible to cut down this storage requirement, and this does indeed become the critical storage component of DYNASMART. We have developed data structures that reallocate the storage space of drivers who have left the network to new drivers, thus preventing this storage requirement from increasing based on the simulation time. This is not yet incorporated in the version of DYNASMART reported here.

External paths are also stored as node-lists for each node towards each destination. Again for the above example, this results in 400*40*35 = 560,000 locations. All three kinds of path storage discussed here are implemented with INTEGER*2 declaration. This is possible as the node numbers in practical networks fall below 32,767.

## 2.5 Traffic Control Component

DYNASMART provides the ability to explicitly model different traffic signal control strategies, which includes pretimed control and actuated control. The major component in DYNASMART which deals with the intersection control is node pass as mentioned before, which is examined here in detail. The node pass is designed to simulate the input and output flows of vehicles on each approach at intersections operating under a number of control strategies. It calculates the number of vehicles that traverse each intersection in the network during each simulation time step as well as the number of vehicles entering and exiting the network. Signal control can be separated into pretimed signal control, pretimed coordinated control, multidial pretimed signal control, and actuated signal control. All such signal controls are modelled explicitly in DYNASMART. Outflow and inflow concepts of vehicle flows in the node pass are discussed next, followed by a discussion of the signal control simulation.

### 2.5.1 Outflow Constraints

The outflow constraints limit the maximum number of vehicles that are allowed to leave the approach per lane at an intersection. These constraints are described in the following equation which states that the total number of vehicles that enter an intersection (from a given approach) depends on the number of vehicles waiting in the queue at the end of the current simulation interval, AT, and the capacity of this approach. The definition of capacity based on the 1985 HCM is the maximum number of vehicles that can be allowed under prevailing traffic signal operation.

$$VI_i = \text{Min} \{ VQ_i ; VS_i \} \tag{4}$$

where,

$VI_i$ = Max number of vehicles that can enter the intersection during AT,

$VQ_i$ = Number of vehicles in queue on link i at the end of AT,

$VS_i$ = Maximum number of vehicles that can enter the intersection during AT,

$= G_i * S_i$

$G_i$ = Remaining effective green time during AT,

$S_i$ = Saturation flow rate, and

AT = Simulation interval (say, 5 to 10 seconds).

### 2.5.2 Inflow Constraints

The inflow constraints determine the maximum number of vehicles that are allowed to enter a link. These constraints bound the total number of vehicles from all approaches that can be accepted by the receiving link, they include the maximum number of vehicles from all upstream links wishing to enter link j, the constraint due to the available physical space on the outbound link and the section capacity constraint of link j.

$$VO_j = \text{Min}\ \{ \sum_{k \in Cl} VI_{kj};\ VE_j;\ C_j * AT \} \tag{5}$$

where,

$VO_j$ = Number of vehicles that can enter link j,

U = Set of inbound links into link j (i.e. in the backward star of j),

$VI_{kj}$ = Number of vehicles that wish to move from k to j,

$VE_j$ = Available space of link j, and

$C_j$ = Approach capacity of link j.

### 2.5.3 Pretimed Signal and Pretimed Coordinated Control

Input data include phase number, offset, green time, red time and amber time for every phase. For pretimed signal control, green times are set for every phase according to this data. Since DYNASMART is not intended as an optimizer of signal system control, the model user will be able to input offsets obtained exogenously from other models to coordinate arterials or the network as a whole. Conversion programs need to be developed for direct use of data prepared from other models such as TRANSYT, but we believe that this will not be a difficult task because DYNASMART does not use any signalization conceit that is different than what is found in common practice (Cycles, splits, phasing etc). Alternatively, optimization modules could be developed for ATMS applications.

### 2.5.4 Actuated Signal Control

For microscopic simulation, signal data and detector data will need to be prepared for actuated signal control. Such calculations are too time-consuming for DYNASMART. Instead of detecting individual vehicles, macroscopic modeling is adopted to capture the essential features of actuated signal control : “max out” and “gap out”. “Max out” occurs when the green time for a given phase reaches a preset maximum green time. “Gap out” occurs when a preset time elapses with no detector actuations (generally specified to avoid excessively long delays at conflicting approaches) for the phase in progress, resulting in discontinuation of the green for that phase. The input data set in DYNASMART includes maximum green time, minimum green time, default cycle length and the other signal data, such as phase number. The equation used in calculating green time in an actuated signal control is given below. The concept is to allocate green time depending on incoming volume. If the required green time is larger than the maximum green time or smaller than the minimum green time, the maximum or minimum green time is assigned, respectively.

$$G_i = (CV_i / \Sigma CV_i) * (C - \text{lost time}) \tag{6}$$

where,

$CV_i$ = Critical Volume for phase i, and

$C$ = Default cycle length, subject to Min Green $\leq G_i \leq$ Max Green

Therefore, "max out” and “gap out” can be captured. If the critical volume for phase i is less than the maximum number of allowable vehicles, the green time will be reduced accordingly. These calculations are performed at the end of the current cycle. Cycle length will change every cycle. This modeling approach is expected to be fairly accurate in allocating green time as congestion increases in the network.

### 2.5.5 Entrance Ramp Control

Ramp closure, ramp metering, and traffic-responsive metering are modelled in DYNASMART.

1. Closure: For ramp closure, drivers need to select other routes from that node to their destination from the path information set. This is also related to driver behavior and requires an observational basis to develop appropriate path selection rules.

2. Ramp Metering: In ramp metering, a fixed ramp rate or a dynamic ramp rate determines the maximum number of vehicles that can enter the ramp during a specified time period.

3. Traffic-Responsive Metering: Two different ramp controls are commonly practiced by traffic engineers and are described in the Traffic Control Systems Handbook: occupancy control and demand control. We simulate an occupancy-based real-time metering method called ALINEA, which is defined by the following flow relationship.

$$\text{Rate}(T + 1) = \text{Rate}(T) + \text{Cons1}*(\text{Cons2} - \text{OCC}) \tag{7}$$

where,

Cons1 = 0.32 (or, as externally specified),

Cons2 = 0.20 (or, as externally specified), and

o c c = Upstream Detector occupancy.

5 veh/min-lane < Rate(t) < 25-35 veh/min-lane

### 2.5.6 Left-Turn Movement

Left-turn movements are a critical factor causing delay in urban networks. However, it is very difficult to model the left-turn movement in a macroscopic simulation model, In this section, the left-turn issue is discussed and the modelling process used in DYNASMART is introduced.

For the left-turn movement without a turning phase, the analytical approach is to calculate the blocked time by opposing vehicles flow at the onset of green and then use gap acceptance models to calculate the actual number of vehicles which can pass the intersection during the residual green interval. See Figure 2.3 for a graphical representation of the left-turn scenario.

The left-turn capacity is determined by several factors: opposing volume, number of lanes of the opposing approach and green time for the phase. The blocked time from the onset of green that cannot be used by left-turning vehicles is calculated as follows:

Blocked Time:

$$T_b = (Q/N)(L1 + L2 + R) / (S - Q/N) \tag{8}$$

where,

$T_b$ = Blocked time, time blocked by opposing traffic and/or clear time for queue,

$Q$ = Total opposing flow (veh/hr),

$N$ = Number of opposing lanes,

$L1$ = Lost time for opposing traffic,

$L2$ = Lost time for start-up,

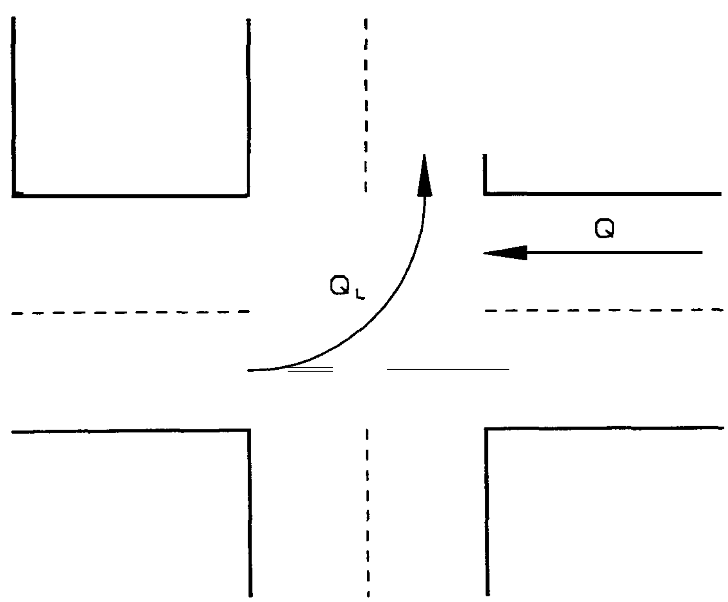


Figure 2.3. Left Turn Movement

R = Red time, and

S = Saturation flow of opposing traffic.

Usable Time for Left-Turn:

$$T_u = G + (T_a - L1) - L2 - T_b \tag{9}$$

where,

$T_u$ = Usable time of cycle for left-turn (sec),

G = Green time, and

$T_a$ = Amber time.

Maximum Number of Possible Left-Turn Vehicles:

$$N = (T_u/h) + 1 \tag{10}$$

where,

h = Minimum turning headway (approximately 2.5 seconds).

A gap acceptance model can be used to calculate the left turn capacity as follows:

$$Q_L = \left(\frac{T_u}{C}\right) Q_{LT} \tag{11}$$

$$Q_{LT} = \frac{Q e^{-(Q/3600)*T_c}}{1 - e^{-(Q/3600)*h}} \tag{12}$$

where,

QL = Left-turn capacity,

$Q_{LT}$ = Left-turn saturation flow rate, veh/hr,

$T_c$ = Critical gap (seconds), and

h = Turning headway (approximately 2.5 seconds).

The modeling process for the left-turn is complex and not easy to combine with any macroscopic simulation. Therefore, a heuristic modeling process is used to capture effects of left-turns in DYNASMART. See Lee et al (1977) for more details on this. The process is summarized as follows:

1. Create a conceptual bay for left-turn vehicles.
2. Calculate maximum flow rate for left-turns;
   This rate can be calculated under different situations;
   a) Protected left-turn phase: saturation flow rate.
   b) Permissive phase: from gap acceptance models or established tables.
3. Calculate an average number of left-turn vehicles and also reduce the saturations flow rate for straight and right-turn approaches.
4. Follow outflow-inflow constraints to transfer vehicles from link to link.
5. Calculate the left turn delay for the K-shortest path calculation.

## 2.6 Communication Interface between Simulation and Path Processing

In DYNASMART, the path processing component utilizes the travel time information generated from the simulation. As explained before, the route trip times are found based on current travel conditions and delay equations. The travel time information for links is separated into two parts: travel time for vehicle movement and queuing time. Traffic on each link segment are modelled as consisting of two parts (as shown in Figure 2.4) : those in the upstream, moving part, and those in the downstream, queuing part.

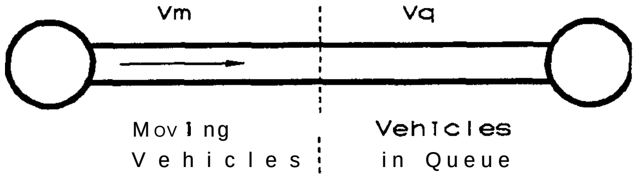


Figure 2.4. Conceptual Segments on a Link

### 2.6.1 Average Travel Time for Moving Vehicles

Average travel time on link segments for each time step is calculated directly from the traffic stream model used in the simulation. The density and speed is obtained for every simulation interval, then travel time is calculated based on the link length and associated speed.

### 2.6.2 Average Queue Delay

a. Queue Delay = ( $V_q$ / S ) + ( # of cycles for discharging $V_q$ ) * ( 1- $\lambda$ )*C (13)

where,

$V_q$ = Number of vehicles in queue,

S = Saturation flow rate (vehicles/second) ,

$\lambda$ = Effective green time (seconds),

C = Cycle length (seconds),

$a$ = Index to reflect the relation of signals and simulation ( T : start of green, $a$ = 1 ).

$\{(V_q/S) / \lambda * C\} - \alpha$ = # of cycles for discharging Vq ( $\geq 0$ );
= 0.5 if no queue exists, and

b. Delay Equations: A modified Webster delay equation is used in DYNASMART when an intersection approach has no queue. To estimate the left-turn delays, we use the delay concepts as explained in section 2.5.6.

## 2.7 Incident Modelling

Incidents are modelled in DYNASMART to reflect accidents or lane closures. These are described as follows:

1. Incidents are specified as reductions of link capacity for a specified time period on any desired link or set of links.
2. All Calculations are based on predefined data sets. An interactive input feature will be included in the future version of DYNASMART (currently under development in PATH research project MOU-84).
3. Complex incidents of varying levels of capacity reduction over time can be modelled as a series of consecutive incidents.

## 2.8 Program Capabilities

DYNASMART has so far been implemented on two different computer platforms: the CRAY YMP supercomputer and the SUN SPARC workstation, both with 64 MBytes primary storage. As the code is written in standard portable FORTRAN 77, it is expected that other platforms such as the IBM PC will be able to run DYNASMART, considering that RAM storage is becoming constantly cheaper. Simulation of up to 75000 vehicles in networks of up to 2000 links with 10 paths from each node to each destination centroid can be achieved on the above platforms faster than real-time. The capability to simulate larger problems directly depends on the available RAM storage. The program capabilities include:

1) Macroscopic modelling of traffic flow dynamics such as congestion formation and shock wave propagation. Tracking of locations of individual drivers.
2) Modelling of different traffic control strategies (freeways, surface streets, signalized intersections, ramp entry/exit etc)
3) Modelling of prescriptive/compulsory guidance as well as non-prescriptive guidance with trip time information on alternative routes.
4) Modelling of various aspects of the controller such as infrequent updates of the network route information database.
5) Modelling of individual drivers’ response to information in the case of prescriptive

guidance and their selection from a set of paths rather than a single shortest path. Random assignment of driver behavioral characteristics. Flexibility to incorporate alternative behavioral rules.

6) Modelling of specified capacity-reducing incidents at any time, anywhere in the network.
7) Modelling of traffic with only a fraction of the vehicles equipped to receive information.
8) Capability to carry out simulations based on externally specified dynamic equilibrium paths for drivers not equipped to receive information (Under refinement in PATH research project MOU-84).
9) Several levels of output statistics for the system, for individual drivers as well as for groups of drivers (equipped drivers, unequipped drivers, drivers on certain O-D pairs etc). Statistics include average trip times, distances, average speeds etc. The number of route switches made, as well as the average fractional distances at which the successive switches are made are calculated. A few other statistics for insights on the path dynamics are also available. (Some of these capabilities are being refined in the PATH research project, MOU-84)

DYNASMART provides the ability to explicitly model an array of control elements, listed in Table 2.1. The major element for surface streets is signal control, which includes pretimed control and actuated control. Ramp metering and variable message signs (VMS) are the major controls for the freeway system. Modelling of VMS is still under development.

**Table 2.1.** Traffic Control Types in DYNASMART

| Surface Street | Freeway System |
|---|---|
| No Control<br>Yield Signs<br>Stop Signs<br>Signal Control<br>(green, red, amber times;<br>cycle time; offsets; phases)<br>Pretimed<br>Pretimed Coordinated<br>Multidial Pretimed<br>Actuated (full ) | In-vehicle Navigator with single or multiple path displays<br>Ramp Metering<br>Variable Message Signs (under development) |

# Chapter 3
# ATMS SIMULATIONS

A test network was used to study the effect of signal controls under ATMS (Advanced Traffic Management Systems) in conjunction with ATIS information. Further simulations with the Anaheim network specifically for studying ATIS strategies are described in chapter 4.

## 3.1 Description of the Test Network

The test network used to simulate an ATMS applications is composed of several arterials and one freeway. There are 163 links and 50 nodes in this network as shown in Figure 4, and intersections are represented by nodes , and streets are represented by link. There are 11 on-ramps and off-ramps connect the freeway with arterials. The test network is shown in Figure 3.1. All other detail information is given in Table 3.1.

