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Event-based ATIS: Practical Implementation and Evaluation of Optimized Strategies (Part I)

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CALIFORNIA PATH PROGRAM
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Event-based ATIS: Practical Implementation and Evaluation of Optimized Strategies (Part I)

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Event-based ATIS: Practical Implementation and Evaluation of Optimized Strategies

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Abstract

This project will further adapt and enhance the previous research of relevance to event-based Advanced Traveler Information Systems (ATIS) and implement the algorithms for traffic management in Anaheim. The implementation involves the Caltrans-UCI ATMS research testbed framework at the UCI Institute of Transportation Studies, as well as the physical hardware available for communication to the city of Anaheim. The analytical algorithms proposed for use here include those for static and dynamic traffic assignment, and the modeling schemes used are the result of previous PATH and Testbed research projects on traffic simulation and driver behavioral response to information.

The essential part of algorithmic research will be to adapt the network optimization algorithms to generate traffic rerouting plans, which involve aggregation of network paths and their translation to a format usable for changeable message signs existing in Anaheim, as well as other event-based information supply hardware. The implementation plan envisages a framework that is usable by the city for event-based congestion management, but its use is left to the city's decision.

Key words: Advanced Traveler Information Systems, Optimal Routing, Dynamic Traffic Assignment, Changeable Message Signs

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Chapter 1

INTRODUCTION

1.1 Project Description

The Advanced Traveler Information System (ATIS) is considered as a promising technology to improve traffic condition by helping traveler to use efficiently existing transportation facilities. Unlike other components of an advanced management system, the effectiveness of traveler information technologies is determined primarily by the traveler's awareness of the information, correct interpretation of the information, evaluation of its usefulness, and implementation of the recommended course of action.

ATIS is now in transition moving from laboratory to real world thank to past studies in this field; however, there are several unanswered questions in ATIS routing, which this research attempts to answer. The main goal of the research is to develop a framework to generate optimal routing schemes. The framework is based on network optimization, heuristics and driver-behavior-based detailed simulation for both evaluation and information design.

A method to find concrete optimal routing scheme is developed. An algorithm to find routing messages for changeable message signs (CMS) is developed as a generalized problem. To find an optimal routing scheme, static network optimization and dynamic simulation approach are used. New sub-path gradient algorithm is used to evaluate re-routing potential. and an iterative real time method to evaluate routing scheme is applied.

The research is certainly ambitious and the success of its component areas may not be uniform; however, the research results are expected to play an important role in advancing ATIS to real world implementation.

1.2 Motivation and Purpose of Study

This research is motivated by several fundamental questions on optimal routing problems in ATIS.

- *Is the traveler information always beneficial?*
- *Why may the information do harm?*
- *What is the importance of driver's behavior in ATIS?*
- *Can system optimality **be** achieved in ATIS?*
- *What is the "bestpossible" routing in ATIS?*

As noticed from the first three questions, traveler information may do harm when information is given to drivers without consideration of drivers' response to it. Drivers' over-reaction, for example, may result in worse conditions both at the individual level and the society level. The goal of ATIS is pursuing optimal state, whether user optimal or system optimal. However, it cannot be achieved just by giving information. Information should be well designed with consideration of drivers' response. The answer for the fourth question

needs more investigation associated with drivers' behavior because optimum at the society level is not sustainable due to inequity in the benefits to individual driver. The last question, which is regarding the "best" routing in ATIS, involves complex practical issues. To answer the question, a comprehensive design and evaluation framework needs to be developed based on the answers to the prior four questions. Analysis of routing with partial information supply, as in changeable message signs (CMS) is more challenging than routing with complete information supply as in map-based in-vehicle navigation systems (IVNS.)

The main goal of this research is to develop a framework to generate routing strategy for drivers. The concrete problems to be studied are: what information to provide, when, where, and what for. To achieve the main goal, objectives can be divided into four categories.

- *to analyze driver's response to various types of information*
- *to investigate routing policy in the context of information reliability*
- *to generate routing scheme for ATIS*
- *to construct a comprehensive ATIS design and evaluation framework.*

There are two purposes in analyzing driver's response to various types of information. There has been numerous research on driver's response to information. but behavior models for simulation are not enough to capture driver response to various types of information supplied by different information sources. So this research will develop a framework for driver behavior that can capture driver response to various types of information. The behavior framework will be incorporated into DYNASMART, which will be used in this research as a traffic simulation and ATIS evaluation tool. The other purpose is information design based on understanding of how drivers perceive information before responding to it. Guideline for information design can be addressed by understanding this behavior.

Routing policy, whether to minimize total system cost (system optimum) or to minimize individual cost (user optimum,) is an issue in ATIS. It needs to be investigated whether system optimal routing schemes can be applied without deteriorating reliability of information which affects drivers' compliance, because drivers can find better routes for themselves while drivers are guided based on system optimum. This makes the routing unsustainable over time, as the system could tend to revert to a user equilibrium state; however, in a dynamic system there is the possibility of routing based on the tolerances in the driver behavior under dynamics. If so, real optimal solution considering drivers' compliance might be between these two different optimal points. More investigation is needed on this issue.

Purpose of developing a method for optimal routing scheme is to find ultimate solution for implementation of ATIS to real world. This is an important part of this research. Routing schemes can be evaluated using the simulation model into which driver behavior model is incorporated. To find an optimal routing scheme, appropriate network optimization coupled with more accurate evaluation using dynamic simulation is proposed.

Because of the dynamic characteristic of traffic flow over time, dynamic optimization is expected to be more correct, though computationally more intensive. Static assignment may be sufficient to derive a subset of routes in a quick manner for further evaluation, however. Also an adaptive control strategy may need to be considered to reflect uncertainty. This is achieved in a rolling horizon type real time implementation scheme in this proposed research. A comprehensive framework for ATIS design and evaluation is constructed by achieving the above three objectives.

1.3 Overview of the Research Approach

This research project is trying to find optimal routing scheme. In this research CMS routing is the main focus. It is not easy to give full route information to drivers using CMS. So routing using CMS can be used only for certain circumstances. Furthermore, information provided by CMS is very limited. All information should be generally transferred to drivers within at most 3 lines of 18 characters. A solution of generalized CMS problem can be viewed as a similar problem as an IVNS routing in overall modeling purpose. However, each CMS or a series of CMS's can be an independent system that has its own function. From this point of view, unlike IVNS routing system, CMS routing is limited within possible routing area in general. A series of CMS's may work for guidance in certain complex networks. Developing CMS guidance scheme is a much harder task than IVNS guidance due to limitations in providing information and uncertainty of driver's route choice behavior after diverting from the decision point where CMS is located. Note that the frameworks made for partial information supply such as using CMS can, of course, be used for IVNS schemes which are often special case of the general partial information schemes.

In real world implementation of CMS routing, several important factors should be taken into account. In order to provide comprehensively predicted information, which is considered driver's reaction to the information, dynamic O-D demand estimation and dynamic traffic assignment is essential. For the dynamic O-D demand estimation and dynamic traffic assignment as consecutive works, rolling horizon approach is considered as a more realistic approach. Main problem in incorporating this dynamic approach into searching optimal routing solution is that it is very difficult to finish the DTA routine with consideration on driver's response, especially in partial information case. Furthermore, routing schemes for CMS is much harder problem because routing is implemented only by limited information. Therefore, this research is trying to find optimal CMS message using static network flow optimization technique and dynamic traffic simulation model as an evaluation tool.

Static network flow optimization is one way of achieving optimal flow pattern in the network. The main benefit from static assignments is that they are fast by orders of magnitude over the dynamic assignment algorithms which exists now, and thus are very attractive for real-time application. The disadvantage, on the other hand, is that they do not capture network congestion dynamics very well, thanks to the rather simple link travel time functions used. This research project attempts coordinating static and dynamic assignments

in such a way that the computational benefits are gained from the static assignment while the inaccuracies from the results are minimized.

1.4 Significance of Study

Significance of this study can be summarized from three different points of view. The first significance is that this study constructs a comprehensive ATIS design and evaluation framework. Even though there have been many studies on ATIS, only a few studies investigated concrete routes or information to provide and comprehensive ATIS frameworks are rare or nonexistent. In addition, this research will enable partial / restricted information supply systems such as CMS's, which are widely deployed but are not effectively used, to be used as more active dynamic routing devices. The second significance is that this study treats the information system as a closed-loop control system by incorporating driver response to various types of information into a prediction model frame, so as to capture dynamic effects and make it possible to elaborate information to supply. The last, the most significant contribution is that this research is expected to play an important role in advancing **ATIS** to real world implementation.

Chapter 2

OPTIMIZED ROUTING SCHEME

2.1. Routing in ATIS

2.1.1 Information Source and Format

There are various of techniques for communicating with drivers. These techniques range from conventional regulatory, warning and information signs, road markings and roadside post delineators, through Changeable Message Signs (CMS) and Highway Advisory Radio (HAR), to In-Vehicle Navigation Systems (IVNS) which are being promoted as part of a comprehensive intelligent transport system (ITS). Characteristics of CMS and IVNS are discussed here.

CMS differs from the conventional traffic signs in that they can be configured to show a range of different messages which vary according to current need. CMS has main uses: to issue instructions, to warn of dangers ahead, to give advice regarding routing or parking, or to give information on travel or delay of alternative routes for driver's route selection. When not used for these purposes they may be used to provide general information or advice. However, over-use of these signs has led to their losing some degree of credibility. The potential for CMS to manage the demand for car parking and road space is being increasingly realized. Research has indicated that compliance with direction advice depends on the phrasing of the message, and that different categories of drivers respond to CMS in different ways. A major theme of current experiment with CMS is the production of semi- or full-automatic systems which will select and display a message which will result in the most likely degree of rerouting (Bell et al, 1997). CMS is considered as a information supplier to give information at a certain point, so high impacts on the network is expected only in the case of high compliance. So sometimes enough consideration of effects of information will be necessary.

A number of different IVNS can be categorized. The main distinction is between systems with autonomous units, which carry all their intelligence around with them, and those with communicating units, which receive information about the current state of the road system by radio or other means. This is a rapidly growing field and a number of new systems are currently under development. There are two different ways of choosing routes in IVNS: one is with a system capable of performing route selection based on the individual driver's requirements and preference, and the other is receiving guidance made from external systems. The former is likely to be more popular than the later. The potential benefits with the provision of in-vehicle information and guidance may be sufficient to persuade governments and road authorities to permit such systems to exist. The potential benefits to the community of IVNS to drivers include more efficient use of the available network capacity, and reductions in congestion and associated environmental effects. It is also pointed out that the benefit would be particularly impressive if IVNS were coordinated with congestion pricing and traffic signals.

Information being given to travelers can be divided into two categories: one is prescriptive information, and the other is descriptive information. While prescriptive

information gives direction or guidance only to drivers, descriptive information gives more detail information so as for travelers to choose from given alternatives based on their preference. On the other hand, prescriptive information solely depends on the driver's decision whether or not to follow.

In ATIS design driver's compliance should be taken into account. Drivers' preference between prescriptive and descriptive information is dependent on their characteristics and their given circumstances. Some may not want to receive prescriptive information because of their reluctance to follow others' orders, while some prefer receiving decisive guidance. This preference may affect drivers' compliance rate.

2.1.2 Control Strategy and Type of Information

Information influences driver's route choice decision. So information can be viewed as a control variable. The information can be categorized into three based on the way of information generation.

- Instantaneous Information
- Simply Predicted Information
- Comprehensively Predicted Information

Instantaneous information can be provided without further prediction routine. In this system the information could be wrong when the informed drivers are actually experiencing because of dynamic of traffic. However, this system is expected to improve network condition by employing automatic control concept with feedback.

As a more advanced type, simply predicted information system can be considered. Information is obtained from the simple prediction without considering informed driver's route change. The information in this system may not be correct either since informed driver's behavior is not considered although general dynamics of traffic can be captured.

For better system that supplies more accurate information, consideration of driver's response to information is essential. Information may result in unexpected traffic congestion due to driver's over-reaction. In order to avoid this problem, a closed loop control system should be considered, that is comprehensively predicted information system.

2.1.3 Dynamic Optimal Routing

In order to find optimal routing paths for drivers equipped with IVNS, dynamic traffic assignment (DTA) is often applied. The common goal of DTA within the ITS framework is to re-distribute the traffic pattern such that delays incurred by congestion are minimized. There have been many studies on traffic assignment in the dynamic case by Friesz et al (1989), Boyce et al (1991), Janson (1991), Ran (1993), and Jayakrishnan et al (1996.) In general, the different **DTA** methodologies developed so far can be classified into five approaches: (a) simulation-based, (b) optimal control, (c) optimization, (d) variational inequality, and (e) analytically embedded traffic model. The latter four approaches are also

known as analytical models, because they possess the desired analytical properties to guarantee optimality. In contrast, the simulation-based approach is heuristic in nature and does not guarantee optimality. However, the simulation-based approach has been able to capture traffic conditions more realistically and has shown far superior in incorporating signal controls and detailed behavior models.