**Table 3.1.** The Configuration of the Test Network

Simulation Information
- start up time : 5 minutes
- period of interest : 5 - 35 minutes
- Max simulation time : 150 minutes

Network :
- Overall Data
  - number of nodes : 50
  - number of links : 163
  - destinations : 38 ( 1 to 37 + 44 )
  - demand zones : 38 ( 1 to 38 )
  - ramp control : 11 ramps
- Link
  - Jam density = 160 vehicles/mile
  - arterial road
    - length : 1/2 mils
    - # of lanes : 2
    - velocity : 30 miles/hr
  - freeway
    - length : 1/2 miles
    - # of lanes : 2
    - velocity : 55 mph

on-ramp and off-ramp
length : 1/2 mils
#oflanes: 1
velocity : 30 miles/hr

Signal Data
No-control : 17
Pretimed control : 25
2-phases operation
green time : 25 seconds
amber time : 5 seconds
Actuated Signal Control : 8
2 phases operation
min green time : 10 seconds
max green time : 25 seconds
amber time : 5 seconds

## 3.2 Experimental Factors and Simulation Cases

The simulation experiments were conducted in two parts. The first part is used to test the system performance with different demand levels. The second part is to test the sensitivity of the system's performance, under the information strategy with respect to two principal factors: (1) the fraction of users equipped to receive information, and (2) the mean relative indifference band, which captures the propensity of users to switch in response to information. Some assumptions in simulation are summarized as follows:

1. All the non-equipped vehicles are assumed to have the information on the current conditions before their trips ( through radio or T.V.), and they will be assigned to the current best path. After this assignment, they do not change their routes during the trip.

2. Signal control will not be changed during the simulation. The green time is allocated according to arrival flow rates and queue lengths from some initial tests.

### 3.2.1 Different Demand Levels

The original case of loading is set as a peak-period pattern, and the vehicles are generated from 0 to 35 minutes. The number of vehicles is shown in Table 3.2. The total number of

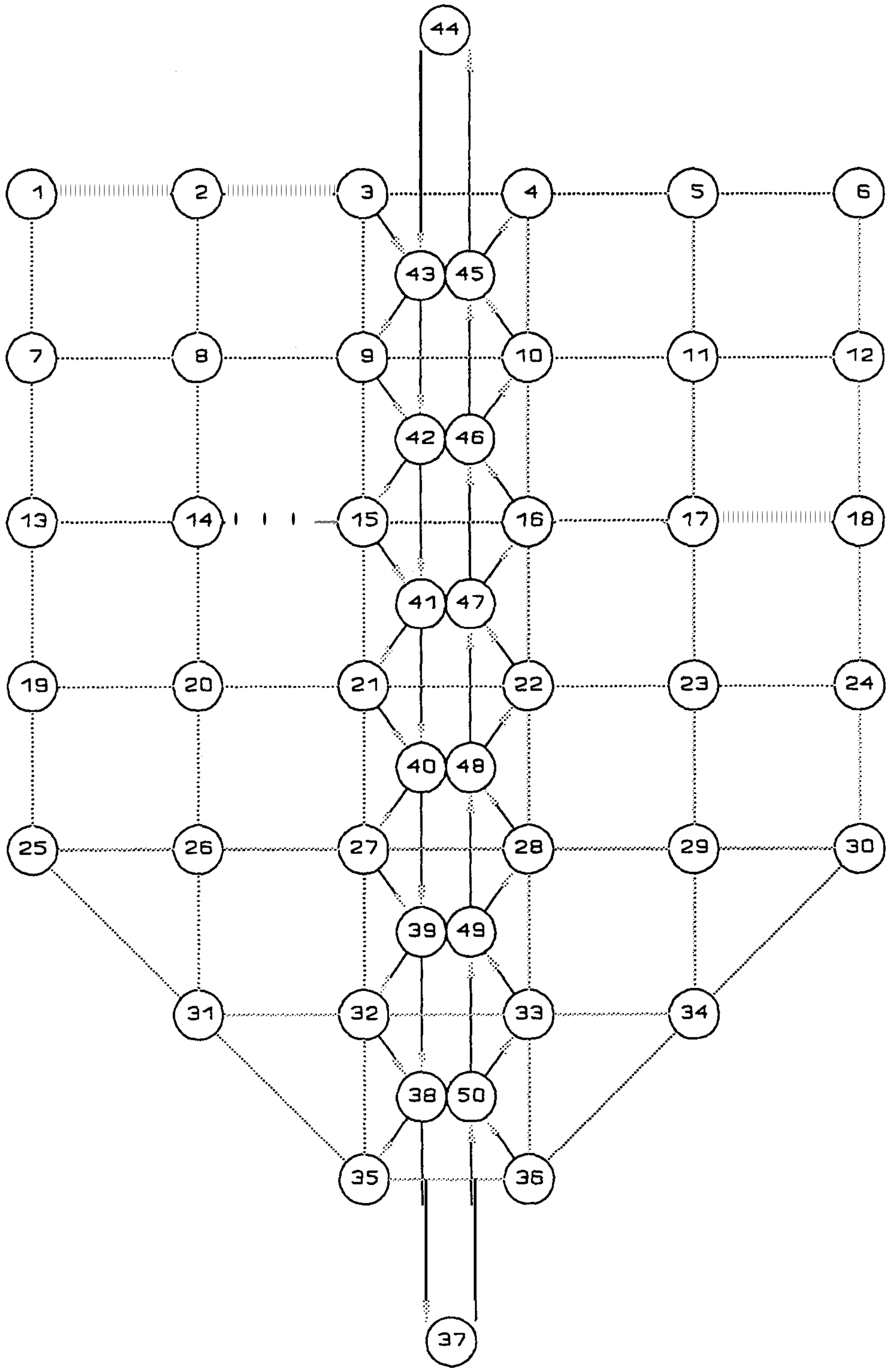


Figure 3.1 Configuration of Tested Network

generated vehicles is about 19,000, which is expected not to cause any congestion in the test network. Then the demand is multiplied by a factor to test the variation of trip time. All the parameters are fixed at this stage: the mean relative indifference band is equal to 0.2 and the minimum threshold is 1.0 minute. For each demand level, six different fractions of vehicles with information will be tested.

**Table** 3.2. The Loading Pattern for the Base Case

| Time Interval | Number of Vehicles | Cumulative Vehicles |
|---|---|---|
| 5 | 1778 | 1778 |
| 10 | 2397 | 4175 |
| 15 | 3054 | 7229 |
| 20 | 3641 | 10870 |
| 25 | 3651 | 14521 |
| 30 | 3035 | 17556 |
| 35 | 1846 | 19402 |

### 3.2.2 Fraction of Users with Information

To examine the effect of this fundamental parameter in the large-scale deployment of any in-vehicle information systems, six levels were considered, spanning the spectrum from luxury gadget to universal availability : 0.0, 0.1, 0.25, 0.50, 0.75, and 1.00. Information availability status is assigned randomly and independently to each vehicle as it is generated, according to the specified fraction.

### 3.2.3 Mean Relative Indifference Band

The quantity $\eta_j$ in equation (4) explained in chapter 2 governs users' response to the supplied information and their propensity to switch. As noted earlier, we treat it as a random variable; when generated, a user is assigned randomly and independently a value for $\eta_j$. For convenience, $\eta_j$ is assumed to follow a triangular distribution, with mean $\eta$ and range of $\eta/2$. To examine the robustness of the results, we consider five different levels of $\eta$ : 0.0, 0.1, 0.2, 0.3, 0.4 and 0.5.

In the no band case, all drivers receiving in-vehicle information are assumed to have a zero band, and thus to always switch to an alternate path if it offers an improvement in travel time, no matter how small its magnitude. The minimum improvement $\tau_j$ in equation (4) is taken to be identical across users, and equal to one minute, though not in the zero band case, where no minimum improvement restriction is imposed. For each level of $\eta$, simulations are conducted for each of the six fractions of users with information, resulting in 30 different cases. The results are discussed in the next section.

## 3.3 Simulation Results

### 3.3.1 Different Demand Levels

The purpose of these experiments is to observe the variations when the demand is increased. The original loading tends to cause no congestion, and the loading pattern is similar to a typical perk-period pattern. The average number of generated vehicles is 554 vehicles per minute, the average trip time is 6.215 minutes and the average trip distance is 2.282 miles. The loading pattern is shown in Table 3.2. Then, the demand is multiplied by a factor which ranges from 1.0 to 1.6. For every demand pattern, six cases with different percentages of vehicles with information are tested. The average trip time, trip distance and the number of switches are shown in Tables 3.3, 3.4 and 3.5, respectively. The average systemwide trip times are shown in Figure 3.2. Average travel times for the two segments of the driver population (with and without information) are shown in Figures 3.3 and 3.4.

As expected, the average trip time increases when the demand is increased. However, the trip time increases more rapidly for demand multipliers beyond 1.4. The overall average trip time for multiplier 1.6 is twice that of the base case. For the different demand factors, the cases with information supply always show lower trip time compared to those with no information supply. However, there is a slight variation within each demand pattern and different market penetrations have different effects. There is a tendency for the trip times to reduce for higher market penetration when the traffic condition is heavier. The random fluctuations are, however, significant. Our experience with the simulation model so far is that such fluctuations occur when the modelled network is small, but not for larger networks (See Chapter 4).

| Demand factor | Info % | Total vehicles | Non Tagged | Tagged | Average TT. | No Info TT. | Info TT. |
|---|---|---|---|---|---|---|---|
| 1 | 0.00 | 19402 | 1778 | 17624 | 6.215 | 6.215 | 0 |
| | 0.10 | 19404 | 1822 | 17623 | 6.168 | 6.176 | 6.103 |
| | 0.25 | 19409 | 1781 | 17628 | 6.146 | 6.168 | 6.083 |
| | 0.50 | 19403 | 1781 | 17622 | 6.166 | 6.214 | 6.118 |
| | 0.75 | 19407 | 1781 | 17626 | 6.158 | 6.185 | 6.148 |
| | 1.00 | 19405 | 1781 | 17624 | 6.151 | n/a | 6.151 |
| 1.1 | 0.00 | 21355 | 1952 | 19403 | 6.931 | 6931 | n/a |
| | 0.10 | 21347 | 1952 | 19393 | 6.889 | 6.885 | 6.920 |
| | 0.25 | 21355 | 1952 | 19403 | 6.745 | 6.792 | 6599 |
| | 0.50 | 21357 | 1952 | 19405 | 6.861 | 6.903 | 6.818 |
| | 0.75 | 21356 | 1952 | 19404 | 6.757 | 6.881 | 6.715 |
| | 1.00 | 21352 | 1952 | 19400 | 6.795 | n/a | 6.795 |
| 1.2 | 0.00 | 23307 | 2151 | 21156 | 7.718 | 7.718 | n/a |
| | 0.10 | 23301 | 2148 | 21153 | 7.489 | 7910 | 7.292 |
| | 0.25 | 23303 | 2148 | 21155 | 7.456 | 7.486 | 7.364 |
| | 0.50 | 23302 | 2148 | 21154 | 7.506 | 7.560 | 7.452 |
| | 0.75 | 23298 | 2148 | 21150 | 7.464 | 7.504 | 7.451 |
| | 1.00 | 23303 | 2148 | 21155 | 7.344 | n/a | 7.344 |
| 1.3 | 0.00 | 25252 | 2341 | 22911 | 9.074 | 9.074 | n/a |
| | 0.10 | 25248 | 2336 | 22912 | 8.32 | 8.354 | 8.030 |
| | 0.25 | 25256 | 2336 | 22920 | 8.291 | 8.352 | 8.103 |
| | 0.50 | 25252 | 2336 | 22916 | 8.166 | 8.253 | 8.080 |
| | 0.75 | 25248 | 2336 | 22912 | 8.118 | 8.259 | 8.071 |
| | 1.00 | 25249 | 2336 | 22913 | 8.072 | n/a | 8.072 |
| 1 . 4 | 0.00 | 27202 | 2502 | 24700 | 9.8 | 9800 | n/ |
| | 0.10 | 27201 | 2504 | 24697 | 9.693 | 9.713 | 9.5% |
| | 0.25 | 27192 | 2504 | 24688 | 9.672 | 9.726 | 9.510 |
| | 0.50 | 2719s | 2504 | 24691 | 9.336 | 9.426 | 9.24s |
| | 0.75 | 27197 | 2504 | 24693 | 9.345 | 9549 | 9.277 |
| | 1.00 | 27202 | 2504 | 24698 | 9.479 | n/a | 9.479 |
| 1.5 | 0.00 | 29141 | 2699 | 26442 | 12.738 | 12.738 | n/a |
| | 0.10 | 29141 | 2700 | 26441 | 11517 | 11.551 | 11.203 |
| | 0.25 | 29151 | 2698 | 26453 | 11563 | 11.664 | 11.257 |
| | 0.50 | 29151 | 2698 | 26453 | 11.13s | 11.294 | 10.976 |
| | 0.75 | 29143 | 2698 | 2644s | 10.779 | 10.856 | 10.753 |
| | 1.00 | 29143 | 2698 | 2644s | 10.906 | n/a | 10.906 |
| - 1 . 6 | 0.00 | 31092 | 2882 | 28210 | 13.479 | 13.479 | n/a |
| | 0.10 | 31099 | 2882 | 28217 | 13.123 | 13.183 | 12.562 |
| | 0.25 | 31090 | 2882 | 28208 | 12.866 | 12.955 | 12.560 |
| | 0.50 | 31092 | 2882 | 28210 | 12.877 | 13.072 | 12.662 |
| | 0.75 | 31093 | 2882 | 28211 | 12.788 | 13.060 | 12.698 |
| | 1.00 | 31096 | 2882 | 28214 | 12.702 | n/a | 12.702 |

Table 3.3. Average Trip Times for Different Demand Multipliers

| Demand factor | Info % | Overall Average distance | Average distance (No info) | Average distance (Info) |
|---|---|---|---|---|
| 1 | 0.00 | 2.282 | 2.282 | |
| | 0.10 | 2.285 | 2.289 | 2.256 |
| | 0.25 | 2.282 | 2.285 | 2.270 |
| | 0.50 | 2.280 | 2.289 | 2.271 |
| | 0.75 | 2.285 | 2.297 | 2.281 |
| | 1.00 | 2.277 | n/a | 2.277 |
| 1.1 | 0.00 | 2.316 | 2.316 | n/a |
| | 0.10 | 2.283 | 2.277 | 2.339 |
| | 0.25 | 2.277 | 2.279 | 2.271 |
| | 0.50 | 2.287 | 2.282 | 2.293 |
| | 0.75 | 2.289 | 2.301 | 2.287 |
| | 1.00 | 2.294 | n/a | 2.294 |
| 1.2 | 0.00 | 2.352 | 2.352 | n/a |
| | 0.10 | 2.294 | 2.296 | 2.276 |
| | 0.25 | 2.296 | 2.294 | 2.303 |
| | 0.50 | 2.306 | 2.303 | 2.309 |
| | 0.75 | 2.308 | 2.286 | 2.315 |
| | 1.00 | 2.308 | n/a | 2.038 |
| 1.3 | 0.00 | 2.438 | 2.438 | n/a |
| | 0.10 | 2.324 | 2.331 | 2.265 |
| | 0.25 | 2.330 | 2.344 | 2.289 |
| | 0.50 | 2.322 | 2.342 | 2.303 |
| | 0.75 | 2.331 | 2.350 | 2.324 |
| | 1.00 | 2.325 | n/a | 2.325 |
| 1.4 | 0.00 | 2.455 | 2.455 | n/a |
| | 0.10 | 2.356 | 2.354 | 2.365 |
| | 0.25 | 2.360 | 2.367 | 2.338 |
| | 0.50 | 2.332 | 2.337 | 2.327 |
| | 0.75 | 2.340 | 2.368 | 2.331 |
| | 1.00 | 2.347 | n/a | 2.347 |
| 1.5 | 0.00 | 2.567 | 2.567 | n/a |
| | 0.10 | 2.372 | 2.373 | 2.367 |
| | 0.25 | 2.387 | 2.39s | 2.361 |
| | 050 | 2.373 | 2.372 | 2.375 |
| | 0.75 | 2.371 | 2.367 | 2.372 |
| | 1.00 | 2.365 | n/a | 2.365 |
| | 0.00 | 2.583 | 2.583 | n/a |
| | 0.10 | 2.368 | 2.365 | 2.393 |
| | 0.25 | 2.373 | 2.376 | 2.365 |
| | 0.50 | 2.379 | 2.392 | 2.366 |
| | 0.75 | 2.368 | 2.374 | 2.366 |
| | 1.00 | 2.372 | n/a | 2.372 |

Table 3.4. Average Trip Distance for Different Demand Multipliers

| Demand factor | Info % | Number of drivers making no route switches,1 swdch, 2 switches, etc. | | | | |
|---|---|---|---|---|---|---|
| | | 0 | 1 | 2 | 3 | % |
| 1 | 0.00 | | | | | |
| | 0.10 | 1813 | 9 | | | 0.49 |
| | 0.25 | 4409 | 23 | | | 052 |
| | 0.50 | 8742 | 79 | | | 0.90 |
| | 0.75 | 13061 | 105 | | | 0.80 |
| | 1.00 | 17498 | 126 | | | 0.71 |
| 1.1 | 0.00 | | | | | |
| | 0.10 | 1874 | 70 | | | 3.60 |
| | 0.25 | 463s | 123 | | | 259 |
| | 0.50 | 9369 | 299 | 2 | | 3.11 |
| | 0.75 | 14046 | 429 | 1 | | 2.97 |
| | 1.00 | 18792 | 603 | 5 | | 3.13 |
| 1.2 | 0.00 | | | | | |
| | 0.10 | 1976 | 91 | 1 | | 4.45 |
| | 0.25 | 4965 | 207 | 1 | | 4.02 |
| | 0.50 | 10019 | 501 | 5 | | 4.81 |
| | 0.75 | 15058 | 723 | 9 | | 4.64 |
| | 1.00 | 20176 | 976 | 3 | | 4.63 |
| 1.3 | 0.00 | | | | | |
| | 0.10 | 2191 | 161 | 2 | | 6.92 |
| | 0.25 | 5295 | 317 | 12 | | 5.85 |
| | 0.50 | 10767 | 691 | 18 | | 6.18 |
| | 0.75 | 16193 | 955 | 43 | | 5.81 |
| | 1.00 | 21831 | 1063 | 19 | | 4.72 |
| 1.4 | 0.00 | | | | | |
| | 0.10 | 2280 | 190 | 4 | | 7.84 |
| | 0.25 | 5751 | 437 | 21 | | 7.38 |
| | 0.50 | 11293 | 946 | 31 | | 7.96 |
| | 0.75 | 17140 | 1361 | so | | 7.61 |
| | 1.00 | 22980 | 1626 | 90 | 2 | 6.96 |
| 1.5 | 0.00 | | | | | |
| | 0.10 | 2341 | 250 | 10 | | 10.00 |
| | 0.25 | 5744 | 763 | 48 | 1 | 12.39 |
| | 0.50 | 11774 | 1332 | 87 | 1 | 10.76 |
| | 0.75 | 17797 | 1847 | 119 | 1 | 9.95 |
| | 1.00 | 23139 | 2355 | 176 | 1 | 9.86 |
| 1.6 | 0.00 | | | | | |
| | 0.10 | 2352 | 343 | 20 | | 13.37 |
| | 0.25 | 6051 | 933 | 63 | 1 | 14.15 |
| | 0.50 | 12234 | 1779 | 126 | 1 | 13.48 |
| | 0.75 | 18200 | 2726 | 279 | 8 | 14.20 |
| | 1.00 | 24821 | 3132 | 257 | 4 | 12.03 |

Table 3.5. Route Switching Statistics for Different Demand Multipliers

The statistics of switching routes under different conditions are shown in Table 3.5 and Figure 3.5. The percentage of switching (i.e., the percentage of drivers receiving information who change routes at least once) of vehicles with information increases with increasing demand. However, the highest switching percentage does not usually occur when all the vehicles receive the information. The highest percentage of switching occurs when about 25% to 50% of vehicles receive information. As seen in Table 3.5, there are only a few drivers who make more than two route switches during their trips (however, the average number of nodes in a trip is only about 5, as the network is small). From our experience, we find that such switching behavior is highly dependent on the way in which the initial routes are assigned.

### 3.3.2 Different Information Scenarios

These simulations have a traffic loading pattern that corresponds to a demand multiplier of 1.6, as described in the last section. About 887 vehicles are generated per minute, and the loading is still a peak-period pattern. The highest loading is about 1165 vehicles per minute as shown in Table 3.6 and Figures 3.6 and 3.7.

**Table** 3.6. The Loading Pattern for Tested Cases

| Time Interval | Number of Vehicles | Cumulative Vehicles |
|---|---|---|
| 5 | 2845 | 2845 |
| 10 | 3835 | 6680 |
| 15 | 4886 | 11566 |
| 20 | 5826 | 17392 |
| 25 | 5842 | 23234 |
| 30 | 4856 | 28090 |
| 35 | 2954 | 31043 |

Average route switch indifference fractions from 0.0 to 0.5 are tested for different percentages of vehicles with information. Figure 3.8 depicts the variation of the systemwide trip time with the fraction of the driver population with access to information, under each of the six assumed indifference levels. Note that the trip time is expressed as a percent of the total trip time under the base case with no information supply (i.e. no switching); thus values in excess of 100% correspond to a worsening of systemwide performance compared to the do-nothing case. This did happen when the indifference fraction is 0.5 which represents to the drivers being most reluctant to switch routes. This can be explained as follows: the vehicles switched to certain routes in the early stage of their trips thanks to the initial path assignment not being on equilibrium paths. However, these routes became congested later, but the drivers did not switch to better streets due to their reluctance to switch routes. A route switch indifference fraction of 0.1 seems to yield more significant improvement. The maximum improvement is about 7.5% for this case, but the trip time increase when all the vehicles are allowed to access the information. The 0.0 and 0.1 switching cases show similar trends in trip times; they reduce rapidly till the percentage of vehicle with information goes over 25%, but increase again when the percentage increases to 100. The 0.2 switching case is more stable; the trip time drops rapidly before a 25% market penetration of information, and improves slightly for higher fractions of drivers with information. The 0.2, 0.3 and 0.4 switching cases show similar patterns. The average trip time for vehicles with information and without information are shown in Figure 3.9 and 3.10. The fluctuations are rather drastic, but could be due to the random number seed used. In such cases, our experience has showed that repeating the simulations with different random number seeds gives better results. In general, however, the trip time benefits for vehicles with information reduces when the percentage increases. Again, providing information to all the vehicles with information does not result in significantly change the average trip time benefits, but does not decrease the average benefits to the drivers receiving information (a phenomenon that we have noticed in the simulations of more congested networks).

The above results are discussed only to illustrate how DYNASMART can be used to study the effect of various ATIS strategies (considered broadly in terms of generic information supply here), with specific ATMS controls in place. The network studied is small, but had various ATMS features such as pretimed and actuated signals, and ramp signals. The results are only illustrative, and it should be understood that the effect of ATIS and ATMS are certainly context-specific. Tools such as DYNASMART proves useful for the same reason.