As a simulation approach, Mahmassani et al (1993) developed solution algorithms for user equilibrium and system optimum, and developed a multiple user classes solution algorithm which includes four user classes: user equilibrium (UE), system optimal (SO), boundedly rational (BR), and pre-specified route user class (PS). The algorithm is shown in Figure 2.1. In this algorithm UE and SO routing solutions are obtained using MSA (method of success average) and the simulation results from the current iteration provide the basis for a direction finding mechanism for the search process. In this approach drivers' behavior is merely decided by the fraction of user class. The approach does not consider drivers' behavior in finding paths except for the BR users. The percentage of drivers who follow the guidance is determined by driver's behavior, further modification are needed to use such a framework on a operational framework.

As a optimal routing via Changeable Message Signs (CMS), a CMS information and guidance system was developed based on automatic control concepts suggested by Papageogiou (1990). The automatic control strategy is based on a simple decentralized feedback loops aiming at approximating a user optimal flow distribution. (Mammar et al, 1996; Messmer, 1997) The main goal of decentralized feedback control is equalization of a cost criterion for each pair of alternative routes being addressed by a CMS at a diversion node. The approach relies on and responds to real measurements that reflect the consequences of all uncertain disturbances. Software architecture for the automatic control via CMS is shown in Figure 2.2.

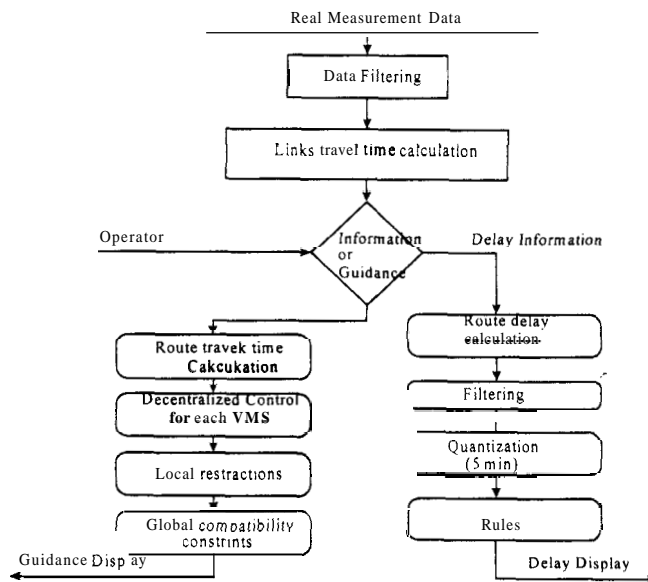


Figure 2.2 Automatic Control Software Architecture (Mammar et al, 1997)

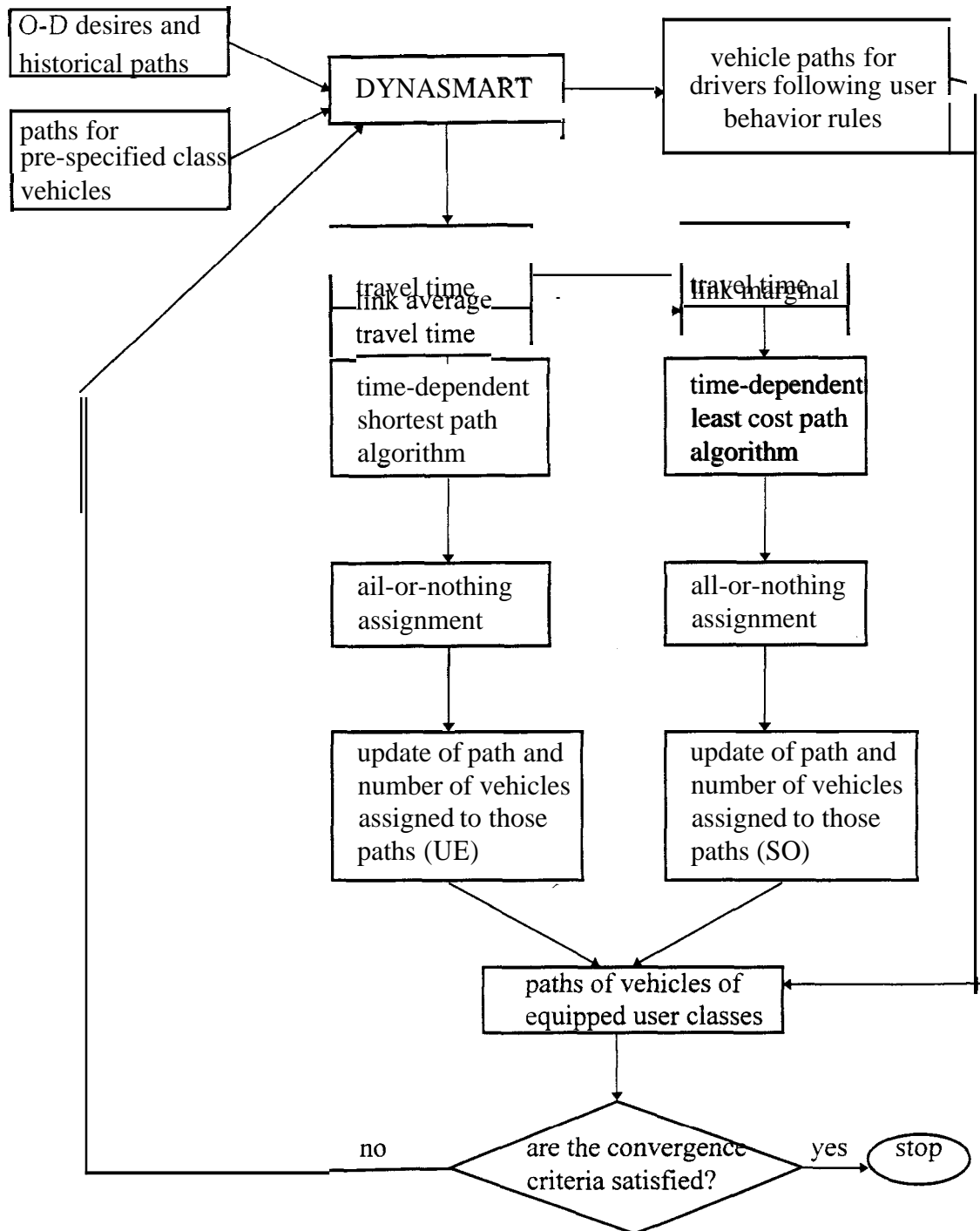


Figure 2.1 Multiple user Classes Solution Algorithm (Mahmassani and et al, 1993)

2.2 Path-base Network Optimization Algorithm

2.2.1 Introduction

The standard traffic assignment problem is for finding traffic pattern in a transportation network with links of known travel cost functions and known travel demand between the origin-destination pairs. It is an essential step in efficient planning and real-time applications in optimal routing, signal control, and traffic prediction in urban traffic networks. Assignment can be carried out for finding the flow patterns under user equilibrium (when no driver can unilaterally change routes to achieve better trip times) or under system optimal (when the total travel time cost in the system is minimum, usually under external control). Both cases are very important in urban traffic networks with ATIS (Advanced Traveler Information Systems) or ATMS (Advanced Traffic Management Systems) when the equilibrium or optimal flow patterns will have to be determined. As is well-known (Sheffi, 1985), both kinds of assignment have been traditionally formulated as mathematical programs with nonlinear objective function with a set of linear constraints.

Consider an urban traffic network represented as a graph $G(N,A)$ where N and A are the sets of nodes and links, respectively. R is the set of origin nodes and S is the set of destination nodes, with several nodes possibly appearing in both R and S . The user equilibrium traffic assignment problem can be stated as

$$\min \quad Z = \sum_{a \in A} \int_0^{x_a} t_a(w) dw \quad (1)$$

subject to the following demand, non-negativity, and definitional constraints,

$$\sum_{k \in K_{rs}} f_k^{rs} = q_{rs}, \quad \forall r \in R, s \in S \quad (2)$$

$$f_k^{rs} \geq 0, \quad \forall k \in K_{rs}, r \in R, s \in S \quad (3)$$

$$x_a = \sum_{r \in R} \sum_{s \in S} \sum_{k \in K_{rs}} f_k^{rs} \delta_{ka}^{rs}, \quad \forall a \in A \quad (4)$$

where Z is the objective function,

x_a is the total flow on link a ,

$t_a(w)$ is a separable, flow-dependent link cost function which is continuously differentiable and convex,

q_{rs} is the total traffic demand between r and s ,

f_k^{rs} is the flow on path k connecting between r and s ,

K_{rs} is the set of paths with positive flow between r and s , and

δ_{ka}^{rs} is the path-link incidence matrix.

The solution to the above mathematical program corresponds to the equilibrium conditions where no driver can unilaterally switch routes to improve his/her travel time. Note that to achieve a system optimal solution, a marginal link cost function is used instead in the objective function. Hence, algorithms developed for the user equilibrium assignment are applicable to the system optimal assignment as well.

The same problem or variations of it appear in the recently proposed dynamic assignment algorithms with time-varying demands, such as the bi-level algorithm of Janson (1995), the analytically embedded dynamic assignment of Jayakrishnan *et al.* (1995). and the instantaneous dynamic assignment algorithm of Ran *et al.* (1993). The effectiveness of the algorithms for solving this problem become even more critical when we consider performing real-time assignments for guidance, control or predictions in a network with ATIS/ATMS, when the assignments may have to be carried out many times (possibly as subproblems in dynamic assignment frameworks). This has been considered to be a difficult problem, as the computational intensity of current methods increases nonlinearly, making assignment-based frameworks impractical when network size increases beyond a few hundred nodes. However, the full benefits of ATIS/ATMS systems may not be achieved unless they operate in an integrated fashion over large networks, and thus effective methods need to be developed for large networks. Our research compares a faster algorithm, based on the Goldenstein-Levitin-Polyak gradient projection method (Bertsekas, 1976) with the conventionally used Frank-Wolfe Algorithm.

2.2.2 Background Review

User equilibrium and system optimal traffic assignment problems in urban networks under given origin-destination demand has conventionally been solved with the Frank-Wolfe optimization algorithm (Frank and Wolfe, 1956) which was originally developed to solve a quadratic mathematical programming problem. LeBlanc *et al.* (1975) was one of the earliest researchers to apply this algorithm to solve the network equilibrium traffic assignment problem and made it popular to the transportation field. Its popularity is attributed to its modest memory requirements and simplicity of the algorithm. The required storage is just two vectors of link flow (i.e., current and auxiliary link flows) and a shortest path tree. It operates directly with link flows and the solutions are also presented in terms of link flows, thus enabling planners to make estimates of future traffic flows on roads based on the origin-destination demand matrices projected for the future, and path flows are not necessary for this. This allows the algorithm to be applied to large scale networks. In terms of the steps of the algorithm, it iterates between a shortest path problem to determine the search direction and a one-dimensional line search problem to find the optimal step size. Both steps can be solved efficiently, using Dijkstra's algorithm (Dijkstra, 1959) for the shortest path problem and any single-parameter optimization algorithm such as Golden Section (without using derivatives) or Bisection Search (using derivatives) for the line search step. Other more efficient line search can also be used.

Frank-Wolfe algorithm is known to have satisfactory convergence in the first few iterations and a poor rate of convergence for subsequent iterations. The reason for such

extremely slow convergence is that the actual descent direction is primarily driven by the constraint corners which cause the search direction to slowly zigzag its way to the minimum. Over the years, various improvements were made to rectify the zigzagging effect by either adjusting the search direction (LeBlanc *et al.*, 1985; Arezki and Van Vliet, 1990; Fukushima, 1984; Holloway, 1974; Hearn *et al.*, 1985; Larsson and Patriksson, 1992) or the move size (Weintraub *et al.*, 1985). While these enhancements have improved the convergence somewhat, there has been a curious lack of exposure among transportation researchers to some of the recent advances in a very closely-related problem, namely the optimal flow assignment in computer communication networks (Bertsekas and Gallager, 1992). Gradient projection algorithms have been found to perform better than the Frank-Wolfe algorithm in such networks, which also have similar structure as traffic networks, with regard to connectivity. In the recent papers by Jayakrishnan *et al.* (1994) and Sun *et al.* (1996), they demonstrate the feasibility of applying the gradient projection algorithm to the traffic networks of reasonable sizes.

2.2.3 Gradient Projection (GP) Algorithm

In this section, we discuss the implementation of the Goldstein-Levitin-Poljak gradient projection formulated by Bertsekas (1976). The algorithm operates directly in the path-flow domain. It does not find auxiliary solutions in the link-flow space that are at corner points of the linear constraint space as the Frank-Wolfe algorithm does. Instead, GP makes successive moves towards the direction of the minimum of a Newton approximation of a transformed objective function which includes the demand conservation constraints. Thus, the feasible space for the gradient projection algorithm is defined only by the non-negativity constraints, as opposed to both non-negativity and demand conservation constraints in the case of the conventional traffic assignment formulation. A projection is made when the move results in an infeasible solution. The basic update step can be concisely expressed by the below iterative equation.

$$f_k^{rs}(n+1) = [f_k^{rs}(n) - \alpha(n) D(n) \nabla \tilde{Z}(n)]^+ \quad (5)$$

where superscript n is the iteration counter, $\alpha(n)$ is the stepsize, $D(n)$ is a diagonal, positive definite scaling matrix, $\nabla \tilde{Z}(n)$ is the gradient of the transformed objective function, and $[]^+$ denotes the projection of the argument onto the positive orthant of the independent variables $f_k^{rs}(n)$.