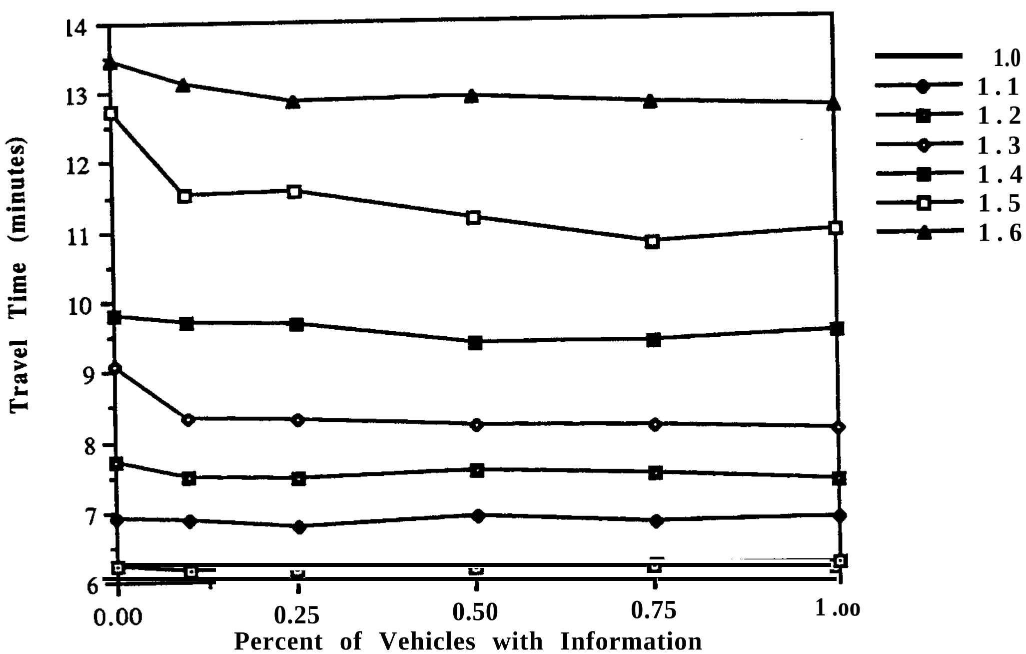


**Figure 3.2.** Average Systemwide Trip Times for Different Demand Multipliers

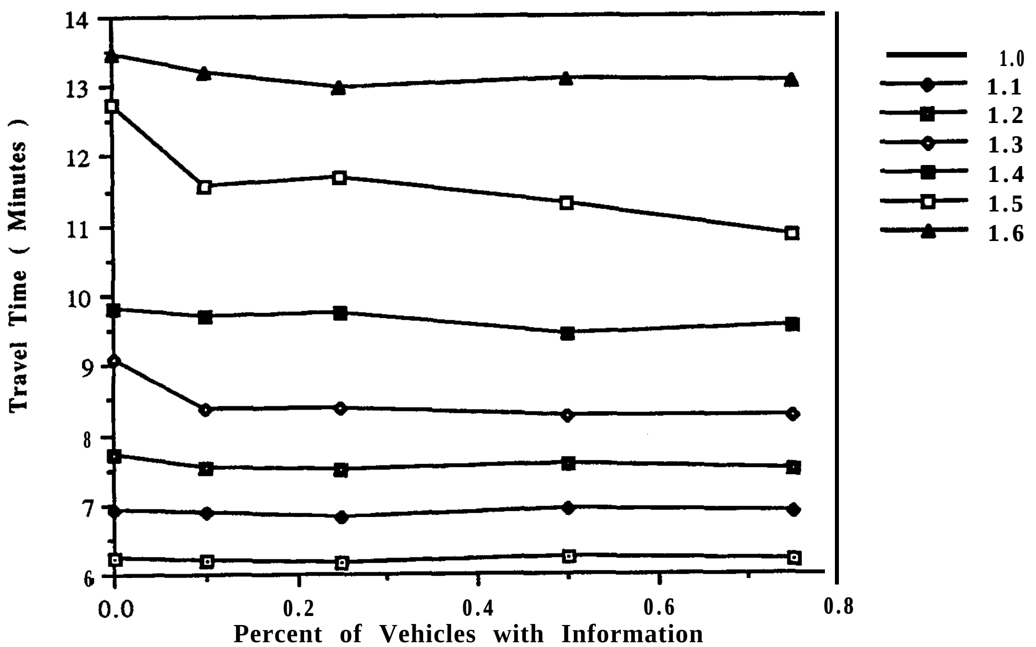


**Figure** 3.3. Average Trip Times for Vehicles without Information

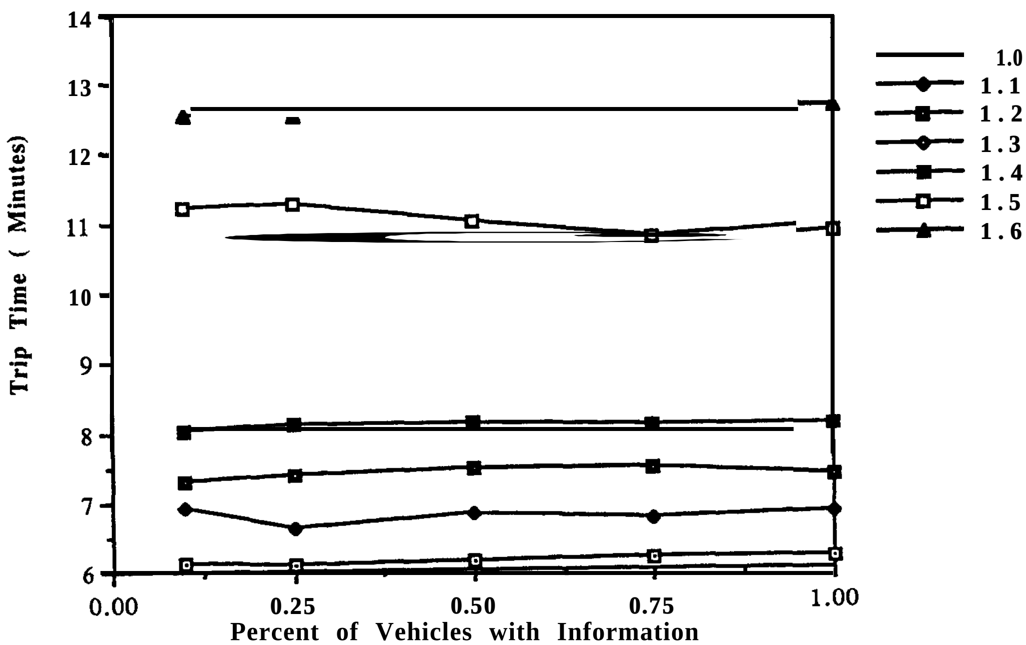


**Figure** 3.4. Average Trip Times for Vehicles with Information

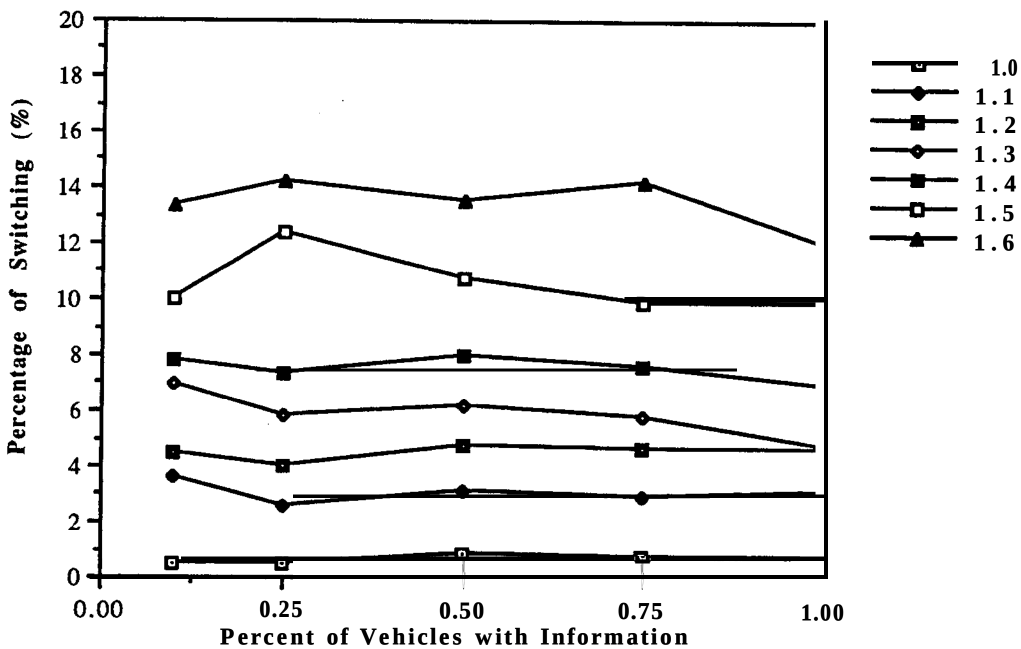


**Figure 3.5.** Percentage of drivers with information who switch routes

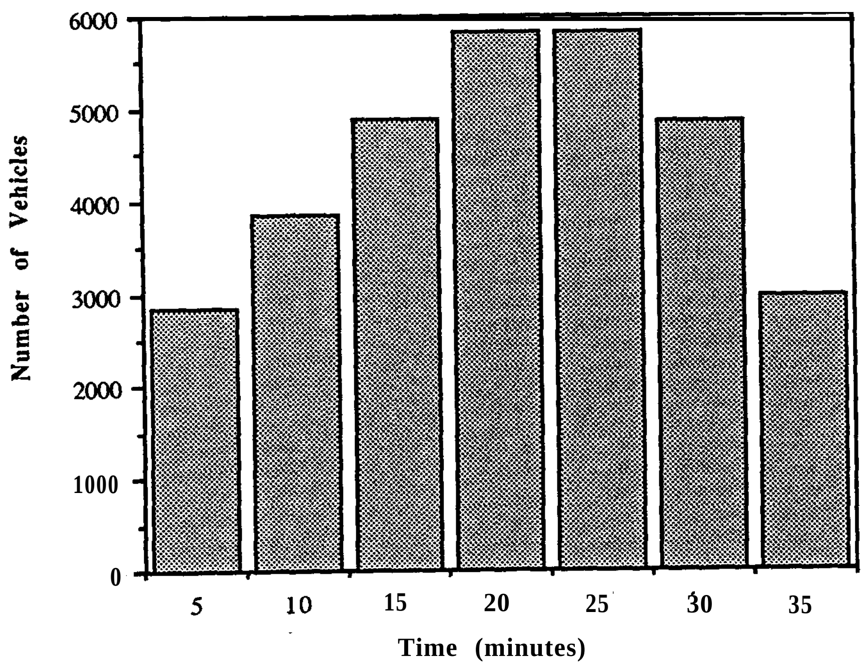


**Figure 3.6.** Vehicle Generation Pattern

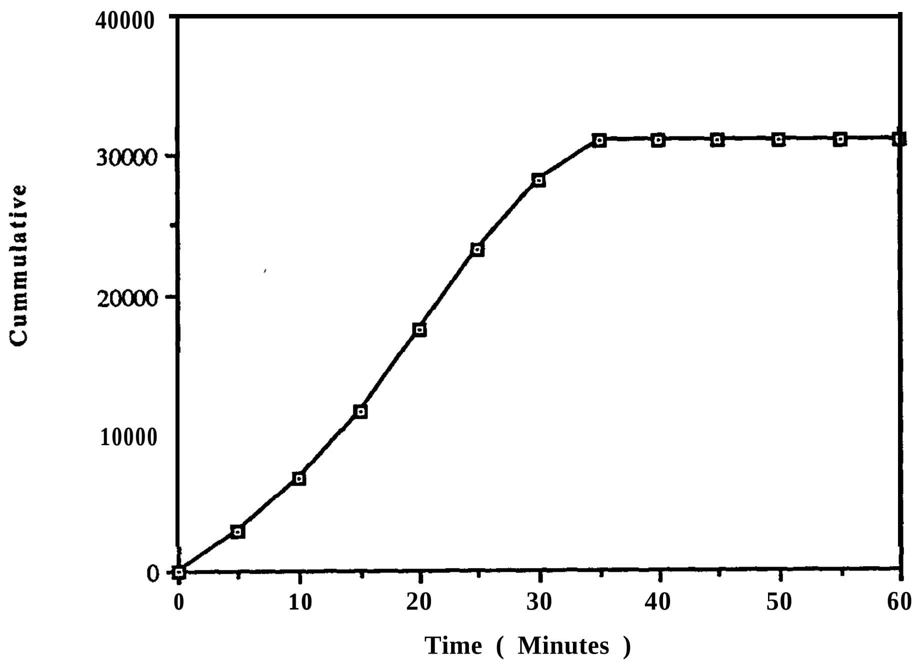


**Figure 3.7.** The Cumulative Number of Vehicles Generated

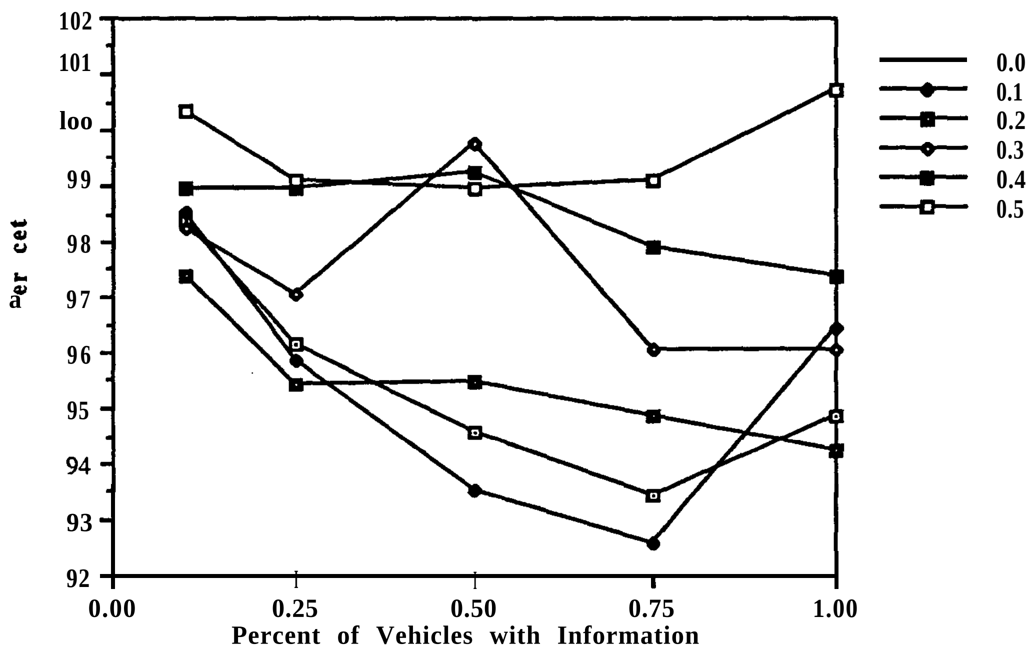


**Figure 3.8.** Average System-wide Travel Times (as a percent of the trip time with no information supply, for different switching propensities, indicated by the indifference threshold)

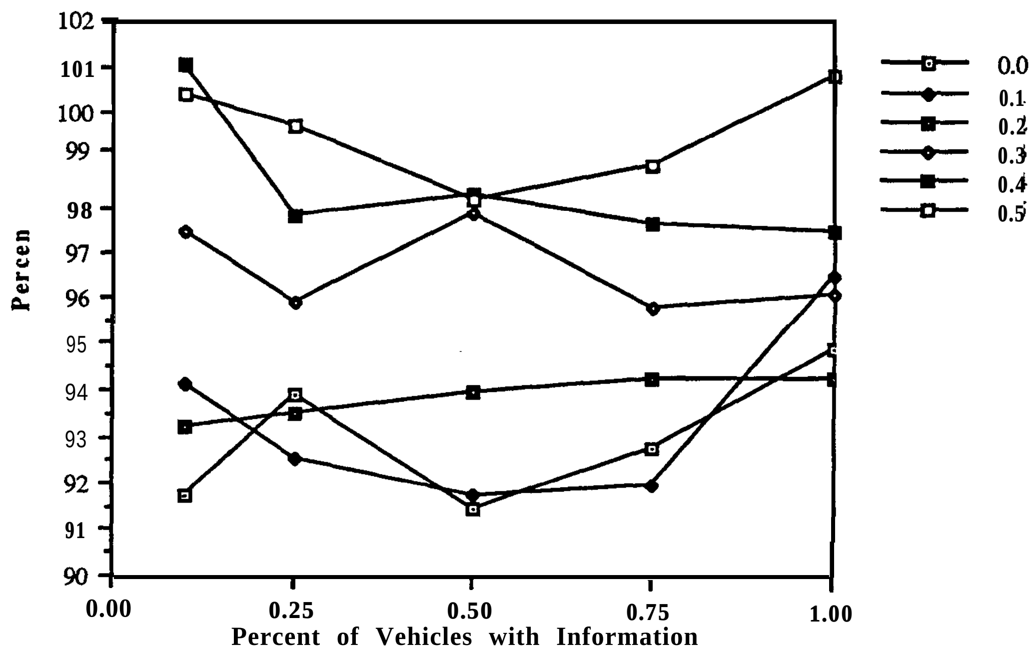


**Figure 3.9.** Average Travel Times for Vehicles with Information

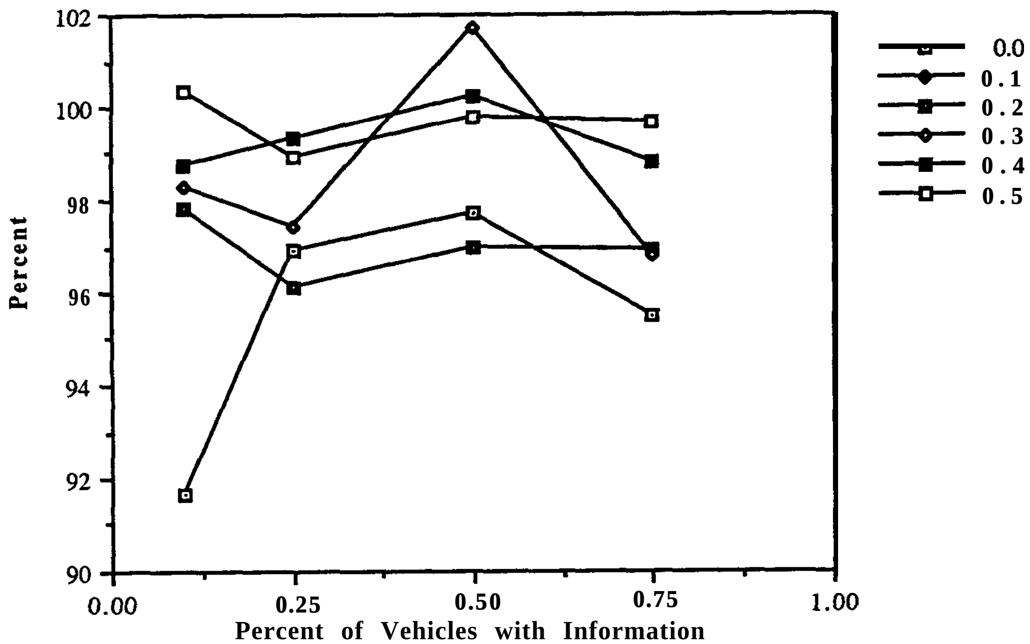


**Figure 3.10.** Average Travel Times for Vehicles without Information

# Chapter 4
# ATIS SIMULATIONS (ANAHEIM NETWORK)

## 4.1 Introduction

The data requirement for this project consists of a coded network and associated dynamic trip tables with which to perform the DYNASMART traffic simulations and the CONTRAM equilibrium assignment. The roadway network and trip table used as data in this project were developed for a sub-area of the City of Anaheim in Orange County, California.

Although the study at this stage is theoretical in nature, the city of Anaheim was selected because that city is participating in an ATMS testbed research project funded by CALTRANS. Thus it is assumed that actual IVHS projects will become operational in the medium-term future, raising the eventual possibility of real-world validation of the analytic tool developed in this project. However, it is beyond the scope and the requirements of the project documented by this report to produce a highly detailed network and an accurate trip table for this region. The coded network is a similar but abstracted model of the actual Anaheim roadway system. Some complex interchanges of the actual roadway system are simplified in the coded network for the purposes of clarity and convenience. As the physical roadway system is currently under a state of intense reconstruction, extensive updating of the coded network in the near-term future would become necessary in any event.

The trip table is created using the COMEST O-D matrix estimation program that accompanies the CONTRAM assignment program. This essentially works with specified approximate seed trip tables and develops a dynamic O-D trip table that matches the specified link counts. We used link counts that we observed on certain arterial streets as well as the 1989 data on the freeway flows. The emphasis during this research is to produce a realistic dynamic trip table which would produce, during DYNASMART simulations, reasonable levels of congestion for the demonstration of the modeling capabilities of the DYNASMART program.

This chapter documents the data preparation as well as the simulation experiments of ATIS based on generic information. Section 4.2 provides a brief overview of the study area on which the network is based. Section 4.3 discusses the network coding process. Section 4.4 discusses the production of the dynamic trip tables. The simulation of a base-case scenario with no ATIS is described in section 4.4. ATIS simulation results follow in section 4.5.

## 4.2 Studv Area

This section consists of two subsections. Section 4.2.1 provides a brief general description of the study area. Section 4.2.2 provides a brief description of the transportation system of the study area.

### 4.2.1 General Description

The study area chosen for this project is the City of Anaheim in northern Grange County, California. Portions of seven additional Grange County cities are partially included in the study area, including Fullerton, Placentia, Grange, Santa Ana, Garden Grove, Stanton, and Buena Park. The study area extends 9.3 miles east-to-west and 6.5 miles north-to-south, for a total land coverage of approximately sixty square miles.

As the large number of municipalities suggest, the study area is a highly developed urban/suburban region in which neighboring cities blend seamlessly into one another. This pattern of land use, combined with a high standard of living and the virtual absence of rapid mass transit systems, has resulted in the use of single-occupancy automobiles for virtually all personal transportation. This essentially complete dependance on the automobile has greatly taxed the already-extensive regional roadway system (Haboian and Mortazavi, 1990).

In addition to the daily recurring background traffic, Anaheim also contains three generators of special-event traffic; (1) the Anaheim Stadium sports facility, (2) the Anaheim Convention Center, and (3) the Disneyland theme park. All three of these facilities contribute an additional burden on the roadway system as large numbers of drivers, many of whom are unfamiliar with the local roads and with the patterns of recurring congestion, enter the system at a few closely-spaced points during short time spans. Therefore, the potential achievable benefits of applying IVHS to the alleviation of special-event generated congestion is of unique interest.

For the purposes of this research, the special-event traffic generated by Anaheim Stadium is chosen as the specific case for which the potential ability of In-vehicle Navigation Systems (IVNS) to alleviate special-event generated traffic congestion is analyzed. The stadium was chosen from among the three possible generators because it produces traffic with the sharpest peak and a well-understood distribution over a period starting a few minutes before the end of the special event, and continuing through a few minutes after it (ITE, 1976).

### 4.2.2 Regional Transportation System

The transportation system in the study area consists of a well-developed arterial grid system integrated with an extensive freeway system. The freeway system is composed of both federal and state routes. The study area itself is bounded on the north by Orangethorpe Avenue, on the east by State Route 55 (the Costa Mesa Freeway), on the south by State Route 22 (the Garden Grove Freeway) and on the east by State Route 39 (Beach Boulevard). The area is bisected diagonally from the northwest comer to the southeast comer by Interstate 5 (the Santa Ana Freeway) and the area also includes State Route 91 (the Riverside Freeway) and State Route 57 (the Orange Freeway). Thus, a total of five freeways are contained within the study area.

In addition to Orangethorpe Avenue, the network contains seven major east-west arterials. In addition to Beach Boulevard, the network contains eight major north-south arterials. Two of the seventeen arterials included in the study area network are county-designated “super streets”, or high-flow arterials (Beach Boulevard and Katella Avenue).

Anaheim Stadium is located in the southeast quadrant of the study area, within one mile of both I-5 and SR-57. Large scale special-event traffic egresses from three stadium parking lots following a variety of special-events including California Angels baseball games and Los Angeles Rams football games.

## 4.3 Network Coding

The coded network consists of 440 nodes, 931 links and 41 zones. Of these 41 zones, 15 are internal surface zones, 19 are external surface zones, 7 are external freeway zones, and 3 are the stadium parking lots which generate the special-event traffic.

Internal surface zones represent surface area within the study area. External surface zones represent points where vehicles enter and exit the study area on arterials and external freeway zones represent points where vehicles enter and exit the study area on freeways. The vehicles with origins in internal surface zones are generated on all the arterial links which are included n that zone. The vehicles with origins in external surface and freeway zones are generated on the external connector links designated for each external zone.

The abstracted, coded network is illustrated in Figure 4.1; this figure also displays the centroids which are affiliated with each zone. The forty-one centroids are numbered from 2 to 44 (there are no centroids numbered 1, 14, or 18), and each centroid corresponds to a DYNASMART zone which are numbered from 902 to 944 (e.g., Centroid 5 corresponds to DYNASMART Zone 905).

The 3 stadium zones (centroids 42,43, and 44 indicated on Figure 4.1) are not destinations for any traffic, as we are modelling the traffic exiting from the stadium after the special event; thus, there are only 38 destinations in the network.

## 4.4 Establishment of Base-Case Scenario

This section discusses the establishment of a base-case scenario against which alternative scenarios can be compared. The base-case scenario assumes there is no implementation of IVNS, and no special-event traffic.

The simulation results (of significance to this set of experiments) reported by DYNASMART presently consist of average travel times (for equipped vehicles, for unequipped vehicles, and for all vehicles), the external path sufficiency statistics, and the link densities during each time step for a set of pre-designated links.

In the DYNASMART simulation, the statistics are collected for vehicles that entered the network after 15 minutes (the first 15 minutes is a warm-up period) till 60 minutes, and the simulation is continued until all these vehicles leave the network. In the base-case simulation, the last tagged vehicle (i.e., those vehicles for which statistics are collected) reaches its destination during the eighty-sixth minute of the simulation.

The average travel time for all vehicles of 12.28 minutes is judged reasonable. This figure represents average trip time within, the study area; i.e., for the external O-D trips that pass through the network, the travel time is only the time period that they take to travel through this network. During the period of interest (i.e., between the fifteenth and sixtieth minute of the simulation) 47,481 vehicles enter the network. This is a base-case scenario which assumes no IVNS implementation, thus, all of the vehicles are unequipped and search for external equilibrium paths as discussed in Section 3.6.

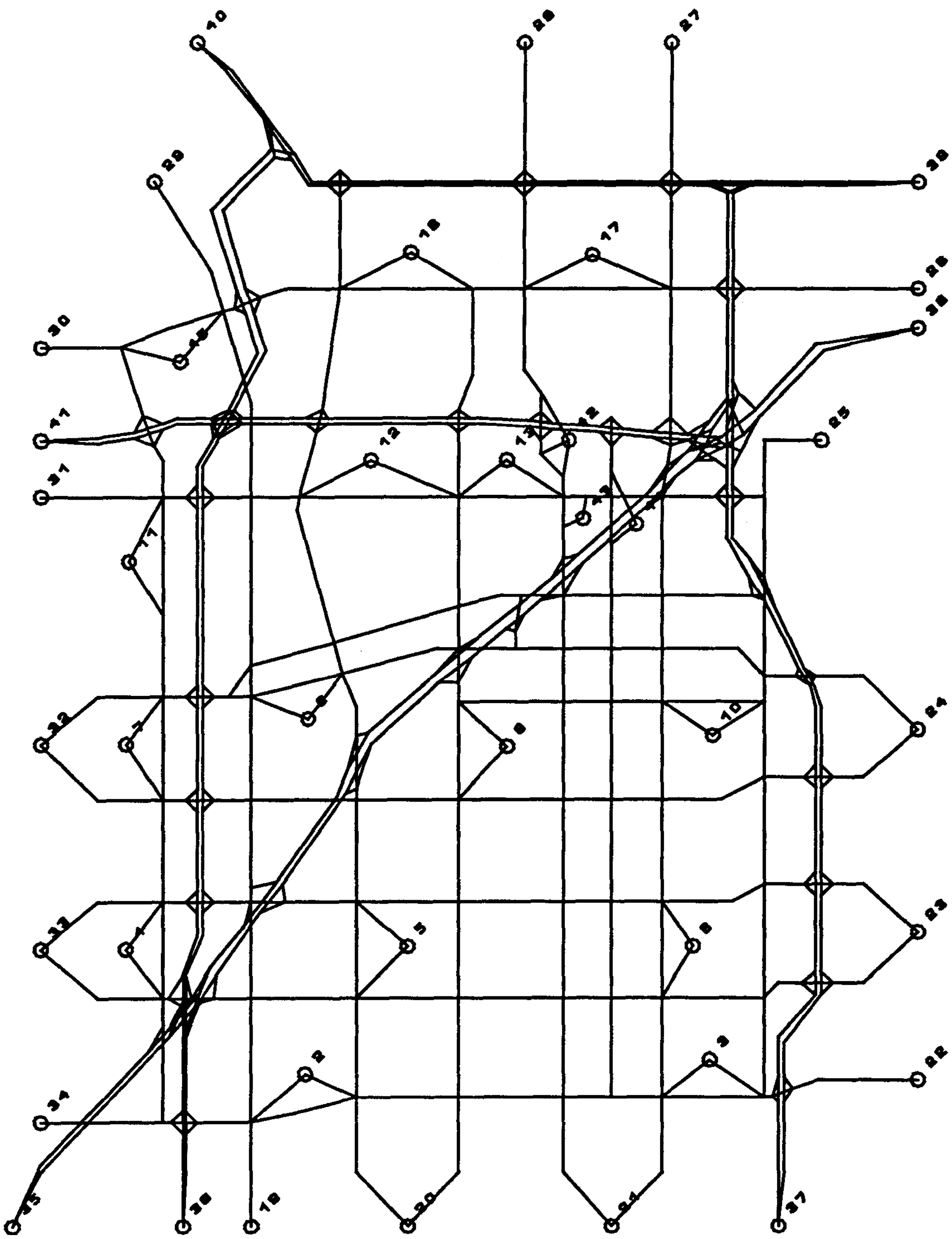

**Figure 4.1** **Anaheim Area Network**

The external path sufficiency statistics indicate that although 20,133 vehicles (42 percent) did not receive an external equilibrium path at their time of generation, no vehicle was unable to find an external path at any time during the simulation. The average distance traveled by one of these vehicles before being assigned to an external path is 0.083 miles. Therefore, the external paths are sufficient to assign all of the unequipped vehicles to at least one path.

A realistic simulation of traffic during a peak period would produce moderate levels of congestion on links in the southeast quadrant of the network, and low congestion on links outside this area. The southeast quadrant tends to be moderately congested, even during this post PM-peak time period, due to several factors including the confluence of three major freeways, high-density commercial and residential land uses, and the presence of the Disneyland theme park. In this model, the theme park is not treated as a generator of special-event traffic, but as a generator of heavy background traffic.

Density profiles plot the link density (measured as a fraction of the jam density of 160 vehicles per lane per mile) as a function of simulation time. To demonstrate that the background-traffic trip table adequately reproduces this pattern of traffic congestion, density profiles have been provided for four representative links. The profiles are presented on two graphs, with each graph containing the profiles of one link from the southeast quadrant (designated Link 1) and one link from outside this area (designated Link 2).

Figure 4.2 presents the density profiles of two freeway links. Link 1 is northbound I-5 (the Santa Ana Freeway) south of the Ball Street exit; this is one of the most congested links in the base-case network. Link 2 is eastbound SR-22 (the Garden Grove Freeway) west of Magnolia Avenue. As expected, the I-5 link is moderately congested, peaking at 80 percent of jam density at 30 minutes of simulation time, and remaining above 50 percent until after the sixtieth minute. The density of the SR-22 link, which should not be congested, remains between 10 percent and 20 percent of jam density during the first eighty minutes.

Figure 4.3 presents the density profiles of two arterial links. Link 1 is westbound Ball Road east of West Street. Link 2 is eastbound Lincoln Avenue west of Magnolia Avenue. As can be seen on the density profiles, the Ball Road link is highly congested (greater then 90 percent of jam density) between fifteen and thirty minutes of the simulation period, before clearing; the density than oscillates between 25 and 70 percent for the remainder of the simulation. The

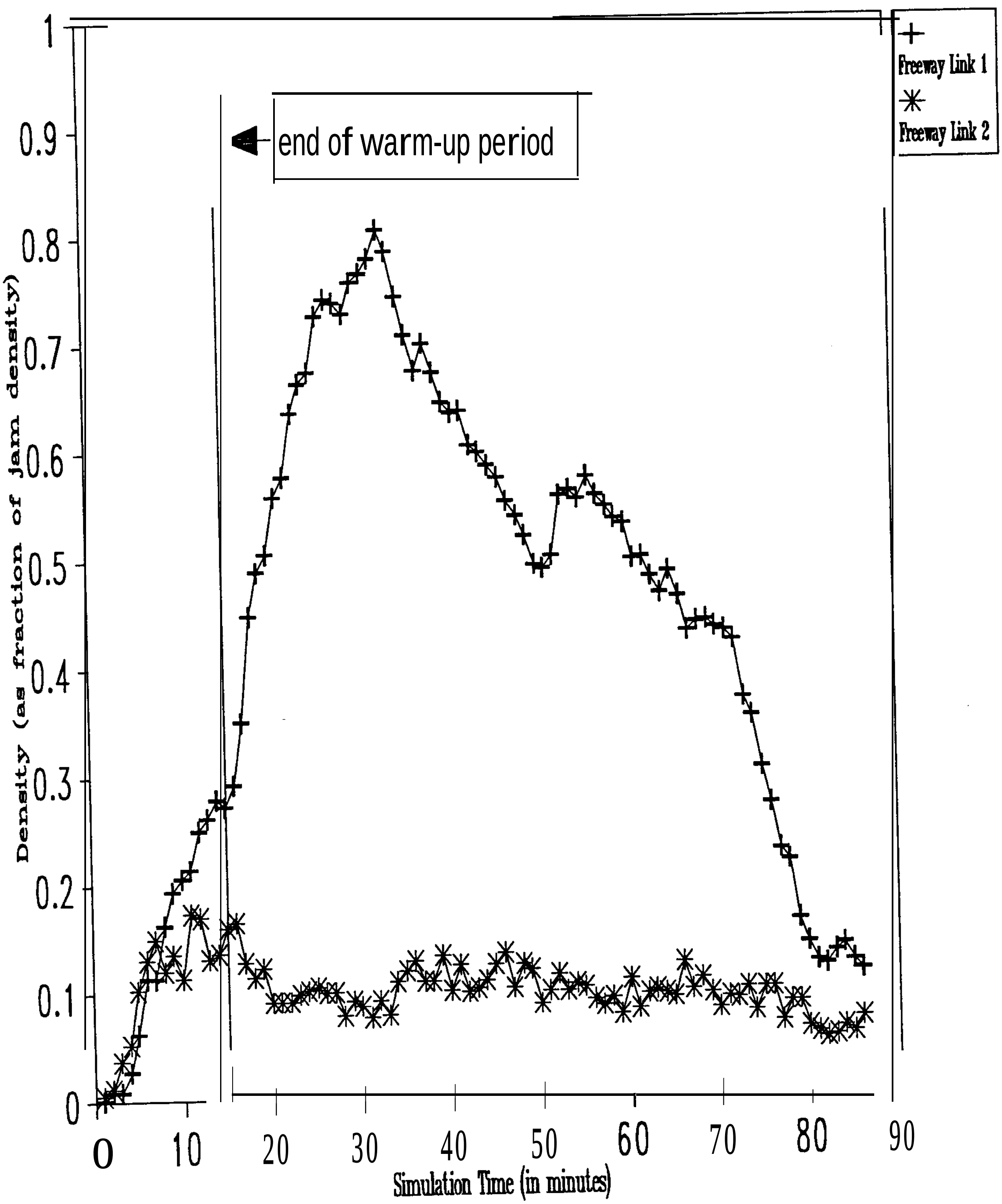


**Figure 4.2** **Density Profiles of Representative Freeway Links**

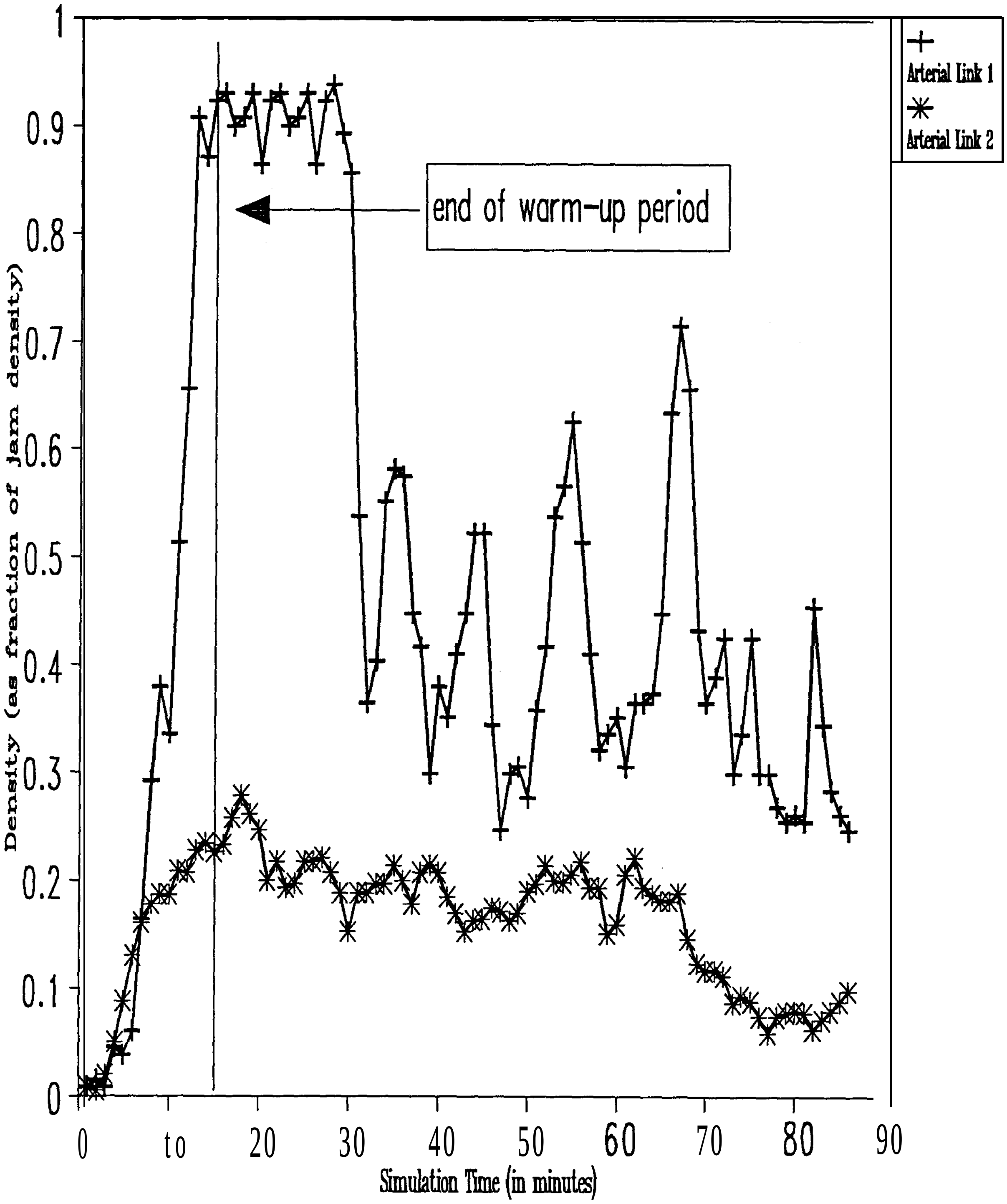


Figure 4.3 Density Profiles of Representative Arterial Links

Lincoln Avenue link density peaks at 28 percent at thirty minutes, then oscillates between 15 and 20 percent until the sixty-fifth minute, when the density drops below 10 percent.

These density profiles establish the adequacy of this base-case scenario for the purposes of the research here. The next section discusses the effects of enroute diversion and IVNS implementation this base-case scenario. Results of ATIS under special-events congestion are discussed in the next chapter.

Average travel time is generally considered to be the most important measure of overall traffic system performance, and the reduction of this value is considered to be the greatest benefit than can occur from installation and deployment of IVNS. Therefore, the value of the average travel time will be the main focus of analysis.

## 4.5 Benefits of Svstem Implementation

This section will provide an analysis of the effects of IVNS deployment on traffic system performance for the case of no special-event (i.e., background traffic only). Although the results presented at this point in the project are quite preliminary, this will illustrate the analysis and conclusions which are possible from this modeling process.

Thirty simulations are performed for this analysis. All the simulations utilize the background traffic trip table; the variable factors between simulations were the market penetration of IVNS, and the propensity of drivers to switch routes.

Six different levels of market penetration of IVNS are simulated. These six levels are: ten percent, twenty-five percent, fifty percent, seventy-five percent, ninety percent, and one-hundred percent of vehicles equipped with IVNS.

For each level of market penetration, five levels of driver propensity to switch are simulated: mean indifference bandwidth values of 0.0, 0.1, 0.2, 0.3 and 0.5 (indifference bands have a triangular distribution over the driver population with a range between 0.75 and 1.25 of these means). The first level, referred to as myopic switching, indicates a maximum propensity to switch; drivers will switch to any shorter path, regardless of minimal benefits. The fourth level indicates a maximum aversion to switch; drivers, on average, will only switch to a route which is no more than one-half the travel time of their current route. It is quite reasonable to assume that real-world driver behavior will fall between these two extremes of inclination to switch; thus they are the chosen boundaries for the simulation parameter of driver behavior.

The results of these simulations are presented on three graphs and one table. Figures 4.4, 4.5 and 4.6 present graphs of the value of the average travel time of the equipped vehicles, unequipped vehicles, and all vehicles, respectively, as a function of IVNS market penetration. Each graph contains five separate lines, each one connecting the simulation results for the same indifference bandwidth. By definition, there are no equipped vehicles at zero percent market penetration, and no unequipped vehicles at one-hundred percent market penetration.

Table 4.1 contains one row for each behavioral scenario. The first column identifies the mean indifference bandwidth of that scenario. The second column contains the maximum benefits achievable from IVNS (measured as the percentage reduction in the base travel time for all vehicles), and the third column contains the optimal level of market penetration. Finally, the fourth column contains the percentage of the maximum achievable benefits which are already achieved at a market penetration of fifty percent; this level of market penetration can be identified as a point of diminishing returns from the graph in Figure 4.6.