The rationale for moving the demand conservation constraints from the constraint to the objective function is to make the projection simpler, because only the non-negativity constraints need to be ensured. This operation can be performed efficiently by setting the variable to zero if it becomes negative (i.e., $\max \{0, f\}$, taking maximum of the two values). To do that, $f_k^{rs}(n)$ is partitioned into the shortest path flow $f_{k_{rs}}^{rs}(n)$ and the non-shortest path

flows $f_k^{rs}(n)$ belonging to the path set K_{rs} . The demand conservation constraints can be removed from the constraint set by expressing $f_{\bar{k}_{rs}}^{rs}(n)$ in terms of $f_k^{rs}(n)$.

$$f_{\bar{k}_{rs}}^{rs}(n+1) = q_{rs} - \sum_{\substack{k \in K_{rs} \\ k \neq \bar{k}_{rs}}} f_k^{rs}(n+1), \quad \forall \bar{k}_{rs}, r \in R, s \in S \quad (6)$$

where \bar{k}_{rs} denotes the shortest path from r to s . Substituting the shortest path flow $f_{\bar{k}_{rs}}^{rs}(n)$ for each OD pair into the objective function, we obtain the new optimization problem of the form

$$\min \tilde{Z}(\tilde{f}) \quad (7)$$

$$\text{subject to } f_k^{rs} \geq 0, \quad \forall k \in K_{rs}, k \neq \bar{k}_{rs}, r \in R, s \in S \quad (8)$$

where \tilde{Z} is the new objective function and \tilde{f} is the set of non-shortest path flows for all OD pairs. Analogous to the steepest descent method, a better solution in terms of improving the objective value can be obtained by moving in the negative gradient direction. The gradient of the transformed objective function is found with respect to the set of non-shortest paths, and a diagonal scaling of the gradient direction is found using the second derivatives of these independent variables.

$$\frac{\partial \tilde{Z}}{\partial f_k^{rs}} = \frac{\partial Z}{\partial f_k^{rs}} - \frac{\partial Z}{\partial f_{\bar{k}_{rs}}^{rs}}, \quad \forall k \in K_{rs}, k \neq \bar{k}_{rs}, r \in R, s \in S \quad (9)$$

where Z is the original objective function with all paths in the path set, including both the shortest **and** non-shortest paths. Each component of the gradient becomes the difference between the first derivative cost of a non-shortest path and the shortest path. Note that the first derivative of Z with respect to any path is simply the sum of the link costs on that path calculated at the current flow pattern.

$$\frac{\partial Z}{\partial f_k^{rs}} = \sum_{a \in A} t_a(x_a) \delta_{ka}^{rs} \quad (10)$$

$$\frac{\partial Z}{\partial f_{\bar{k}_{rs}}^{rs}} = \sum_{a \in A} t_a(x_a) \delta_{\bar{k}_{rs},a}^{rs} \quad (11)$$

The diagonals of the Hessian (second derivatives) of the transformed objective function is just a straightforward differentiation of the gradients.

$$\frac{\partial^2 \tilde{Z}}{(\partial f_k^{rs})^2} = \sum_{a \in A} t'_a(x_a) (\delta_{ka}^{rs} - \delta_{\bar{k}_{rs},a}^{rs})^2, \quad \forall k \in K_{rs}, k \neq \bar{k}_{rs}, r \in R, s \in S \quad (12)$$

where $t'_a(x_a)$ is the first derivative of the link cost (travel time) function evaluated at the current link flow solution.

Observe that a small increase in the flow on a path k results in an equal amount of reduction of flow on the corresponding shortest path \bar{k}_{rs} , and causes in no change in the flow on the common part of the two paths. Thus, the second derivatives are calculated using only links not common to k and \bar{k}_{rs} .

Let d_k^{rs} and $d_{\bar{k}_{rs}}^{rs}$ be the first derivative costs of path k and the shortest path \bar{k}_{rs} of OD pair (r,s) given in equations (10) and (11), respectively, and s_k^{rs} be the second derivative cost given Eqn. (12), the iterative (flow update) equation given in (5) can be expressed as

$$f_k^{rs}(n+1) = \max \{0, f_k^{rs}(n) - \frac{\alpha(n)}{s_k^{rs}(n)} [d_k^{rs}(n) - d_{\bar{k}_{rs}}^{rs}(n)]\}, \quad \forall k \in K_{rs}, k \neq \bar{k}_{rs}, r \in R, s \in S \quad (13)$$

where $\alpha(n)$ is a scalar stepsize modifier which may be chosen by different methods. **4** constant stepsize of 1 seems to work well with methods that employ automatic scaling based on second derivatives (Bertsekas and Gallager, 1992). Once all the non-shortest paths are updated, the flow on the shortest path is appropriately updated so that demand is conserved.

From the discussion above, the gradient projection algorithm can be formalized as follows:

Step 0: Initialization - Set $x_a(0) = 0$, $t_a = t_a[x_a(0)]$, $\forall a$, and iteration counter $n = 1$. Perform a one-OD-at-a-time all-or-nothing (AON) assignment for all origins (note that the shortest path tree is built for an origin but the flow updates are done at one-OD-at-a-time). This yields path flows $f_k^{rs}(n)$, $\forall k \in K_{rs}$, for all OD pairs $(r,s) \in (R,S)$ which form the initial path set K_{rs} . Link flows $\mathbf{x}_a(n)$, $\forall a$ are readily available once the AON flow assignment for all the origins is complete.

Step 1: Update - Set $t_a(n) = t_a[x_a(n)]$, $\forall a$, and update the first derivative costs $d_k^{rs}(n)$ for all paths in K_{rs} .

Step 2: *Direction finding* - Find the shortest path \bar{k}_{rs} from each origin r to each destination s based on $t_a(n)$. If different from all the paths in the existing path set K_{rs} , add it to K_{rs} and record $d_{\bar{k}_{rs}}^{rs}$. If not, tag the shortest path among the paths in K_{rs} as \bar{k}_{rs} .

Step 3: *Move* - Update path flows as follows:

$$f_k^{rs}(n+1) = \max \{0, f_k^{rs}(n) - \frac{\alpha(n)}{s_k^{rs}(n)} [d_k^{rs}(n) - d_{\bar{k}_{rs}}^{rs}(n)]\}, \forall k \in K_{rs}, k \neq \bar{k}_{rs}, r \in R, s \in S$$

where $s_k^{rs}(n)$ is the second derivative path cost and $\alpha(n)$ is a scalar step size modifier, usually $\alpha(n) = \alpha = 1$ for all iterations. If the updated path flow is zero (i.e., assigning a zero flow value by the projection to ensure nonnegativity), then the path is no longer active and is dropped from the path set K_{rs} . After all the path flows have been updated, the flow on the shortest path is readily determined from the conservation equation below:

$$f_{\bar{k}_{rs}}^{rs}(n+1) = q_{rs} - \sum_{\substack{k \in K_{rs} \\ k \neq \bar{k}_{rs}}} f_k^{rs}(n+1), \quad \forall \bar{k}_{rs}, r \in R, s \in S$$

Assign flows onto the paths in K_{rs} to obtain the corresponding link flows $\mathbf{x}, (n+1), \quad \forall a$.

Step 4: *Convergence test*

If the stopping criterion is met, then stop. Otherwise increment iteration counter $n = n+1$ and go to Step 1.

In Step 3, since $s_k^{rs}(n)$ acts as an automatic scaling, $\alpha(n)$ can be chosen as a constant ($\alpha(n) = \alpha$, for all iteration n). It can be shown that given any starting set of path flows there exists an $\bar{\alpha} > 0$ such that if $\alpha \in (0, \bar{\alpha}]$ the sequence generated by this algorithm converges to the optimal (Bertsekas and Gallager, 1992). In Step 4, the stopping criterion used is the maximum percentage path length deviation, weighted by its path flow fraction, of all OD pairs and can be expressed as follows:

$$E = \max_{rs} \sum_{\substack{k \in K_{rs} \\ k \neq \bar{k}_{rs}}} \frac{f_k^{rs}(n)}{q_{rs}} \left(\frac{d_k^{rs}(n) - d_{\bar{k}_{rs}}^{rs}(n)}{d_{\bar{k}_{rs}}^{rs}(n)} \right) \quad (14)$$

As gradient projection is a path-based algorithm, though not enumerating all possible paths connecting each origin-destination pair in the network, it requires storing the paths generated during the execution of the algorithm. Using a predecessor arc list to store the shortest path trees, the main memory requirements amount to $N_i * N_o * N$ storage locations where N_i is the number of iterations to reach convergence, N_o is the number of origins, and N is the number of nodes in the network. N and N_o are readily fixed by the network topology, but N_i depends on the performance of the algorithm. Hence, it is crucial that gradient projection can achieve fast convergence for it to be of practical use. The numerical

results shown in the next section indeed show much faster convergence compared to the Frank-Wolfe algorithm.

Unlike the gradient projection algorithm, the storage requirement for the Frank-Wolfe algorithm does not depend on its convergence speed since paths are not stored. At any one iteration, the algorithm just needs to maintain two columns of link flows and one shortest path tree. This allows the Frank-Wolfe algorithm to perform large scale networks (with many thousands of links) on most of the available computers which would not be possible with the path-based gradient projection algorithm even a few years back. However, the rapid improvement in the availability of computer storage in recent years makes it possible to revisit such algorithm that finds not only the link-flow solution but also the useful path-flow solution, which are needed in many of the proposed ATMS/ATIS applications of assignment.

2.2.4 Numerical Results

The path-based gradient projection algorithm was coded in FORTRAN and the platform used for the numerical results was UNIX Sun Sparc 20 work station. Table 1 shows the numerical results of the well-known Sioux Falls network, taken from LeBlanc *et al.* (1975). This network consists of 24 nodes, 76 links, and 528 OD pairs with positive demands. The final objective value reported in (Larsson and Patriksson, 1992) is 42.3 136. The complete assignment results with timings at each iteration for the conventional Frank-Wolfe algorithm and the gradient projection algorithm are provided in Table 1.

Both the Frank-Wolfe (FW) and gradient projection (GP) algorithms are initialized with zero flows on all links in the network, but the objective values of the first iteration are obtained differently. FW uses an all-at-once¹ flow update while GP updates the flow pattern one-OD-at-a-time². Our results show that GP converges several orders of magnitude faster than FW. Typically, the 5th or 6th iteration in GP corresponds to the 100th iteration in FW. As the algorithm approaches the neighborhood of the optimal solution, FW performs extremely poor. As can be seen from the results, FW slowly zigzags its way toward the minimum solution. The objective value in the 9th iteration in GP is even better than the 1000th iteration in FW. In terms of computational times, GP is at least 10 times faster than FW. Though not reported here, we perform another test with FW starting at the same objective value in the first iteration using a one-OD-at-a-time flow update. Same convergence characteristics were observed. That is, the objective value of FW in the 100th iteration is in-between the objective values of GP in the 5th and 6th iterations, and the objective value of FW in the 1000th iteration is exactly the same as starting FW with the all-at-once flow update. Hence, the slow convergence of FW is not affected by the initial solution.

¹The all-at-once flow update adjusts the total link-flow pattern after the traffic demands from all origins (or all OD pairs) have been assigned to the network.

²The one-OD-at-a-time **flow** update revises the total link-flow pattern after the assignment of an OD pair before continuing to the next OD pair.

Table 2.1 Computational Performance for the Sioux Falls Network

Iteration #	Frank-Wolfe		Gradient Projection	
	Objective Value	Time (sec)	Objective Value	Time (sec)
1	167.2832	0.0564	57.9274	0.0689
2	73.2656	0.0652	45.0029	0.1104
3	59.1770	0.0732	42.9825	0.1582
4	55.6344	0.0809	42.5276	0.2053
5	51.8796	0.0884	42.3808	0.2474
6	50.1956	0.0959	42.3419	0.2880
7	47.2447	0.1035	42.3270	0.3275
8	46.2040	0.1111	42.3202	0.3665
9	45.6163	0.1186	42.3166	0.4046
10	45.2057	0.1260	42.3146	0.4423
11	44.7447	0.1334	42.3136	0.4805
12	44.3051	0.1407	42.3134	0.5179
20	43.0143	0.1996		
50	42.4501	0.4206		
100	42.3686	0.7896		
200	42.3384	1.5244		
500	42.3231	3.7142		
1000	42.3181	7.3589		

We also tested the two algorithms on various sizes of randomly generated grid networks. These networks are grid only in terms of the connectivities of the links, with the link lengths being randomly distributed between specified limits. About 12.5 percent of the network nodes are randomly selected to be origins/destinations. The externally specified nodal traffic generation was distributed to various destinations based on O-D distances. The results reported below are for demand levels that we considered were reasonable based on average and maximum arc v/c ratio at equilibrium. The assignments were carried out using the Bureau of Public Road (BPR) link cost function, $t = t_0(1 + 0.15(x/c)^4)$, where t is the link travel time, t_0 is the free-flow travel time, x is the flow and c is the link capacity.