The graph in Figure 4.4 indicates that the first vehicles which install IVNS achieve significant savings (10 percent reduction of travel time in the myopic case), and benefits continue to increase slightly as market penetration increases to fifty percent. Beyond this point, the benefits to the equipped vehicles actually decrease for scenarios with high driver propensity to switch (i.e., indifference bandwidth 0.2 or less) and the benefits level off in the scenarios with low driver propensity to switch.

The increase in benefits to equipped vehicles as market penetration increases to fifty percent is counter-intuitive and can be explained as the result of the background traffic trip table producing relatively low levels of congestion. In such a case, the alternative routes to which the equipped drivers switch retain high speeds, while speeds increase on the equilibrium routes as some of the equipped drivers switch off the routes. Because many of the equipped vehicles do not switch but remain on the equilibrium routes, average total travel time for the equipped vehicles will decrease. When market penetration reaches fifty percent, enough equipped vehicles are switching to the alternative routes that the benefits they receive no longer increase. In the scenarios where drivers have high propensity to switch, enough drivers will switch to congest the alternative routes. In the scenarios where drivers have less propensity to switch, not enough drivers switch to the alternative routes to congest them; thus the benefits level off instead of decrease. In more congested networks, it would be expected that the benefits to equipped vehicles would decrease as the percentage of equipped vehicles increase over the entire range of market penetration.

Figure 4.4 also indicates that a greater propensity to switch almost uniformly results in greater benefits to the equipped vehicles. The value of the indifference bandwidth can cause a significant difference in the benefits which accrue to equipped vehicles; at a market penetration of fifty percent, the benefits which accrue to equipped vehicle in case of myopic switching (11 percent) are more than twice that which accrue in the case of extreme aversion to switching (5.2 percent).

Figure 4.5 indicates that unequipped vehicle always achieve greater benefits as the market penetration increases and more equipped vehicles switch off the equilibrium routes on which the unequipped vehicles travel, thus decreasing congestion on the equilibrium routes. As expected, the benefits to the unequipped vehicle nearly always remain below those to the equipped vehicles, with the maximum occurring at market penetrations of ninety percent. Maximum benefits of 7.7 percent reduction in average travel time for unequipped vehicles are achievable in the myopic case; this decreases to 6.2 percent in the case of extreme aversion to switching.

**Table 4.1**
**Benefits of IVNS for Background Traffic**

| Indifference Bandwidth | Maximum Benefits | Optimal Market Penetration | Percent of Maximum Benefits at Fifty Percent Market Pen. |
|---|---|---|---|
| 0.0 | 9.3 percent | 90 percent | 93.0 percent |
| 0.1 | 9.5 percent | 100 percent | 89.9 percent |
| 0.2 | 8.5 percent | 90 percent | 86.7 percent |
| 0.3 | 7.3 percent | 90 uercent | 82.1 percent |
| 0.5 | 5.7 percent | 90 percent | 80.2 percent |

Different levels of driver propensity to switch results in less variation in the benefits which accrue to the unequipped vehicles than to the equipped vehicles; this can be graphically observed by the closer spacing of the lines in Figure 4.5 than in Figure 4.4. This result is expected because the benefits to the unequipped vehicles are an indirect effect of actions taken by the equipped drivers; thus variations in the behavior of the equipped drivers will have less of an effect on the unequipped drivers than the equipped drivers.

Figure 4.6 indicates that benefits accrue to all vehicles as market penetration increases. Again, this graph shows that greater propensity to divert is virtually always better than lower propensity to divert. This is a different result than some of the earlier research results (Mahmassani and Jayalaishnan, 1991), which showed that myopic switching may not yield the best benefits in corridors with limited route switch alternatives. Maximum potential benefits vary from a high of 9.3 percent in the case of myopic switching, to 8.5 percent in the more realistic case where drivers require a 20 percent travel time reduction to induce a switch, to a low of 5.7 percent in the case of extreme aversion to switching.

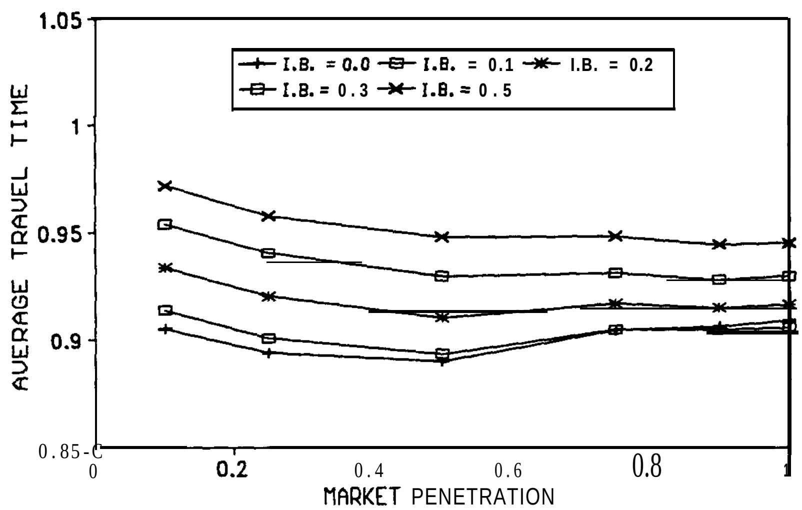


**Figure 4.4** Average Travel Times for Vehicles with Information

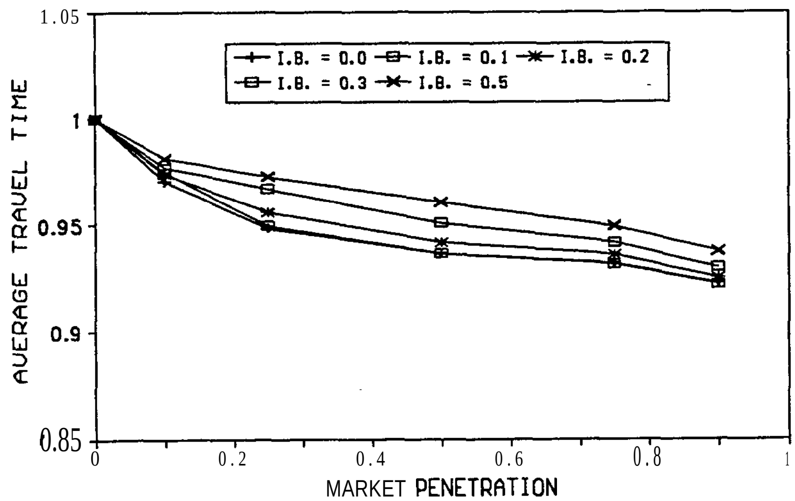


**Figure** 4.5 Average Travel Times for Vehicles with No Information

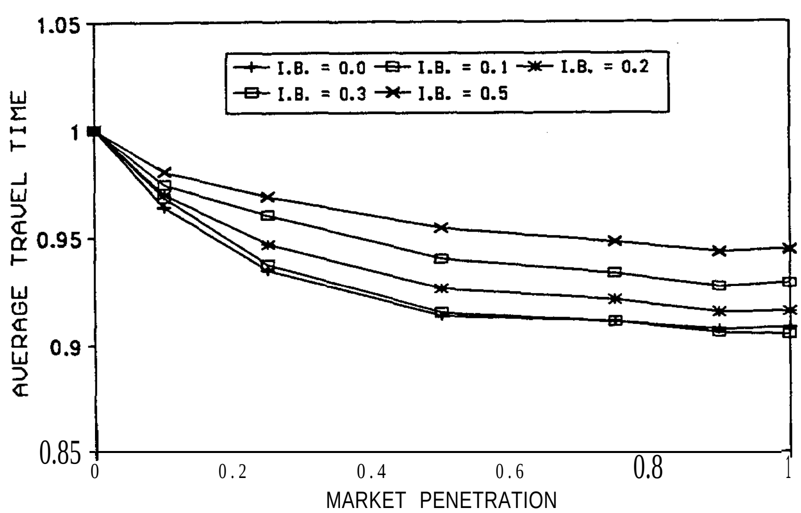


**Figure** 4.6 Average Travel Times for All the Vehicles

Higher benefits may accrue to those vehicles traveling over the most congested sections of the freeway. One of the outputs from DYNASMART is a list of the one-hundred most congested O-D pairs in each simulation (congestion being defined as the ratio of travel time to distance traveled). In two examples (O-D pairs 912-911 and 913-911) the average travel time for all vehicles traveling between these two zones decreased approximately 20 percent under a market penetration level of 25 percent.

Under no behavioral or market penetration scenario does the system ever perform worse with information than without information. System performance does appear to deteriorate slightly as market penetration increases from ninety percent to one-hundred percent.

This graph also indicates that noticeable benefits (i.e., greater than 2 percent) are achieved by a market penetration level of 10 percent, and a market penetration level of fifty percent appears to be a point of diminishing returns (i.e., a point beyond which further benefits are marginal) in every behavioral scenario. As Table 6.1 illustrates, at this level of market penetration, at least 80 percent of the maximum benefits have been achieved. For scenarios with high levels of propensity to switch, ninety percent of the savings have been achieved by this level. Depending on the cost function of IVNS systems, market penetration levels of fifty percent may be optimal levels when considering cost-benefit analysis.

In conclusion, this simulation framework has indicated that IVNS can produce significant benefits to drivers even in the case of the moderate to low congestion resulting from daily recurring background traffic. Maximum benefits of between 5 and 10 percent reduction in total travel time appear to be feasible, with a large proportion of these benefits realized by a market penetration level of fifty percent.

# Chapter 5
# SIMULATION OF SPECIAL EVENTS (ANAHEIM STADIUM)

## 5.1 Introduction

This chapter discusses the DYNASMART simulations which were performed with the special-event trip tables. Special-event scenarios of three different magnitudes are analyzed. System performance statistics are disaggregated by vehicle status as special-event attendee or non-attendee in addition to status as equipped or unequipped. Analysis will be presented as to the potential benefits which may accrue to all classes of vehicles as a result of the implementation of IVNS during special-event congestion.

There are two additional sections to this chapter. Section 5.2 will discuss the implementation of the special-event scenario simulation. Section 5.3 will analyze the results of the various simulations.

## 5.2 Special-Event Simulation

DYNASMART simulations are performed with three special-event trip tables. These trip tables are produced using the COMEST dynamic trip table estimation program, based on observed counts on some network links, as discussed in Section 4.1. Separate tables are produced to simulate scenarios of five thousand, ten thousand and fifteen thousand vehicles egressing from the special-event traffic generation zones, over a 35 minute period (simulating the vehicles leaving the stadium at the end of, say, a baseball game).

Unequipped vehicles which egress from the three designated special-event origins are assigned to the post warm-up period shortest paths instead of the externally-provided equilibrium paths. This reflects the assumption that special-event attendees do not attend these events very often (by definition of special-event), and thus are not familiar with the recurring traffic patterns.

In addition, the equilibrium routes provided for the initial route assignment of unequipped non-attendee vehicles are not updated, the same equilibrium routes provided in the no-event scenario are provided in the special-event scenarios. This again reflects the assumption that special-events are, by definition, scenarios under which drivers usually have little prior knowledge of associated traffic patterns. Therefore, drivers with no real-time information will remain on the equilibrium paths of the no-event scenario.

Benefits which accrue to event-attendees and non-attendees are analyzed separately. This is to avoid combining the average travel times of attendees, who expect significant congestion and delays, and other drivers, who do not expect such conditions.

For each special-event scenario, nine simulations are performed. One simulation assumes no market penetration of IVNS, thus establishing a pre-IVNS deployment level of performance. The remaining eight simulations assume market penetration levels of ten percent, twenty-five percent, fifty percent, and seventy-five percent for indifference bandwidth levels of both 0.0 and 0.2.

## 5.3 Simulation Results

This section discusses the results of the simulations described in the previous section. The results are presented in two tables (Tables 5.1 and 5.2) and eighteen graphs (Figures 5.1-5.18). Table 5.1 presents the base travel times of the attendees and non-attendees for each of the three special-event scenarios. The occurrence of a special-event causes the average travel time of the background traffic (non-attendees) to rise from the 12.28 minutes of the no-event scenario to 12.74 minutes (an increase of 3.7 percent), 13.18 minutes (7.3 percent) and 13.27 minutes (8.1 percent) in the 5,000, 10,000 and 15,000 vehicle special-event scenarios respectively.

In the 5,000 vehicle special-event scenario, the base travel time of attendees is lower than the base travel time of non-attendees. This is possibly due to the location of the stadium. As discussed in Chapter Four, vehicles egressing the special-event are assigned to the destination zones based on the distribution of the background traffic to the destination zones. However, the location of the stadium near the center of the network may reduce the average travel time to many of the destination zones, thus resulting in the lower base travel time.

In the 15,000 vehicle special-event scenario, not all of the tagged vehicles reach their destination by the end of the simulation of the base case; 2725 tagged vehicles are still in the network at the end of ninety minutes and thus do not have their individual travel times included in the average travel times listed in Table 5.1. Only vehicles entering the network between the fifteenth and sixtieth minutes of simulation are tagged; thus the uncounted tagged vehicles must all have individual travel times of at least thirty minutes. Since the average travel times recorded in the table for this scenario are lower than thirty minutes (17.15 minutes for attendees, 13.27 for non-attendees) this clearly biases the base case statistics towards lower travel times, and therefore the potential benefits of IVNS may be underestimated in this special-event scenario. This could be corrected in the future by extending the simulation time for several minutes until all of the tagged vehicles can reach their destinations.

Table 5.2 presents the maximum estimated benefits to attendee and non-attendee vehicles in each of the three special-event scenarios. The benefits are for all vehicles (i.e., both equipped and unequipped vehicles). Since the graphs for total vehicles indicate no points of negative returns, all of these maximum benefits occur at seventy-five percent market penetration, and it is reasonable to assume slightly greater benefits may occur at higher market penetrations. However, the existence of the points of diminishing returns does not become clear from this table; in fact virtually all of the benefits listed in Table 5.2 are achieved by market penetrations between 25 and 50 percent.

Each of the three special-event scenarios requires six graphs; average travel time as a function of IVNS market penetration for equipped, unequipped, and all vehicles, for both event attendees and non-attendees. These graphs are presented in Figures 5.1 to 5.18.

The horizontal axis of each graph is the market penetration of the IVNS, measured as the percentage of vehicles with access to information. The vertical axis of the graph is the average travel time for that class of vehicles, measured as the percentage of the base travel times (i.e., the average travel time with no IVNS deployment) which are presented in Table 5.2.

Each graph contains two lines; each line connects the results of the simulations of each indifference bandwidth. The indifference bandwidth (LB.) associated with each line is identified in the legend box at the top of each graph.

Figures 5.1 to 5.6 illustrate the results of the 5,000 vehicle special-event; Figures 5.1 to 5.3 illustrate the average travel times for attendees, and Figures 5.4 to 5.6 illustrate the average travel time for non-attendees. In a similar manner, Figures 5.7 to 5.12 illustrate the results of the 10,000 vehicle special-event, and Figures 5.13 to 5.18 illustrate the results of the 15,000 vehicle special-event.