Using equation (14) as the stopping criterion, the GP algorithm is terminated when the maximum of the violations does not exceed 1% (note that this stopping criterion also serves as a measure of the Wardrop's equal travel time principle). Then using GP's objective value as the basis for comparison, we find the corresponding iteration number in FW that gives approximately the same objective value. Table 2 reports the performance in terms of computational times and number of iterations for the two algorithms tested on various grid network sizes, ranging from 100 to 2500 nodes. In all cases, GP takes much less iterations and also significantly less computational times than FW to reach the same objective value. The objective value in the 10th iteration of GP is substantially better than the FW's objective value in 100th iteration. The last row of Table 2 shows the computational time ratio of FW

over GP. As network size increases, the ratio decreases but still maintains three to four times faster than the conventional FW algorithm. This suggests that running the GP algorithm in decomposed networks of smaller size (in the order of several hundred nodes) under a distributed framework can achieve significant benefits in computational times.

**Table 2.2 Computational Times (Number of Iterations)
to Convergence for Various Grid Networks**

	100 nodes 360 arcs 132 ODs	400 nodes 1520 arcs 2450 ODs	900 nodes 3480 arcs 12432 ODs	1600 nodes 6240 arcs 39800 ODs	2500 nodes 9800 arcs 97032 ODs
Frank-Wolfe (FW)	19.17 (1000)*	83.89 (417)	812.44 (846)	1466.36 (466)	6449.26 (801)
Gradient Projection (GP)	0.23 (6)	7.67 (10)	77.72 (14)	372.18 (16)	1417.90 (20)
Ratio of cpu (FW/GP)	83.35	10.94	10.45	3.94	4.55

* Maximum number of iterations is reached before obtaining the same objective value as in GP.

2.2.5 Findings

From the discussion of the Gradient Projection (GP) algorithm and the comparative numerical results with the Frank-Wolfe (FW) algorithm, several benefits of using GP can be derived:

- (1) Much faster convergence (i.e., number of iterations and computational times) than conventional Frank-Wolfe algorithm.
- (2) The availability of path-flow solutions in addition to the link-flow solutions from the gradient projection algorithm. It is true that FW can also provide path-flow solutions if implemented with path storage, but it is not viable alternate unless the number of iterations required to reach convergence can be reduced considerably (Chen and Jayakrishnan, 1996).
- (3) Path-flow solutions, though not unique, are very useful in optimal assignment and routing.
- (4) No explicit need to microcode each intersection (i.e., adding additional nodes and arcs) to obtain turning movements since the path-based solutions implicitly contain this information. This is not possible with the link-based FW algorithm unless specific turning links are added which would increase the size of the network.

(5) Path-based solutions open up interesting possibilities to planners in better analyzes of environmental impact, fuel consumption etc., based on path profiles of travel speeds.

The main drawback of using a path-based algorithm in the past is the memory requirement, but this restriction has now been relaxed considerably by the recent advances made in the computer RAM technology. Furthermore, the real potential applications of GP for large scale networks are using a distributed processing framework which decomposes the network into several smaller networks with each being handled by its own processor. The amount of memory required for each sub-network in the distributed system is well within the capabilities of most ordinary computers. Taken these factors into consideration, it is important to reexamine the viability of the path-based gradient projection algorithm for the traffic assignment problem that was rejected in the past due to intensive memory requirement.

2.3 Optimization for CMS Routing

Static network flow optimization is one way of achieving optimal flow pattern in the network. The main benefit from static assignments is that they are fast by orders of magnitude over the dynamic assignment algorithms which exists now, and thus are very attractive for real-time application. The disadvantage, on the other hand, is that they do not capture network congestion dynamics very well, thanks to the rather simple link travel time functions used. This research project attempts coordinating static and dynamic assignments in such a way that the computational benefits are gained from the static assignment while the inaccuracies from the results are minimized.

Even though optimal flow pattern is found from network flow optimization, the optimal flow pattern may not be achievable in CMS routing because of driver's compliance problem. It is extremely difficult or almost impossible to split drivers to the optimal flow pattern found. Rather, selecting the closest CMS message among prepared message set would be more realistic method. Therefore, this research generalizes CMS messages and develops algorithms which are based on network optimization to select the best CMS routing scheme and corresponding messages.

2.3.1 Classification and Generalization of CMS Messages

CMS can display only limited information, so it is very hard for CMS to give full path information. A certain path should be explained with two streets at most, for example, "ANAHEIM STADIUM / EXIT BALL / AND TAKE STATE COLLEGE." If names of streets are not well known, the advice is not conveyed to drivers except those who know well about the area. A route guidance message with descriptive information is expected to result in higher compliance. For example, "JSATELLA CONGESTED / ANAHEIM STADIUM / EXIT BALL." Intuitively, higher compliance rate is expected with proviso that drivers know how to go the stadium via Ball Road due to a word, "CONGESTED." Intelligent word choice is required for better route guidance. Sometimes just minor

AHEAD / TAKE ROUTE AAA,” will be projected to driver’s perception as “AAA will be 10 minutes faster than current road.” The relative value of information (VOI) is + 10 for the current route. This projection to the relative value of information is also a core part of the routing algorithm. Also messages can be sorted by the order of relative value of information. so that the message can be searched later. CMS messages are completed by adding or ignoring optional arguments. such as destination designator and cause terms.

In fact, most CMS messages, except special messages, can be grouped into three types as follows:

- Single Descriptive Message Type
- Prescriptive Route Guidance Type
 - Route Guidance with Descriptive Type

The single descriptive message type is the most simplified one with one sub-path argument. An “AVOID *Path-A*” type message is a representative form of this type. In this case selection of alternative route can vary depending upon driver’s knowledge on network and preference. The message, “KATELLA CONGESTED” is an example of this type. Drivers would seek alternative routes, and decisions will be made after comparison between Katella and their alternative routes. The level of avoidance would be different by the literal expression.

The prescriptive route guidance type is represented by a “TAKE *Path-A*” type. This type explicitly or implicitly includes a Destination Designation Argument, so a “(TO GO *Destination-D*) TAKE *Path-A*” type would be a more general form. A message, “ARROWHEAD POND / EXIT BALL” is an typical example of this type. In this case drivers just make their decision whether to follow or not. Of course, alternative routes suggesting could be multiple like a message, “STARDIUM / EXIT BALL / OR KATLLA.”

A little more complicated message is one that includes both descriptive and prescriptive messages. A ”TAKE *Path-A* / AVIOD *Path-B*” type is the representative form. Reducing driver’s misperception with more detail and supportive information, this message can achieve better performance. For example, the message, “USE BALL / KATELLA CONGESTED” will help reducing traffic on Katella by guiding drivers to take Ball.

Messages could become clear by adding optional arguments. For instance, the message “STADIUM / USE BALL / KATELLA CONGESTED / DUE TO ACCIDENT” will be better for understanding the network condition. However, it should be noted that a long message might lessen driver’s understanding the meaning of the message.

2.3.2 Interaction between Information Provider and Drivers

Information/guidance is helping drivers to find better routes by supplying current network condition. Figure 2.3 depicts interaction between information provider and drivers. Information/guidance affects driver’s perception of travel time (cost) on alternative routes, and drivers select their best alternative routes based on their judgment. For predictive route guidance system, the information provider (TMC) should be able to predict driver’s reaction

to information they provided. So the system can be interpreted as a game between information provider and drivers.

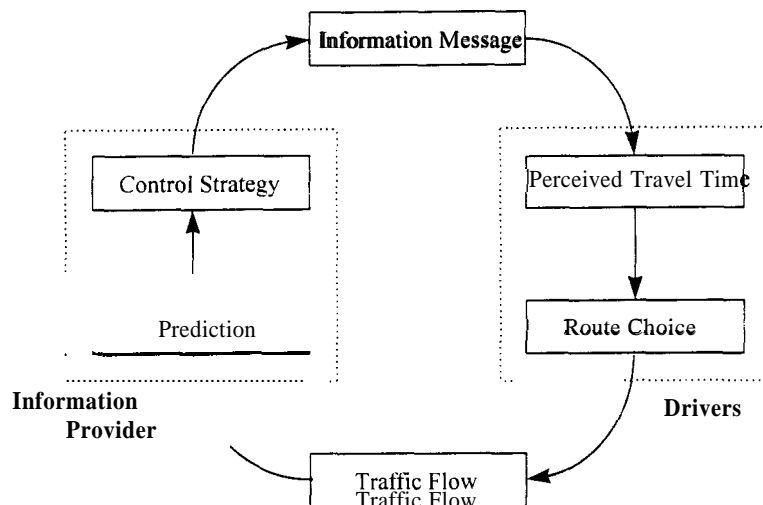


Figure 2.3 Interaction between Information Provider and Drivers

There are two decision variables in this game: one is a set of path flow as a result of driver's route choice behavior, and the other is a set of path travel time information (or a set of link travel time since path travel times are obtained by summing link travel times) as a result of information provider's control strategy. The information providers will set the control variables (information) to achieve their objective. The object can be expressed a mathematical form. Therefore, the problem of information provider side can be expressed as a mathematical minimization problem,

$$\min_{\alpha} Z_{\alpha}(\alpha, x^*(\alpha))$$

where α is a vector of information affecting driver's perception on travel time, and $x^*(\alpha)$ is a vector of traffic flows fixed by a traffic assignment problem which is a mathematical formulation of driver's route choice problem. The vector α is regarded as control strategy using information. Based on the information vector α fixed by the above problem, traffic flow patterns are obtained by solving the traffic assignment problem. The traffic assignment problem representing driver's route choice behavior can also be expressed as a minimization problem,

$$\min_x Z_x(\alpha^*, x(\alpha^*))$$

Under the assumption of error free prediction (information provider side) and 100% compliance (driver side) even though there are always stochasticities in reality, the system is determined depending on the control strategy. In the case that objectives of two players,

both system manager and drivers, are identical, the problem becomes a monopoly game which can be solved at the same time. That is, if drivers behave as user equilibrium manner and the system manager provides travel time information resulting user optimal state, the solution can be obtained by solving a user equilibrium traffic assignment problem. However, the system manager is more interested in minimizing total system costs, this problem is explained as a Stackelberg game between the information provider and drivers. Therefore, a solution of optimal routing can be obtained by understanding interrelationship between information provider and drivers. Especially understanding driver's response is a key component of information strategy in transportation. Driver's response to information is further discussed in Section 3.1.

2.3.3 Optimization for CMS Routing and Message Generation

While considering on-line implementation of the information/guidance strategy, a fast computational algorithm is required because information/guidance needs to be updated as often as possible. Detailed simulation- evaluation cannot be accomplished for more than a few information message options, and the combinations involved with the message argument need to be handled in a fast manner. Paths found from even static assignment can be considered as possible routes to be used in the dynamic case, as long as more detailed evaluation is done on these paths. This section introduces a simple optimization algorithm for CMS routing in the view of Stackelberg game between the information provider and drivers.

Here the algorithm is based on the assumption—that drivers' objective is to minimize their travel costs (time) with full knowledge on network condition (user equilibrium assumption) while the objective of information provider is to minimize total system cost (system optimal assumption). Another assumption is that driver's knowledge on traffic condition can be changed by information provided via CMS. A guidance indicator is introduced as a value indicating whether or not to encourage to take the path. If we are seeking indicators for all paths, the solutions can be obtained by comparing system optimal path costs with user equilibrium path costs. However, a CMS message cannot deliver all paths' information. so the problem is, unlike the case, solved by evaluating sub-paths represented by CMS messages. The indication value is found when minimizing total system cost regardless guidance indicator while demand is assigned under user equilibrium behavior with path costs multiplied by guidance indicator. Then the problem can be expressed as a bi-level structure problem,

(UP) minimization of total system cost

(LP) path-based UE problem with path costs multiplied by guidance indicators

The formulation of upper level problem is the system optimal assignment problem, while the lower level problem can be solved by using path based user equilibrium assignment. that is GP explained in section 2.2. The main objective of the problem is to find optimal guidance

indicators which are constrained by traffic flow pattern. The flow pattern is decided by driver's user equilibrium behavior also constrained by guidance indicators. Therefore, the optimal guidance can be obtained by solving this bi-level problem.

CMS message is displayed at a certain location. so for a single CMS the problem becomes a single-origin multiple-destination problem. While assuming that only informed drivers change their routes, the optimal solution can be obtained by solving the single origin problem. The solution algorithm for optimal CMS routing can be formalized as follows:

Step 0. Pre-assignment

Step 1. Find sub-demand associated with CMS, and freeze background traffic

Step 2. Input a sub-path to test

Step 3. Find the optimal guidance indication value minimizing total cost by line search

3.0 Initialize indicator value

3.1 User equilibrium assignment

3.2 Calculate total cost

3.3 Stop if satisfying stopping criteria, otherwise repeat line search

Step 4. List sub-path, indicator, and total cost by descending order of total cost if no more sub-path, otherwise go to step 2.

The algorithm evaluates guidance indicators of alternative sub-paths associate with CMS, and total system costs corresponding to each indicator value. If a indicator associate with a sub-path is grater than 1.0, it implies that the sub-path should be avoided. The value of an indicator lower than 1.0 implies taking the sub-path is beneficial. Finally, a path resulting minimum system cost with a certain indicator value means that the path has the highest potential to minimize total system costs among others when guided to be taken or avoided the path as much as the indicator shows. However, it should be noted that the algorithm developed here is still under investigation and will be further developed

In order to generate the optimal CMS message using the optimization results, there should be a step to translate optimized results into CMS message. Messages are generalized by their arguments as shown in section 2.3.1. Since each sub-path is defined by its literal name, the sub-path argument can be found directly from the sub-path. Action/description arguments can be determined using guidance indicators. So basic required arguments can be decided through this translation stage. The detailed method is shown through an example in section 2.3.4.

2.3.4 An Example of Optimized CMS Routing

This section shows a simple example of optimized CMS routing and message generation. A imaginary network has been built for this example. It contains an event place and a CMS on the freeway crossing the area as shown in Figure 2.4. It is assumed that there are a lot of traffic heading to the event place. Six sub-paths associated with the CMS are selected to be examined.

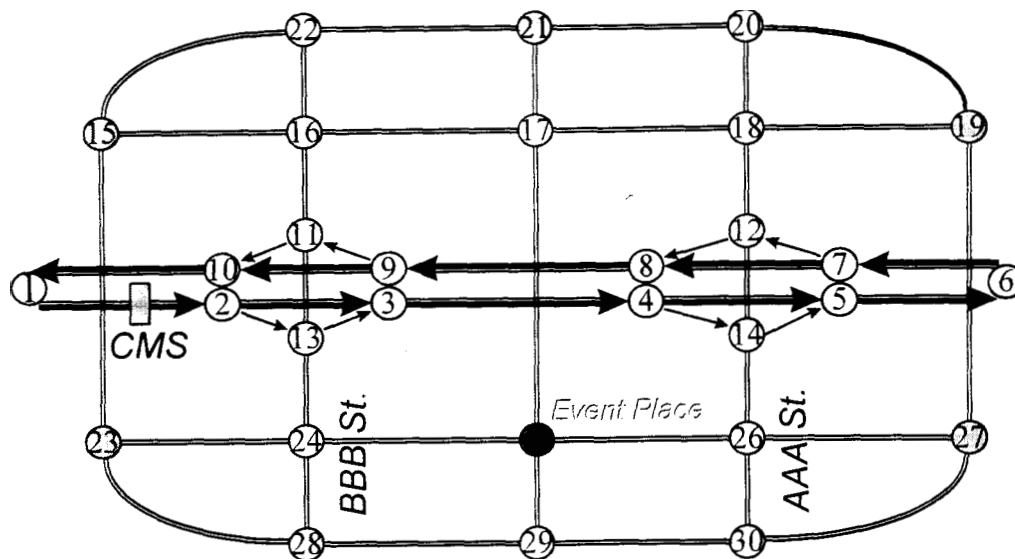


Figure 2.4 Imaginary Test Network

Table 2.3 Result of Optimization for CMS Routing

Sub-Path	Total System Cost	Indicator Value	Meaning
13 → 24	199,579	2.01	Guide to avoid
11 → 16	204,928	1.16	Guide to avoid
14 → 26	199,579	0.00	Guide to take
12 → 18	294,928	0.00	Guide to take
16 → 17	205,780	1.00	--
3 → 4	199,579	0.00	Guide to take

Table 2.3 shows optimization results for these six sub-paths. Among six sub-paths, three sub-paths are expected potentially to show better performance when guided as indicator values. The indicator value for the sub-path 13→24 is evaluated as 2.01, which implies that the system will be better off when drivers perceive the travel cost of the sub-path as 2.01 times higher than they will actually experience. That is, the sub-path 13→24

should be guided to be avoided. On the contrary, sub-paths, 14→26 and 3→4 , should be guided to be taken more since whose indicator values are 0.0. In fact, the sub-paths, 14→26 and 3→4. are essentially same in this case because these two are associated with the CMS and the event place, but the sub-path 14→26 would be more clear designation.

The next step is to translate this optimized results into a CMS message. As shown in Figure2.5, three facts found from the optimization results can be translated into a CMS message. The first message is destination specific argument which is optional. The second and third messages are consisted of an action/description argument and a sub-path argument. The action/description argument is directly determined from the indicator value, and sub-path argument is obtained from the prepared literal name of the sub-path. The CMS message generated from the optimized results can be used in real world without further processing.

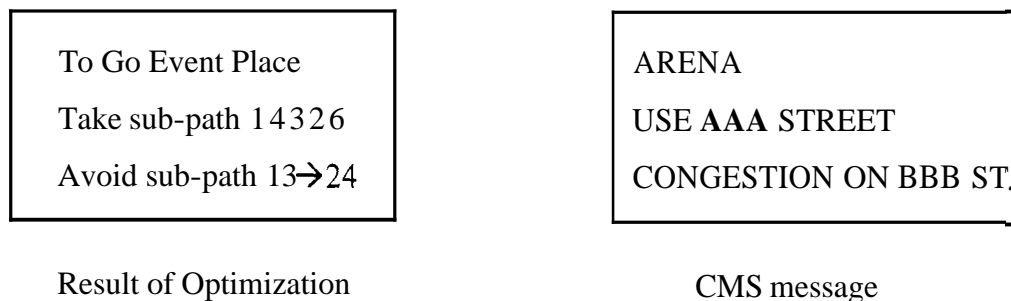


Figure 2.5 Translation of Optimized Results into CMS message

Chapter 3

MODELING FOR EVALUATION OF ATIS SCHEMES AND ROUTING PLANS

The CMS messages found using static network optimization technique need to be evaluated within the simulation framework. The evaluation framework is based on DYNASMART (Dynamic Network Assignment Simulation Model for Advanced Road Telematics). The simulation-assignment model, DYNASMART was developed specially for studying the effectiveness of alternative information supply strategies as well as alternative information/control system configurations for urban traffic networks with ATIS and/or ATMS. In this research most attention will be paid to the development of driver's behavior model to complete the evaluation framework. Driver's response to the information will be modeled and incorporated into the DYNASMART. This chapter investigates driver's response to information, and illustrates feature and capability of the simulation model, DYNASMART. Then evaluation framework of ATIS will be addressed.

3.1 Driver Response to Information

Analysis on driver's response to information is not only an essential part for evaluation of ATIS schemes, but also important for proper message generation. This section reviews driver's route choice behavior models and manifests modeling approach and other related issues.

3.1.1 Review on Route Choice Behavior Models

Most operational models of network scale route choice are based on the assumption that drivers are seeking to minimize a simple objective function such as travel time. Modelers' main efforts have been directed towards adequate representation of aggregate equilibrium processes at work in the network rather than towards realistic representation of the dynamics of individual behavior or potential for influencing that behavior. A somewhat detailed discussion of previous research is provided here as this is an important aspect of proposed work and much will be borrowed from these models in this research.

Early research focused on predicting aggregate route or mode choice pattern based on utility and probabilistic choice models. This was followed by studies on distinct aspects of trip making, such as departure time or route choice. As work progressed, system performance, habitual travel patterns, dynamic and day-to-day adjustment, the impacts of real time information, and other related issues were brought to center of attention.

A simple boundedly rational path switching rule could be that users switch from current path at a decision point if travel times savings on an alternative route exceed a threshold value (Mahmassani and Jayakrishnan, 1991). Its mathematical model is as follows:

$$\beta_p(m) = \begin{cases} 1 & \text{if } \hat{T}_{mjk(u)}^{\tau u} - \hat{T}_{mjk(u)}^* > \max(\zeta_p \cdot \hat{T}_{mjk(u)}^{\tau u}, \xi_p) \\ 0 & \text{otherwise} \end{cases}$$

where $\beta_p(m)$ is a binary indicator variables equal to 1 when user p switched from the current path to the best alternate path (from node m to the destination), and 0 if the current path is maintained; and $\hat{T}_{mjk(u)}^u$ and $\hat{T}_{mjk(u)}^*$ are respectively the trip times on the current and best paths from node m to the destination is the relative indifference threshold (or band), and ξ_p is an absolute minimum travel time improvement needed for a switch.

Various types of data collection methods have been used to investigate driver's behavior under travel information. These methods are route choice survey (Khattak et al., 1992; Hatcher and Mahmassani, 1992), interactive computer simulation games (Bonsall and Parry, 1990; Karge and Mark, 1991; Adler, 1993; Liu, 1997), route choice simulation and modeling (Mahmassani and Chen, 1991; Lotan and Kousopoulos, 1992), and state preference approach (Haselkorn et al, 1991; Wardman et al, 1996; Abdel-Aty et al, 1997) Research on driver's behavior can be categorized to be focused in day-to-day evolution, travel time variation and reliability, en-route diversion, and response to CMS information.

Day-to-day dynamics of commuter decision are found in models of departure time and route choice, daily switching decision, and learning rules. A framework for day-to-day adjustment is developed by Hu and Mahmassani (1997), based on pre-trip behavior model calibrated by Small (1982), and Hendrickson and Plank (1984.) Vahghn et al (1996) calibrated a multinomial route choice model under ATIS. Expected time and delay, and habit strength which are updated day-to-day are used as variables in their model. Abdel-Aty, Kitamura, and Jovanis (1997) investigated the effects of travel time variation on route choice using stated preference data.

There have been many studies on en-route diversion behavior. Khattak et al (1991) found that diversion behavior is influenced by the source of information, expected length of delay, regular travel time on the usual route, number of alternative routes used recently, anticipated congestion level, self-evaluation statement about risk behavior (personality), and stated preference about diverting. Polydoropoulou et al (1992) included perceptions and attitude, actual travel condition, and en-route information for selection of a new route in their model. Polydoropoulou et al (1994, 1996) explored how travelers deal with unexpected congestion and how they might respond to alternate types of ATIS, such as qualitative, quantitative, prescriptive, and predictive information. Six major categories of variables are included in their combined RP and SP model: 1) Travel time, 2) Expected delay, 3) Congestion on alternative route, 4) Knowledge of travel times, 5) Trip direction, 6) Cause of delay, and 7) Information sources. Adler and McNally (1994) divided en-route diversion into two models: primary diversion and secondary diversion (see Table 3.1). The models were calibrated using data collected from the interactive computer simulator named FASTCAR.

Wardman, Bonsall, and Shirs (1996) calibrated driver's response to various CMS displays using stated preference data. Their finding is that value of delay is greater than travel time with the ratios varying between 1.30 and 1.70, and the value of time of delay is quite sensitive to the amount of delay time with increasing sensitivity as delay time increases. Table 3.2 shows overall model for driver's response to CMS.

Table 3.1 Model of Diversion Behavior (Adler and McNally, 1994)

Independent Variables	Primary Diversion	Secondary Diversion
Model constant	5.45 (3.76)	-1.41 (-1.00)
Actual link speed	-0.0088 (-3.71)	
Ratio of actual to expected link speed		-2.30 (-2.28)
Previous trip on current street	-1.55 (-3.19)	
Familiarity with current street	-3.86 (-3.70)	-2.30 (-2.85)
Familiarity with alternative street	3.49 (3.50)	1.80 (2.26)
Road type current street		-3.44 (-3.46)
Road type alternative street	-1.57 (-2.23)	4.34 (4.25)
CMS	0.50 (1.81)	
Number of previous diversion		1.12 (4.58)
Distance to destination		0.16 (3.37)
Initial log likelihood	-89.42	-111.59
Log likelihood at convergence	-33.83	-54.96
Likelihood test	110.82	113.26
Number of observations	129	161
Percent correctly predicted	88.372	85.71
Rho squared	0.6217	0.5057

Table 3.2 Driver's response to CMS (Wardman et al, 1996)

Variable	Coeff	Incremental	Variable	Coeff.	Incremental
Road-Mins	-0.041	Age<35 0.0043 Female 0.0040	Cong-Long	-2.450	
Cong-Mins	-0.042		Acc-Long	-3.337	
Acc-Mins	-0.048		None-Long	-2.623	
None-Mins	-0.036		Clear	0.815	
Road-Likely	-0.595		Vis-Q	-0.043	Age<35 0.0129 Freq<6 0.0145 Unreliable CMS -0.0133
Cong-Likely	-1.876		Time	-0.068	
Acc-Likely	-2.100		RSC(M56)	-1.489	
None-Likely	-0.835		RSC(A580)	-1.328	
Road-Long	-2.732		RSC(A57)	-1.470	
ρ^2	0.217				

3.1.2 Modeling Approach

This research will be based on a generalized two part behavior model: one is the Perception Model (PA), and the other is the Decision Model (DM). The first step is to transfer various type of information to driver's perception, and this model is named as "perception model". The perception model has to be capable of dealing with various types of ATIS information and reliability of information earned from drivers' previous experience. The second part, the decision model, is to decide whether or not to divert using driver's perception and other factors on current route and alternative route. While the second decision model can be more generally used, the perception model has facility specific characteristic varying by each information source.