**Table 5.1**
**Base Travel Times**

| Special-Event Magnitude (Vehicles) | Vehicle Class | Base Travel Time (Minutes) |
|---|---|---|
| 5,000 | Attendees | 11.62 |
| 5,000 | Non-Attendees | 12.74 |
| 10,000 | Attendees | 15.24 |
| 10,000 | Non-Attendees | 13.18 |
| 15,000 | Attendees | 17.15 |
| 15,000 | Non-Attendees | 13.27 |

**Table 5.2**
**Potential Benefits of IVNS**

| Special-Event Magnitude (Vehicles) | Vehicle Class | Average Indifference Bandwidth | Maximum Travel Time Reduction |
|---|---|---|---|
| 5,000 | Attendees | 0.0 | 17.0 percent |
| | | 0.2 | 14.6 percent |
| 5,000 | Non-Attendees | 0.0 | 11.6 percent |
| | | 0.2 | 10.4 percent |
| 10,000 | Attendees | 0.0 | 33.3 percent |
| | | 0.2 | 30.0 percent |
| 10,000 | Non-Attendees | 0.0 | 12.9 percent |
| | | 0.2 | 11.5 percent |
| 15,000 | Attendees | 0.0 | 34.7 percent |
| | | 0.2 | 27.1 percent |
| 15,000 | Non-Attendees | 0.0 | 12.7 percent |
| | | 0.2 | 10.5 percent |

**Special-Event Magnitude : 5,000 Vehicles**

**Special-Event Attendees**

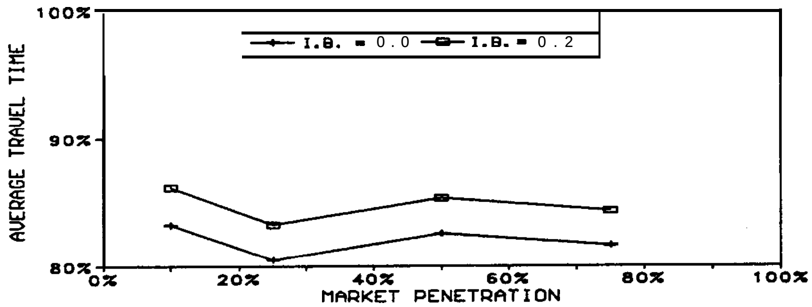


**Figure 5.1** **Equipped Vehicles**

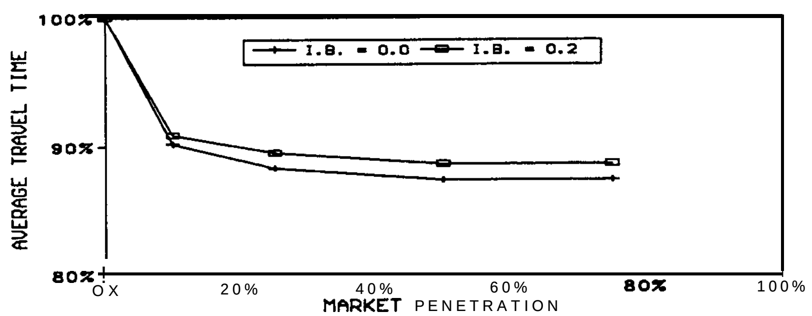


**Figure 5.2** **Unequipped Vehicles**

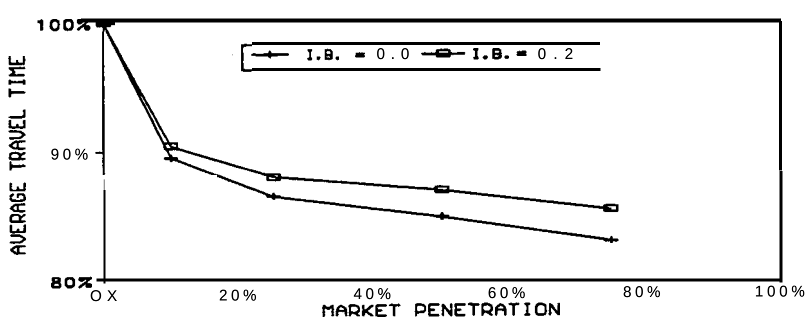


**Figure 5.3** **All Vehicles**

## Special-Event Magnitude : 5,000 Vehicles

## Non-Attendees

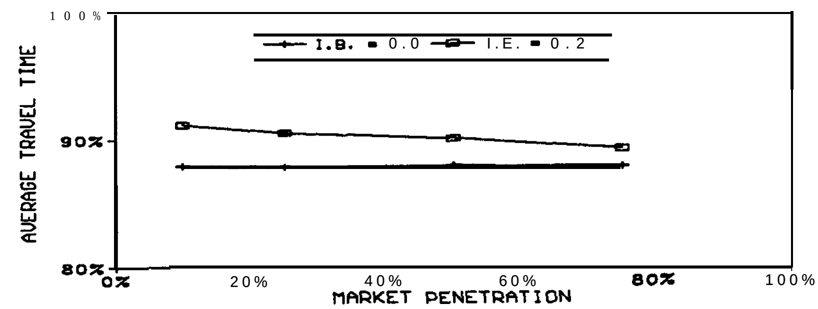


**Figure 5.4** **Equipped Vehicles**

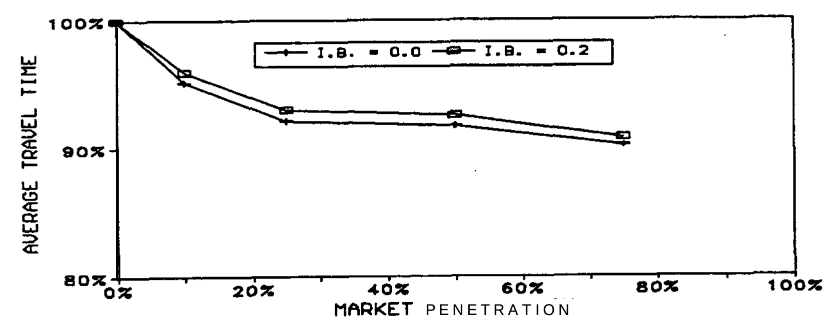


**Figure 5.5** **Unequipped Vehicles**

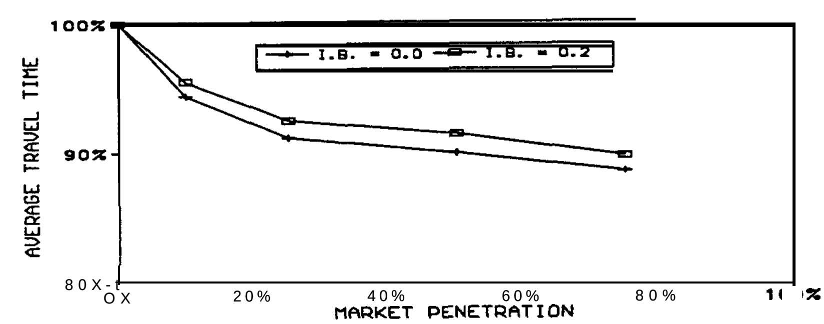


**Figure 5.6** **All Vehicles**

**Special-Event Magnitude : 10,000 Vehicles**

**Special-Event Attendees**

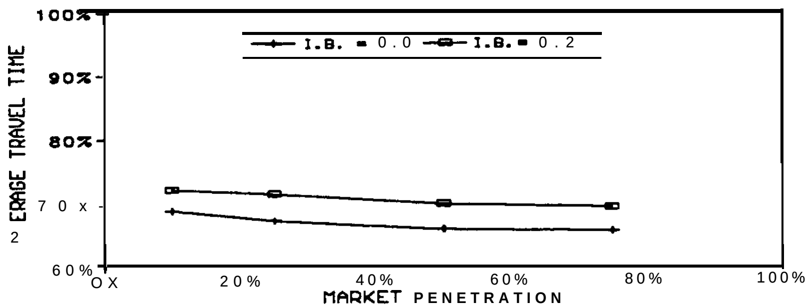


**Figure 5.7** **Equipped Vehicles**

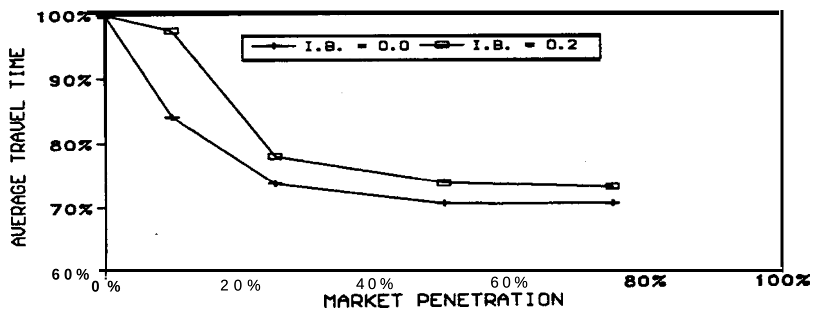


**Figure 5.8** **Unequipped Vehicles**

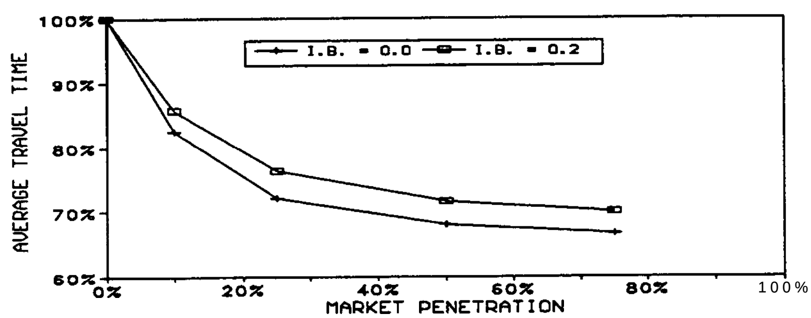


**Figure 5.9** **All Vehicles**

**Special-Event Magnitude : 10,000 Vehicles**

**Non-Attendees**

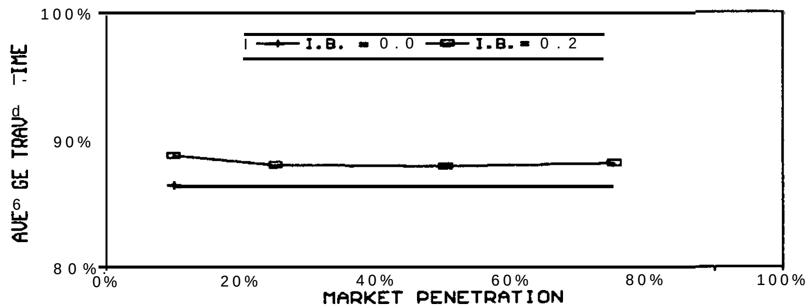


**Figure 5.10** **Equipped Vehicles**

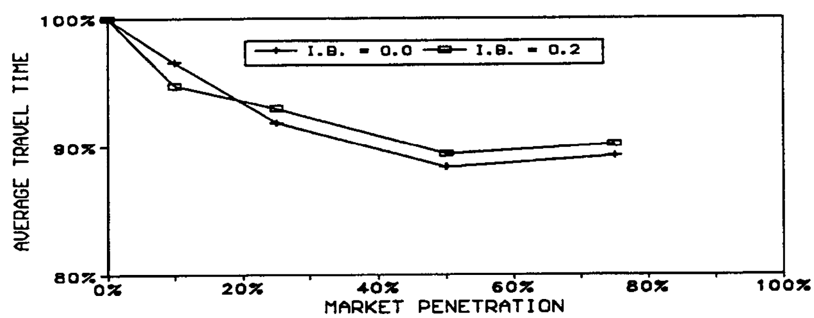


**Figure 5.11** **Unequipped Vehicles**

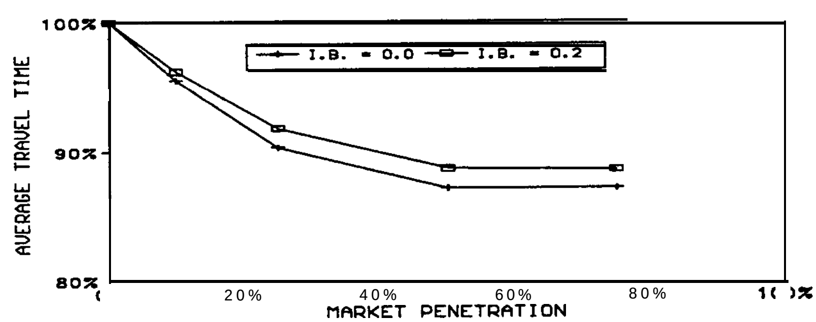


**Figure 5.12** **All Vehicles**

**Special-Event Magnitude : 15,000 Vehicles**

**Special-Event Attendees**

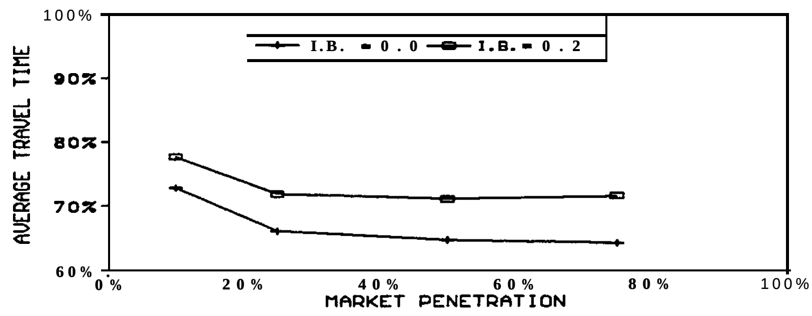


Figure 5.13 Equipped Vehicles

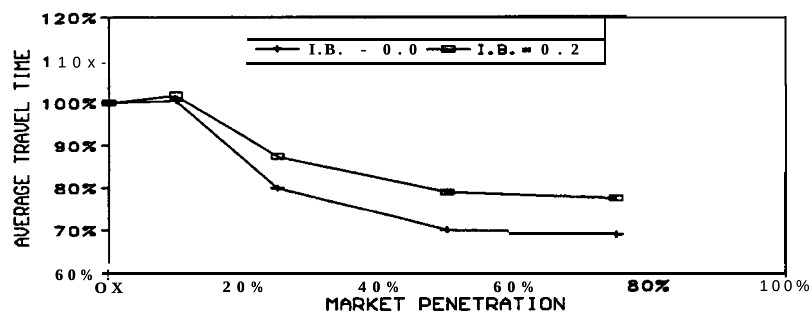


Figure 5.14 Unequipped Vehicles

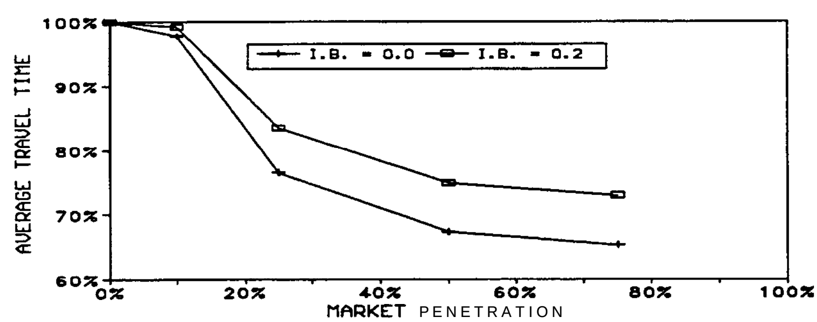


Figure 5.15 All Vehicles

## Special-Event Magnitude : 15,000 Vehicles

## Non-Attendees

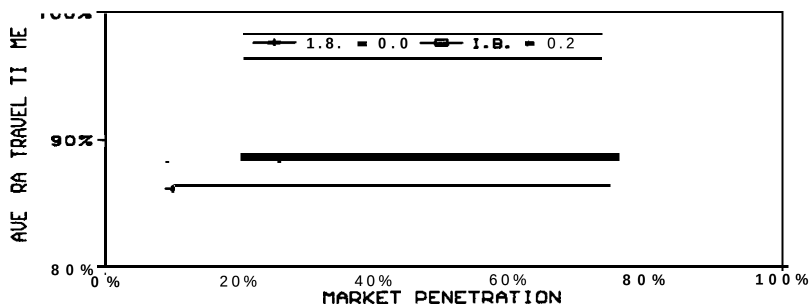


Figure 5.16 Equipped Vehicles

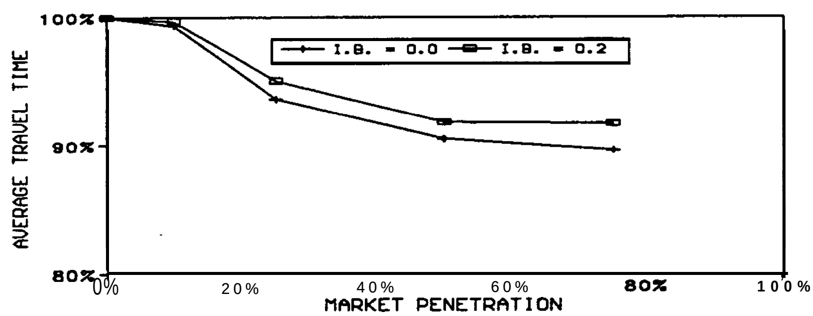


Figure 5.17 Unequipped Vehicles

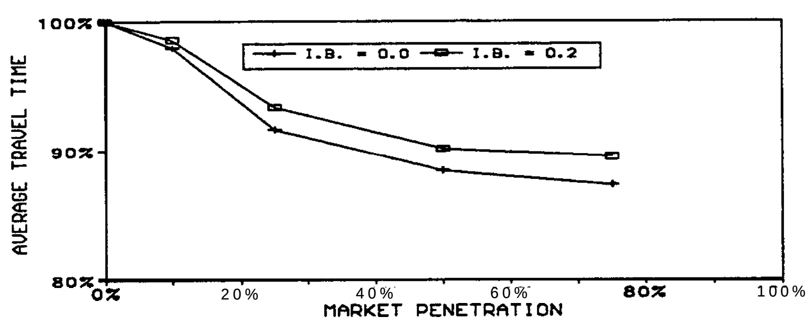


Figure 5.18 All Vehicles

The results presented in the preceding tables and graphs suggest that benefits up to even thirty-five percent reduction in travel time are achievable for special-event attendees from the implementation of IVNS. Maximum benefits for non-attendees remain consistent at between ten and thirteen percent; this is expected considering the relatively large size of the non-attendee population in comparison to the attendee population.