In the perception model, the most important factors are reliability of information and relative value of information by type and content. The reliability of information is an important factor influencing driver's compliance; however, it is not easy to determine how the reliability can be measured and how it will be reflected in the driver's perception. In order to measure the reliability of information, day-to-day updates become necessary because reliability is a result from past experience. Questions on reliability will be discussed mode in the next issue, routing policy and reliability. Another major factor, the relative value of information by type and content, possibly does not vary based on the information source, since factors specific to information sources are screened by the reliability variables. The concept of relative value of information is very similar to that of value of time. For instance, if the value of travel time information is 1.0, what is the value of delay relative to travel time? It may be greater than 1.0 in driver's perception. More interestingly, what is the value of the information in a message that says "Take Route A"? A driver may think that he can save 10 minutes if he take route A, which implies that the relative value of the information is 10 minutes according to the driver's perception. This is an intermediate process transferring various types of information to driver's perceptive value.

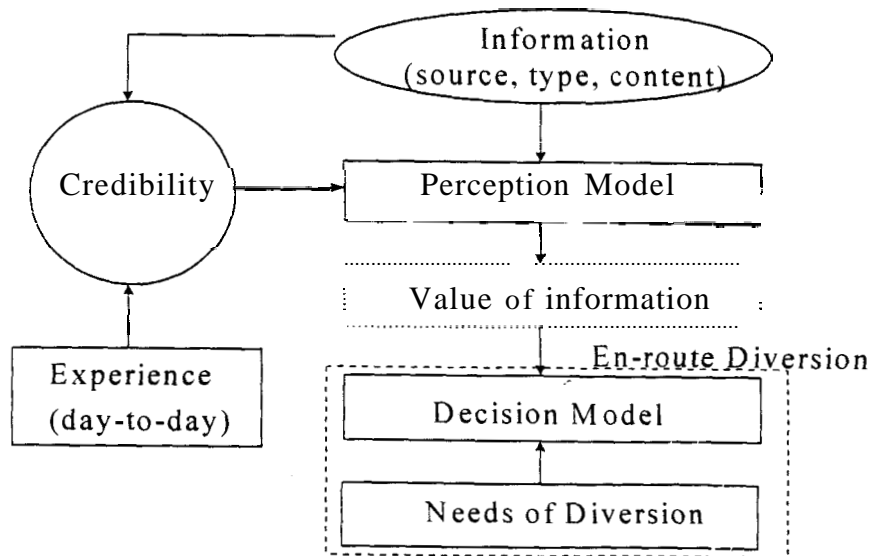


Figure 3.1 A General Structure of En-route Diversion Model

The second part, the decision model, is more general. This model also may have two steps effects: one is driver's needs of diversion (for instance, level of congestion on current route), and the other is the perceived relative values of current route and alternative route. In order to reflect the drivers' heterogeneity in the model, each driver's characteristics, such as socio-demographic information and network knowledge, can be incorporated. However, variables to be used in the model will be limited ones that can be reasonably generated in simulation framework since the purpose of en-route diversion model is to predict its effects in a simulation model framework.

It is not determined yet whether the model framework proposing will be calibrated with data collection. Although parameters for the model need calibration and validation, developing a model framework itself is also meaningful. Furthermore, this research is intended to construct overall framework for information design and ATIS evaluation. Therefore, efforts to find comparable parameters from other calibration results obtained from previous research will be made. It is expected to be enough to fulfill our purpose to some degree. However, it is not guaranteed that the model is usable through the approach. So in case that model parameter found from other research is not enough, an interactive computer simulation game similar to FASTCAR will be used for data collection, and the model will be calibrated using various efforts. There are many different types of modeling approach, such as logit type, probit type, fuzzy logic type, and neural network type. In this research, however, more attention will be paid to logit or probit type model.

As a CMS data fusion issue within simulation modeling framework, CMS message expressions need to be transferred to DYNASMART data format for simulation. It is needed to translate CMS message to driver's perception that can be processed inside of en-route diversion model in DYNASMART. Critical work is how to scale the strength of message. The answer to this question will be sought from driver's behavior studies. Translating CMS message into DYNASMART data is being conducted with driver's behavior study.

3.1.3 Reliability Issues

Main issue in this part is optimal routing and maintenance of information reliability. Routing policy in the ATIS need to satisfy these two conditions. ATIS can be interpreted as a soft controller from a traffic control point of view because compliance is up to drivers, while other controllers can control vehicles to follow their signs. In the ATIS, role of traffic management center is influencing driver's decision by giving information or guidance. System optimal solution, which minimize total system cost, can be obtained using network optimization technique. The question is that "Can this system optimal be obtained in the ATIS?" The optimal routing policy in the ATIS involves some complexity because of the lack of enforcement.

In the context of information reliability, drivers will have travel experience everyday and cumulate their experience. Credibility is one of driver's experience which is updated day-to-day. So credibility problem is analyzed through day-to-day dynamics. In this

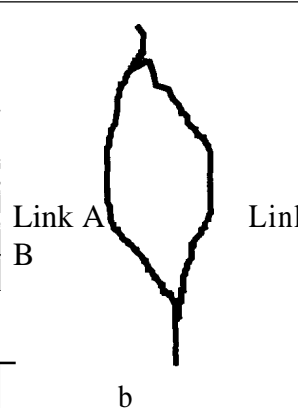
research this credibility updating method will be investigated along with routing policy evaluation.

Simple example in static case

Basic routing policies can be classified as three categories: user equilibrium (UE), system optimal (SO), and stochastic user optimal(SUE.) The system optimal assumption is a goal to pursue, but not one that results from actual drivers' behavior. A problem in SO is that certain amount of drivers should take high cost routes for minimizing the overall cost for the whole system. The user equilibrium condition is reached only when no traveler can improve his travel time by unilaterally changing routes. The assumption is that each driver chooses the minimum travel time route with full information, and all drivers are identical in their behavior. Relaxing the assumptions in UE, SUE takes drivers' perception error into account, and the drivers are assumed to change their routes choose those with minimum perceived travel cost.

To investigate routing policy, let us assume that a single O/D pair with two independent routes A and B is given, and that the driver behavior is solely dependent on travel time. When drivers' perception error is Gumbel distributed, the route selection can be determined by binary logit model. Let us consider an information scenario where the drivers' actual travel times are the same as informed by the system. That is, to maintain information reliability, predicted travel time information will be provided. We can find the solution assuming that driver behavior-- logit type model in this case-- is known. This is a fixed point problem.

Table 3.3 **Simple network for comparison**

	Link A	Link B	Network
Free speed travel time (min)	12	10	
Link Capacity (veh/min)	70	60	
Total Demand (veldmin)	100		
Link performance function	$t = t_0 * (1 + 0.15 (V/C)^4)$		
Route choice model	$P(i) = U(i) / \{U(A) + U(B)\}$		
Utility function	$U(i) = - 0.15 * \text{travel time}(i)$		

In this simple example case, the predicted travel time information can be obtained by iterative calculation. Eventually this information is same solution as stochastic user equilibrium assignment result. Figure 2.2 shows a comparison between user equilibrium (UE), system optimal (SO), and stochastic user equilibrium (SUE) for this example. The information will be reliable only when it is based on prediction with consideration on drivers' behavior. If other travel time information, such as based on SO or UE, is given to drivers, the information will be always different from actual travel time, and will cause decreasing information reliability. We can control the demand split between two routes using travel time information, but drivers will recognize that the information is wrong from their experience when any times other than SUE travel times are provided. On the other hand, reliability of the information will increase when travel time information satisfying stochastic user equilibrium is provided, and the system will approach to user equilibrium state with a decrease of drivers' perception error. In this two route example, total cost corresponding to the SUE split happens to be between SO and UE, but it can be anywhere.

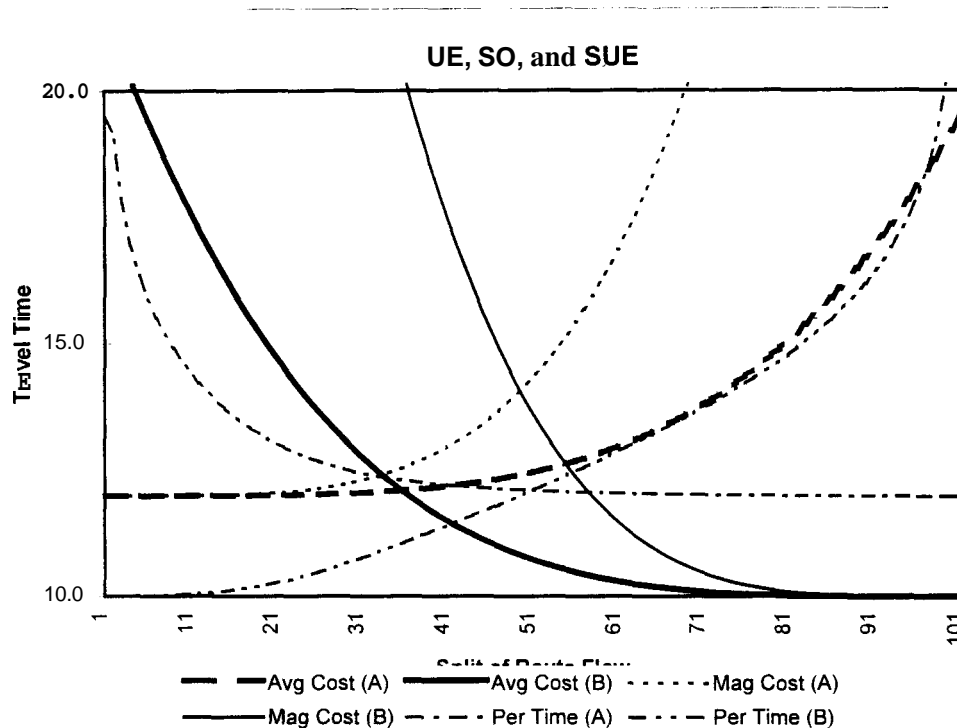


Figure 3.2 User Equilibrium, System Optimal, and Stochastic User Equilibrium

Day-to-day dynamics of credibility

Consideration of the reliability of information is critical because it will directly affect drivers compliance as discussed before. Credibility can be an endogenous variable within a day-to-day dynamics framework. This study will investigate how to measure and update the credibility of information with driver behavior analysis. Figure 3.3 shows the framework for updating driver credibility associated with day-to-day dynamics under the ATIS.

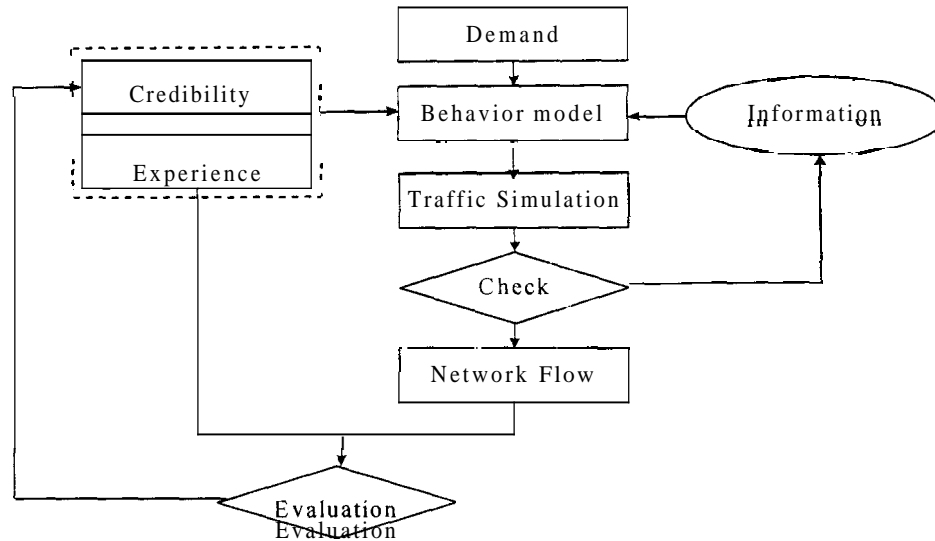


Figure 3.3 Framework for day-to-day credibility update

3.2 Simulation Framework for Evaluation

The existing simulation facilities on the Caltrans-UCI Advanced Testbed is perhaps the most comprehensive ATMS work-bench available anywhere. The primary modeling component is a hybrid simulation framework incorporating INTRAS and DYNASMART actively communicating and passing vehicles between them in real-time. The ATIS modeling is completely handled by DYNASMART and most of the microscopic modeling facilities will be disabled during this research, other than for some specific stretches of freeways where more detailed information on congested traffic is sought. The focus here is on the DYNASMART model, and in enhancing its behavioral modeling capabilities using the calibrated models.

3.2.1 Simulation Methodology and Fundamental Aspects

The simulation-assignment model, DYNASMART (Dynamic Network Assignment Simulation Model for Advanced Road Telematics) was developed specially for studying the effectiveness of alternative information supply strategies as well as alternative information/control system configurations for urban traffic networks with ATIS and/or ATMS. This simulation program models, in an integrated fashion, the three main components of such systems: (1) the response of drivers to the information/control. (2) the nature of the traffic flow that results from driver responses and applied network control and

(3) the dynamics of the route in the network (in terms of the changing travel times on them) which affect the driver and control system decision. The traffic movement is based on macroscopic speed-concentration relationship, even though individual vehicle (or platoon) positions are kept track of, and the route or link choice decisions of the vehicles are modeled individually. This approach is based on the belief that driver route-choice decisions and collective delays at the nodes are more significant in capturing the effectiveness of the guidance systems rather than the microscopic details of the traffic in the links.

The traffic simulation approach in DYNASMART has elements from both macroscopic and microscopic models which have been developed in the past. DYNASMART moves the vehicles individually according to the prevailing speed and keeps track of their position. The speed-density relationship currently used is a modified version of the well-known Greenshield's equation. There is no simulation of lane changing maneuvers or car following. These approaches are essential to keep the computations manageable, especially in the case of reasonably large networks, which is where DYNASMART can be effectively applied to study information strategies.

The driver behavior modeling is currently based on simple threshold mechanism, where the routes are switched only if alternative routes are sufficiently better. There is also the capability of overriding driver choice and modeling the compulsory routing of vehicles to routes prescribed by a central controller. DYNASMART guides drivers to routes selected from a set of k-shortest paths. This is under the assumption that in the future, the Traffic Operation Center (TOC) controllers will have to provide 'reasonable sets' of paths to the drivers while routing them.

The traffic generation is based on the specified dynamic zone-to-zone demand matrix. Vehicles are generated on links and each vehicle's destination is probabilistically determined based on the demand data. At the time of generation, each vehicle is randomly tagged to be equipped for information or otherwise, based on the specified fraction of equipped drivers. An initial path is assigned to each driver. This could be from among the k-shortest paths stored after the load-up period or equilibrium paths reducing the capacity (in terms of effective lane miles) on specified links by a specified fractions. Any number of such incidents can be simulated by specifying the starting and end times and capacity reduction factors for each incident. When the effective lane-miles is reduced for a link during the simulation, the calculated densities increase instantly. If they increase to more than the maximum allowed density, the vehicles are moved at jam speed, till the density falls below the maximum.

DYNASMART provides the ability to explicitly model an array of control elements. The major element for surface streets is signal control, which includes pre-timed control and actuated control. Ramp metering and variable message signs (VMS) are the major controls for the freeway system. The detailed modeling of intersections and freeway, the inflow-outflow constraints at nodes/intersections, detectors, freeway ramp signals, left-turn etc., can be found elsewhere (Jayakrishnan et al, 1993; Mahmassani et al, 1992).

It is important to recognize that the attractiveness of alternative paths constantly change in networks with ATMS/ATIS, due to the dynamics introduced by the driver

decisions on which routes to drive on. Two different aspects need to be modeled: 1) the route shown periodically by the controller of **ATIS** and 2) the routes that drivers perceive they are driving on or are selecting from. The former is stored as predecessor trees which are frequently updated based on link travel times, and the latter stored as node-lists associated with each driver. In addition to the above, DYNASMART also provides the option of storing externally specified paths which are independent of current traffic conditions, mainly for modeling the driver selection of initial paths, which for instance could be externally-determined dynamic equilibrium paths between O-D pair. Also k-short paths (shortest, 2nd best, 3rd best etc.) are found and stored at specified intervals from all the nodes to all the destinations (which effectively simulated a Traffic Control Center's path-sets. The user can specify the intervals at which paths are updated at the Traffic Operation Center (TOC)

3.2.2 Capability of DYNASMART

DYNASMART has so far been implemented and timed on two different computer platforms: the CRAY-YMP supercomputer and the SUN SPARC workstation. Simulation of up to 75000 vehicles in the 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 runs 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 modeling of traffic flow dynamics such as congestion formation and shock wave propagation. Tracking of location of individual drivers.
- 2) Modeling of different traffic control strategies (freeways, surface streets, signalized intersection, ramp entry/exit etc.)
- 3) Modeling of prescriptive /compulsory guidance as well as non-prescriptive guidance with trip time information on alternative routes.
- 4) Modeling of various aspects of the controller such as infrequent updates of network route information database.
- 5) Modeling 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) Modeling of capacity-reducing incidents at any time, anywhere in the network.
- 7) Modeling of cases with only a fraction of the vehicles equipped for information.
- 8) Capacity 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 time, distances, average speeds and a variety of route switching statistics.

The capabilities described above makes this program the ideal candidate for evaluating the ATIS routing schemes resulting from the algorithmic components of this research.

3.3 Evaluation Framework for ATIS Schemes

Current version of DYNASMART is capable of analyzing traffic networks under real-time information. Dynamic user equilibrium and system optimal solution can also be obtained using DYNASMART as addressed in section 2.1.3. CMS information can also be evaluated under the assumption that compliance rate is known. Through this research the compliance rate will also be obtained within the DYNASMART simulation by incorporating driver's behavior model. By doing so, overall ATIS evaluation framework is completed.

Using the comprehensive evaluation framework tool, solution algorithms for limited information case, such as CMS and HAR. can also be developed. The description on the path can be generalized to a format of travel time or delay (i.e., value of information) using the perception model as discussed before. This case the travel time or delay can be obtained. which is a descriptive information variable, by iterative searching method as shown in Figure 3.4. The measure of effectiveness (MOE) is set by the purpose of system manager, and corresponding results may vary. In addition, overall network performance needs to be evaluated.

Even though solution can be found by evaluating all candidate CMS messages, an optimal message should be determined timely in on-line implementation, which can be achieved by evaluating only messages screened using static network flow optimization technique as addressed in section 2.3. Usefulness of the static approach for CMS message selection will also be evaluated with the evaluation framework.

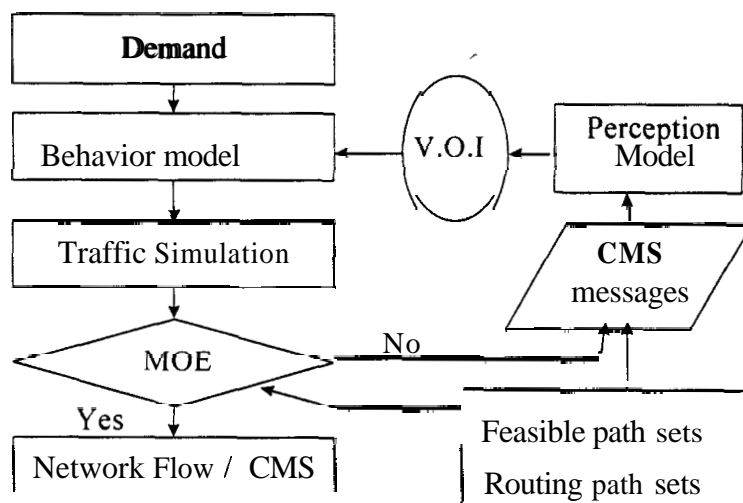


Figure 3.4 Overall Framework for CMS Routing

Chapter 4

REAL-WORLD ATIS IMPLEMENTATION IN ANAHEIM

The methodology proposed here is based on developing routing plans for variety of special-event conditions in the Anaheim network, especially based on traffic from to the four main traffic generators/attractions in Anaheim, namely, 1) the Anaheim Stadium. 2) Arrowhead Pond Arena, 3) Disneyland, and 4) the Anaheim Convention center. Various traffic condition and combinations of events will first be simulated, so that candidate ATIS strategies, such as CMS and HAR messages are developed. These will be first studied in the Advanced Testbed lab, so that a subset of strategies can be developed for selection during real-time operation. This means that modeling framework in the Advanced Testbed needs to be augmented using models of traveler response to ATIS information, as well as their modeling.

As a preliminary field test this report deals with only in-bound event traffic to the Arrowhead Pond Arena. Since most major components proposed here are still under development, the preliminary field test mainly focuses on availability of data and driver's reaction to the new CMS message.

4.1 Site Description

4.1.1 General Description

The site for preliminary field test is the City of Anaheim in Orange County, California. Portions of seven additional Orange County cities are partially included in the site, including Fullerton, Placentia, Orange, Santa Ana, Garden Grove, Stanton, and Buena Park. The area extends **9.3** miles east-to-west and 6.5-miles north-to-south, for a total land coverage of approximately 60 square miles.

As the large number of municipalities suggest, the 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 automobile for virtually all personal transportation. This essentially complete dependence on the automobile had greatly taxed the already-extensive regional roadway system (Haboian and Mortazavi, 1990).

In addition to the daily recurring background traffic, Anaheim also contains four generators of special-event traffic; (1) the Anaheim Angels Stadium, (2) the Arrowhead Pond Arena, (3) the Anaheim Convention Center, and (4) the Disney theme park. All four of these facilities contribute an additional burden on the roadway system as large numbers of drivers, many of whom are unfamiliar with the local area and with the patterns of recurring traffic congestion, enter the system at a few closely-spaced points during short time spans. Therefore, the potential achievable benefits of applying ITS to the alleviation of special-event generated congestion is of unique interest.

For the purpose of this research, the special-event traffic generated by Arrowhead Pond is chosen. Various events are held at the Arrowhead Pond. Especially during the winter season the Arrowhead Pond almost constantly attracts about 17,000 audience a game as the Might Ducks' home arena.

4.1.2 Transportation System and Information Facilities

The transportation system in the 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 corner to the southeast corner 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.

The arena is located in an easily accessible location of Orange County, east of the 57 (Orange) freeway on highly-traveled Katella Avenue, where more than 35,000 motorists pass by daily. For easy access and egress from the site, five major freeways (57, 22, 5, 91, 55) are located within a five-mile radius.

There are 6 CMS's on freeways which are used to guide drivers finding freeway exits to go event places. Three CMS's among many CMS's in this area is used related to the Angels Stadium and Arrowhead Pond Arena. Also static sign board guiding to the these sport facilities are located along the surface roads connecting from freeways to the facilities.

4.2 Description of Preliminary Field Test

4.2.1 Current Route Information for Event Traffic

Two CMS's on freeway 57 are used for guiding event traffic to Arrowhead Pond: one for north bound traffic, and the other for south bound traffic. Usually CMS messages are displayed from two hours before game start for inbound traffic. Current messages are as shown in figure 4.1.

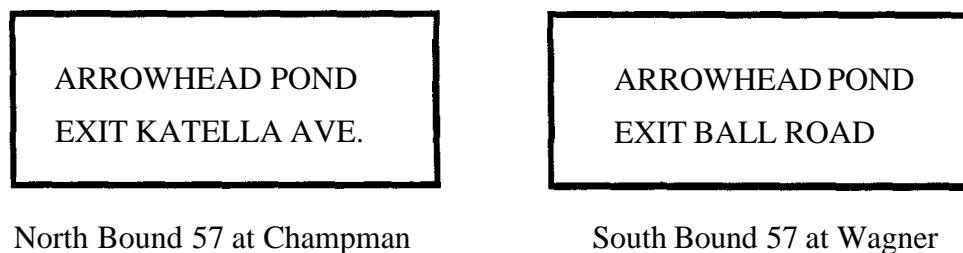


Figure 4.1 Current CMS messages for Arrowhead Pond Traffic

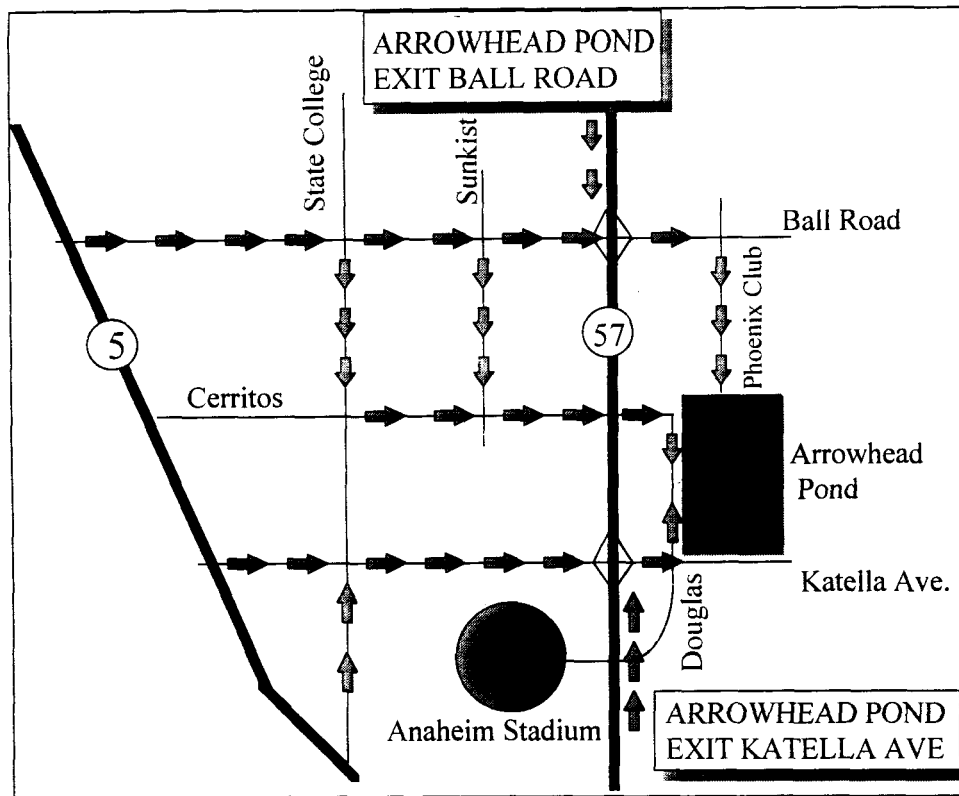
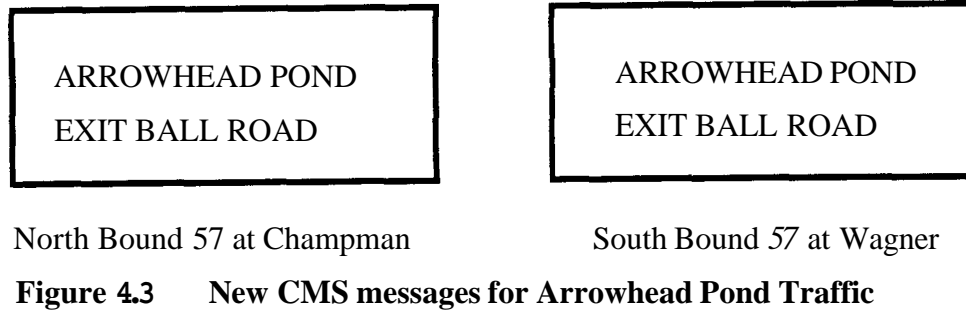