For special-events with 5,000 vehicles, IVNS deployment can result in travel time savings for attendees of up to 17 percent in the behavioral scenario of myopic switching, and 14.6 percent in the more realistic behavioral scenario where drivers require 20 percent savings to switch routes.

For special-events with 10,000 vehicles, the benefits to attendees increase dramatically to 33.3 percent and 30 percent, for the same two behavioral scenarios. This dramatic rise in the achievable benefits is a result of the high base travel time caused by attendees (none of whom have information in the base case) congesting a few paths near the stadium while alternative paths are relatively unused until IVNS is deployed.

The benefits do not significantly increase for special-events with 15,000 vehicles; this is probably a result of the base travel time being biased to the lower side as explained above.

Although increases in market penetration appear to never have a negative effect on total average travel time, the graphs indicate the existence of points of diminishing returns. These points exist because in most of the scenarios, the benefits which accrue to equipped vehicles increase until market penetrations of twenty-five percent, at which point benefits either level off or diminish as the alternate routes used by the equipped vehicles become congested. Although unequipped vehicles always obtain greater benefits as market penetration increases and the equilibrium routes on which the unequipped vehicles travel become less congested because the equipped vehicles are switching to alternative routes, the unequipped vehicles also become a smaller percentage of the vehicle population.

The point of diminishing returns seems to be consistent for both attendees and non-attendees and for both levels of indifference; thus the level of market penetration at which diminishing returns begin is sensitive only to special-event magnitude. For special-events with 5,000 vehicles, the point of diminishing returns is at twenty-five percent market penetration. For special-events of 10,000 and 15,000 vehicles, the point of diminishing returns is at market penetration of fifty percent.

In no case does the provision of information cause total average travel time to be higher than the base case. Also, the case of myopic switching is virtually uniformly more beneficial than the case of 20 percent indifference, indicating that progress towards a prescriptive system (as opposed to a descriptive system) may be desirable.

In conclusion, these simulations appear to indicate that IVNS would be of great benefit to drivers egressing from a special-event, with benefits to attendees approaching a thirty percent reduction in travel time for events with attendance greater than ten thousand vehicles. These benefits appear to be much greater than the 5 to 15 percent benefits reported in the literature for normal network traffic scenarios and thus underscore the increased usefulness of IVNS for congestion relief under special-events conditions. However, the benefits which accrue to the non-attendee vehicles traveling in the vicinity of the stadium appear to be minor.

# Chapter 6
# CONCLUSIONS

## 6.1 Summary of Research Results

Research in this project incorporated more extensive modelling of network node delays into an earlier-developed simulation framework for ATIS and ATMS in urban traffic networks. The model is called DYNASMART and its enhancements were accomplished in conjunction with related research at UCI and at the University of Texas at Austin (where the original framework was developed by this proposer). The simulation framework already is capable of being used for large and realistic city networks of the kind that will eventually be studied by the PATH project. The simulation system is able to consider different configurations of information supply (compulsory/non-compulsory guidance, infrequent updating of path trip-times etc.), and is flexible enough so that different traffic flow and behavioral models of varying complexities can be incorporated to study various levels of fidelity and complexity.

DYNASMART has so far been implemented on two different computer platforms: the CRAY YMP supercomputer and the SUN SPARC workstation. Simulation of up to 75000 vehicles in networks of up to 2000 links with 10 paths from each node to each destination centroid can be achieved on these platforms faster than real-time. As the code is written in standard portable FORTRAN 77, it is expected to run on other platforms such as the IBM PC as well, with the size of the problem determined by the available RAM storage. The program capabilities include:

1) Macroscopic modelling of traffic flow dynamics such as congestion formation and shock wave propagation. Tracking of locations of individual drivers.
2) Modelling of different traffic control strategies (freeways, surface streets, signalized intersections, ramp entry/exit etc)
3) Modelling of prescriptive/compulsory guidance as well as non-prescriptive guidance with trip time information on alternative routes.
4) Modelling of various aspects of the controller such as infrequent updates of the network route information database.

5) Modelling of individual drivers' response to information in the case of descriptive guidance based on a set of paths rather than a single shortest path. Random assignment of driver behavioral characteristics. Flexibility to incorporate alternative behavioral rules.
6) Modelling of capacity-reducing incidents at any time, anywhere in the network.
7) Modelling of cases with only a fraction of the vehicles equipped for information.
8) Capability to carry out simulations based on externally specified dynamic equilibrium paths for drivers not equipped to receive information.
9) Several levels of output statistics for the system, for individual drivers as well as for groups of drivers (equipped drivers, unequipped drivers, drivers on certain O-D pairs etc). Statistics include average trip times, distances, average speeds and a variety of route switching statistics.

There are also other enhancements to DYNASMART that are underway now. Modelling of dynamic route trip times by the TOC controller is being incorporated. Using this program as a dynamic performance predictor in an optimal assignment framework is also under study (by Dr. Hani Mahmassani at the University of Texas, with funding from FHWA).

The results from the first year of research on the PATH project (MOU-39) at UCI on DYNASMART are very encouraging. The network of the prototype urban area (the Anaheim IVHS test-bed network) was coded and a dynamic O-D matrix was prepared. The model was used for simulating the effect of information supply in reducing traffic congestion caused by special events (from the Anaheim stadium). Some results of this research can be found in Jayakrishnan et al. (1993), Cohen (1992) and McNally et al. (1993). Some results on using DYNASMART for the simulation of the combined effect of various network control options and information supply strategies can be found in Mahmassani et al. (1992). Even though this was not specifically laid out in the proposal for MOU-39, attempts were made at porting the program to a workstation environment from the earlier supercomputer mainframe environment. This produced extremely encouraging results. The experience so far is that workstations are not substantially slower than supercomputers. The program was benchmarked on various workstations including HP9000/7 10, Sun SPARC-II and DEC5013. All the workstations performed simulations in at most 3 times the computation time of a CRAY YMP-8/64 supercomputer, and at most 1.5

times the computation time on a Convex C-240 mini-supercomputer. The simulations were performed on a large urban network (1600 links), and the workstations performed the simulations faster than real-time. These are significant results, and point to the viability of the framework for practical application. In fact all the development work on DYNASMART now is on the workstation environment.

This project has demonstrated the basic feasibility of analyzing the potential benefits of IVNS deployment through the technique of computer simulation. Realistic simulations have been performed utilizing a network and demand level based on the Anaheim testbed. The CONTRAM equilibrium assignment model has been successfully utilized for the provision of dynamic equilibrium paths to DYNASMART for the initial route assignment of unequipped vehicles.

The modeling of the specific case of traffic egress from a special-event was performed in this project to demonstrate the capability of DYNASMART to be modified for the analysis of various specific scenarios under which deployment of IVHS may be most feasible and beneficial. Special-event attendees and non-attendees were initially assigned to the network according to different assumptions, and benefits for each class of vehicle were presented separately.

Results of simulations of the background traffic suggest achievable system-wide benefits of up to ten percent reduction in average travel time for all vehicles, with benefits for both equipped and unequipped vehicles increasing as market penetration increases, until market penetration reaches fifty percent, at which point decreasing returns to scale begin. Possibly greater benefits may occur under special-event scenarios of large magnitude (i.e., attendance greater then ten-thousand vehicles); drivers egressing from special-events of large magnitudes can expect travel time reductions of up to thirty percent.

Under no condition of market penetration, driver behavior, or special-event congestion, does the provision of information result in system performance worse than the base-case (i.e., no information) scenario.

The driver-behavior scenario of myopic switching, which assumes a very high propensity to switch routes, appears to offer the greatest benefits at low levels of market penetrations. This indicates that system operators may wish to implement a strategy of misrepresenting travel times in order to induce drivers to switch in cases where drivers demonstrate high aversion to switch; it also indicates the desirability of prescriptive systems which compel the driver to follow shortest paths.

## 6.2 Directions for Future Research

It is possible that several refinements will be made to this model before it will be considered a highly accurate predictor of the behavior of traffic flow under information. Progress towards this goal will continue as part of the Caltrans ATMS research testbed project at UCI. Additional research is underway on incorporating graphics front-end to make DYNASMART more user-friendly (PATH project MOU-84, 1992-93). This includes on-screen network editors as well as run-time network displays.

The driver behavior component of DYNASMART will be modified to consider more complex paradigms for route choice decision-making. As accurately calibrated models of driver behavior become available, it may become desirable for DYNASMART to generate socioeconomic variables from a specified population distribution, which would be associated with each vehicle (e.g., drivers' gender, age category, and income level). The consideration of factors other than travel time may also be added. The results presented by Adler et al. (1992) will be particularly useful in this aspect of the refinement of DYNASMART.

It is also necessary to incorporate a mechanism for the modeling of the enroute diversion of unequipped drivers due to the self-observation of congestion.

Furthermore, the traffic simulation components of DYNASMART require calibration and validation through extensive comparison with real-world traffic data. This will require the production of very accurate dynamic trip tables, finely detailed microscopic coding of the testbed network, and extensive gathering of time-varying traffic counts, particularly freeway counts. Progress has been made concurrently with this project at the University of Texas at Austin in incorporating the modeling of intersection signalization to DYNASMART (Mahmassani et al., 1992).

Additional research may include the investigation of long-term changes in driver behavior as IVNS deployment reduces expected travel time. This would include changes in departure time and preplanned routes resulting in establishment of a long-term equilibrium.

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Appendix A. DYNASMART INPUT FILE GUIDE

To aid the user in the use of DYNASMART, this section of the report describes the necessary input file formats to run the program. There are seven input files required by the program and they are identified by FORTRAN unit numbers **41, 42, 43, 44, 45, 47** and 48. Each input file is described in detail hereafter. The user may wish to implement the units with appropriate file names if needed (using 'OPEN' statements, for instance). This is only for the current version of Dynasmart. The future versions of the program may include a graphic front-end which will have capabilities to automatically generate the data from screen inputs (currently under development in the PATH project MOU-84).

We also provide the names of the variables in the program

**Unit = 41: NETWORK DATA**

Includes characteristics of the network to be analyzed.

FORMAT(10I5) nzones,nnodes,narcs,n,ndests,kay (one line)

nzones = number of zones
nnodes = number of nodes
narcs = number of arcs
n = number of links (link can have 1 or more arcs)
ndests = number of dests
kay = number of shortest paths

FORMAT( 1015) ipz(i)

ipz(i) = pseudo-zone number for i-th zone (i =l,nzones)

FORMAT( 1015) idz(i)

idz(i) = destination zone in i-th zone

FORMAT(2I5) i1,i2 (one line per node)

il = node number

i2 = zone in which node il is located

FORMAT(3I5,2I2,F6.3,F5.2,I2) iunod(i), idnod(i), i3, i4, nlanes(i), vmax(i), sat(i), link_iden(i)
(one line per link)

iunode(i) = upstream node of link i
idnode(i) = downstream node of link i
i3 = link length
i4 = volume source,
O=no volume
l=from zone of iudnode(i)
2=from zone of idnode(i)
nlanes(i) = number of lanes of link i
vmax(i) = free-flow speed of link i
sat(i) = saturation volume (?) of link i

**Unit = 42 : ZONAL DEMAND DATA**

The zonal trip interchange data of network area (spatial and temporal).

FORMAT(I5) nints (one line)
nints = number of time intervals

FORMAT(10F6.1) begint(i) (one line)
begint(i) = start time of interval i (i=l,nints)

FORMAT(6F10. 1) zdem(iz,izz,int)
zdem(iz,izz,int) = trips from zone iz to zone izz for time interval int

**Unit = 43 : GLOBAL SIMULATION VARIABLES**

Global specifications of the simulation run.

FORMAT(3F5.2,F5.2,I10,I2) fracinf, ribfa, bound, mumber, iseed, ipinit
(one line)

fracinfo = fraction of users with information

ribfa = average time-indifference-band for route change as a fraction of remaining trip time. It has a triangular distribution over this mean value and so is different for different drivers.

bound = lower limit of indifference band, which is min trip time advantage needed for a route change.

mumber = initial random number

iseed = random number seed

ipinit = switch to determine whether users without information will pick the best stored route or randomly pick from the stored k-routes.

FORMAT(I5,F5.2) ntto, tii (one line)

ntto = total time of simulation, minutes

tii = time interval increment

FORMAT(I4) index-sig (one line)

index-sig = index for signal control

FORMAT(I4) left-factor (one line)

left-factor = index for left capacity

FORMAT(I4) left-option (one line)

left-option = option for left turn test

FORMAT(I4) bay-option (one line)

bay-option = option for bay (l=bay, O=no bay)

**Unit = 44 : SIGNAL DATA**

The signal control data for each intersection of the network.

FORMAT(I5,I2,I2,I4) node(i,l), node(i,2), node(i,3), node(i,4)
(one line per node)

node(i,j) = type of traffic control for node i
node(i,l) = number of node i
node(i,2) = control : 1 = no control
2 = yield control
3 = stop control
4 = signal control (pre-timed)
5 = signal control (actuated)
node(i,3) = phase number
node(i,4) = cycle length

FORMAT(12I4) itmp, nsign(i,l), nsign(i,2), nsign(i,3),..., nsign(i,11)
(one line per node)

itmp = node number
nsign(i,j) = type of signal control (if any) for node i
nsign(i,l) = phase number
nsign(i,2) = offset (maximum green for actuated)
nsign(i,3) = actual green time (minimum green for actuated)
nsign(i,4) = amber time
nsign(i,5) = number of approaches having green
nsign(i,6 through 11) = list of upstream nodes of approaches having green

**Unit = 45 : RAMP CONTROL DATA**

Parameters governing freeway ramp control.

FORMAT(2I6) dec_num,vms_num (one line)

dec_num = number of ramp detectors
vms_num = number of variable message signs (future development)

FORMAT(7I6,F7.3,2F6.2) detector(i,j), ramp_par(i,j) (one line per ramp detector)

detector(i,j) = ramp control data for ramp detector i
detector(i,l) = detector number
detector(i,2) = from node
detector(i,3) = to node
detector(i,4) = detector pos 1
detector( i,5) = detector pos 2
detector(i,6) = control ramp from node
detector(i,7) = control ramp to node

ramp_par(i,j) = ramp parameters for ramp detector i
ramp_par(i, 1) = cons 1, used in rate=ratep+consl (cons2-occ)
ramp_par(i,2) = cons2
ramp_par(i,3) = ramp rate

## Unit = 47 : LEFT-TURN MOVEMENT INFORMATION

Factors governing the left-turn movements in the network.

FORMAT(6I5) ifrom,ito,ileft,ist,iright,iother (one line for each arc)
ifrom = from node
it0 = to node
ileft = left movement volume
ist = straight movement volume
iright = right movement volume
iother = other movement volume (u-turns)

## Unit = 48 : LEFT TURN CAPACITY

FORMAT(4X,F3.1) gcratio
gcratio = g/c value

(if gcratio = 0.3, then igc = 1
if gcratio = 0.4, then igc = 2
if gcratio = 0.5, then igc = 3
if gcratio = 0.6, then igc = 4
if gcratio = 0.7, then igc = 5)

FORMAT(I1,3X,7I5) itmp, leftcap(igc,itmp,j)
(three lines per each gcratio)
itmp = number of opposing lanes
leftcap(igc,itmp,j) = protected left turn capacity
(if volume < 200, then j = 1
if volume < 300, then j = 2
if volume < 400, then j = 3
if volume c 500, then j = 4
if volume < 600, then j = 5
if volume < 800, then j = 6
if volume < 1000, then j = 7)

NEXT LINE MUST BE EMPTY

FORMAT(4X,F3.1) gcratio
gcratio = g/c value
(5 values of gcratio as in the protected case)

FORMAT(I1,I4,I4,6I5) ivolume,itmp, leftcap2(igc,itmp,ivolume,j)
(three lines per each gcratio)
ivolume = left turn volume
itmp = number of opposing lanes
leftcap2(igc,itmp,ivolume,j) = permissive left turn capacity
(j values are the same as with the protected case)