Figure 4.2 Current Routing Scheme for Event Traffic

Purpose of current information system is to guide drivers unfamiliar with the area. Major approaches currently used are as shown Figure 4.2. Audience from south area are using Douglas entrance on Katella Avenue via freeway 57, while audience from north area are using all Cerritos entrance or Phoenix Club entrance via Ball Road. Those who are from west area are using Douglas entrance via Katella Avenue. Therefore, traffic is concentrated on the Douglas Road entrance, and severe traffic congestion is recurrent at the intersections, freeway 57 north bound exit and Douglas on Katella during event traffic hour. The entrance intersection is so close to the freeway 57 that it causes queue on the freeway 57 north bound.

4.2.2 New Routing Scheme for Event Traffic

As shown previous section, routing problem in this event area is apparently how to reduce vehicles concentrating on Douglas entrance on Katella Avenue. As a new routing scheme, it was suggested to guide traffic from south area to take Ball Road instead of exiting to Katella Avenue. So both CMS on freeway 57 are guiding vehicles to take Ball Road as shown figure 4.3. However, high compliance rate is not expected, since the Douglas entrance is much closer than Phoenix Club or Cerritos entrance. Also in order to prevent queue development on Ball Road due to traffic heading to Phoenix Club entrance, an arrow message on Ball Road has changed to the direction of Cerritos entrance. New routing scheme is shown in Figure 4.4.



The messages are turned on from two hours before the game starts. As a matter of fact, if the new message on north bound freeway 57 is turned on only when the Katella Avenue is congested, better performance is expected. As main purposes of the preliminary test are to observe driver’s compliance behavior and to investigate data collection methods. the new message was turned on from 5:30 p.m. that is two hours before the game starts to 7:30 p.m. without alteration of message during 2 hours.

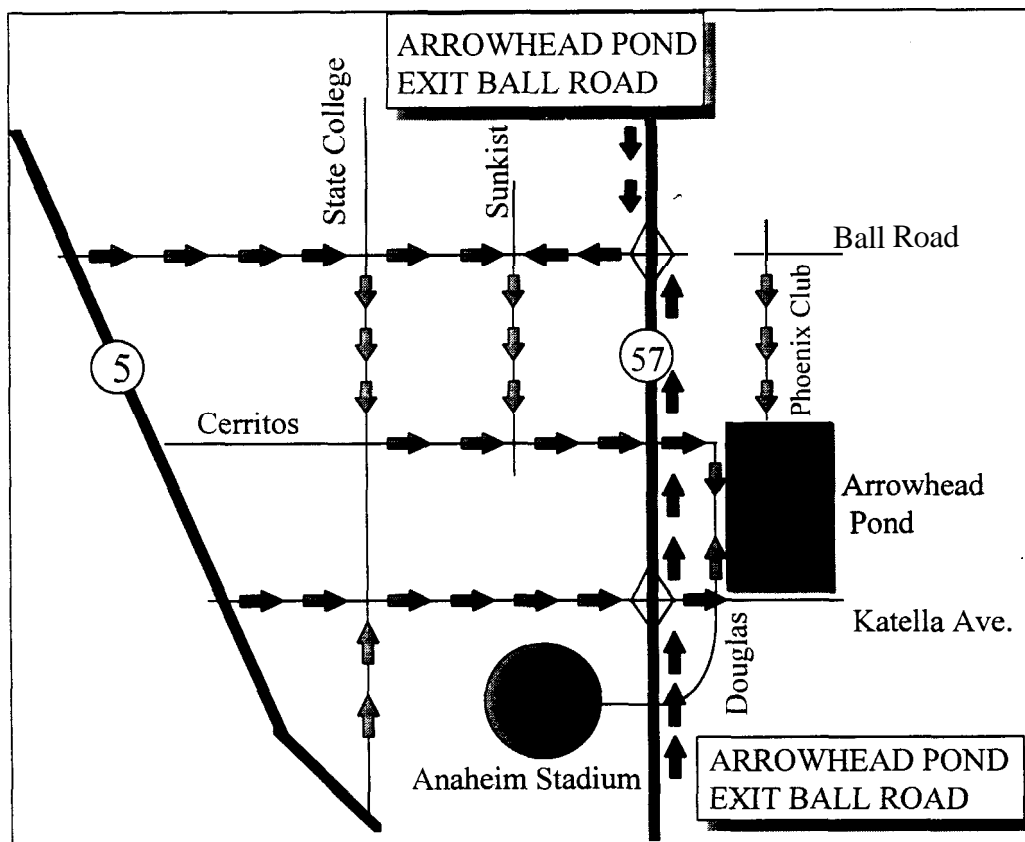


Figure 4.4 New Routing Scheme for Event Traffic

4.3 Off-line Simulation Study

4.3.1 Data for Simulation Study

The network covering the study area consists of 480 nodes, 1060 links, and 42 zones. Of these 42 zones, 15 zones are internal surface zone, 19 zones are external surface zones, 7 zones are external freeway zones, and 4 zones are for special-event facilities. The network data has modified for better explanation of Angels Stadium and Arrowhead Pond area. Anaheim area network is shown in figure 4.5.

Dynamic O-D trip table for Anaheim area was created using COMEST O-D matrix estimation program that accompanies the CONTRAM assignment program. In addition to the O-D demand, event traffic for Arrowhead Pond Arena is added. Daily attendance is almost constantly 17,000 people a game according to the statistics, so we assumed that 5,000 vehicles are gathering to the area. Unlike static O/D demand, time varying demand requires departure time pattern. Even if we know arrival time pattern of event traffic, additional work is required to estimate departure time pattern from every origin. We assumed that arrival pattern to the stadium is skewed Gamma distributed. Then travel time from origin zone to stadium was examined from static assignment. Time varying demand for this test is discretized with 5-minute interval, and departure time was determined according to these travel times. However, initially estimated departure pattern could not replicate the arrival pattern and travel times as we assumed because of delay on links and its interaction. After several times modification based travel times obtained from dynamic simulation, time varying demand for in-bound traffic has been prepared.

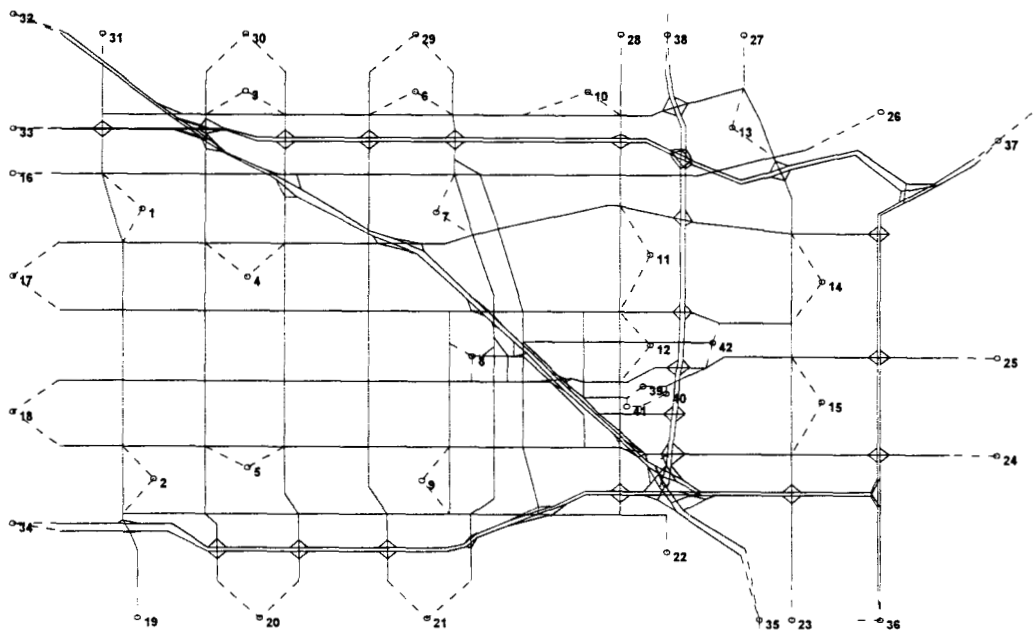


Figure 4.5 Anaheim Transportation Network

4.3.2 Simulation Results

Since driver's behavioral model is under development, this preliminary simulation is performed based on fixed compliance rate. So average travel time, average delay, and average distance traveled are evaluated according to changes of compliance rate. In reality, the compliance rate may vary depending on the traffic condition. That is, under more severe congestion, higher compliance rate is expected. However, in this simulation study, we assumed that the compliance rate is independent from the traffic condition. Also it is assumed that no vehicle are equipped IVNS receiving real time information.

As a base case, total 104,042 vehicles were simulated for 100 minutes, and total number of 56,933 vehicles, which generated during 60 minutes after finishing 15 minutes warm-up period, are taken into account for statistics. Overall performance of simulation result for the base case is as shown in Table 4.1. Total travel time for all the vehicle tagged for statistics and average travel time per vehicle are measured as 17,225 hours and 18.153 minutes respectively. Average distance traveled per vehicle is measured as 9.56 miles. Table 4.2 shows distribution of travel time from origin to destination. Under the current congestion level, it is measured that 11.5% of vehicles travel longer than 30 minutes.

Table 4.1 Overall Performance of Simulation (Base Case)

	Travel Time	Delay	Distance
Total	18,225 hours	2,042 hours	544,410 miles
Average	18.15 minutes	2.15 minutes	7.73 miles

Table 4.2 Distribution of Travel Time

Time Range	0.0-3.0	3.0-6.0	6.0-9.0	9.0-12.0	12.0-15.0	15.0-18.0	18.0-21.0	21.0-24.0	24.0-27.0	27.0-30.0	30.0-
%	0.2	4.0	9.2	15.2	17.8	13.7	11.7	8.0	4.8	4.0	11.5

Arrival pattern to the Arrowhead Pond within the simulation framework shows a Gammar distribution type as shown in Figure 4.6. Approximately 60% of event vehicles are concentrated on the 20 minute duration right before game start.

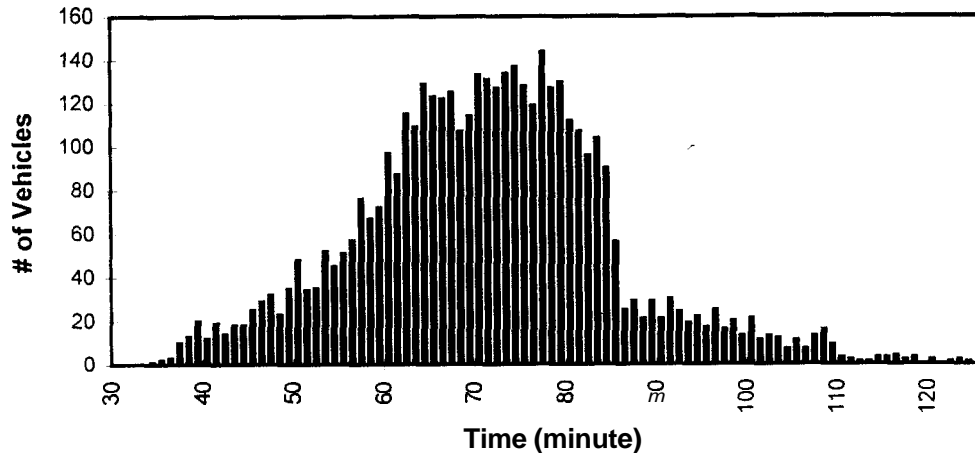
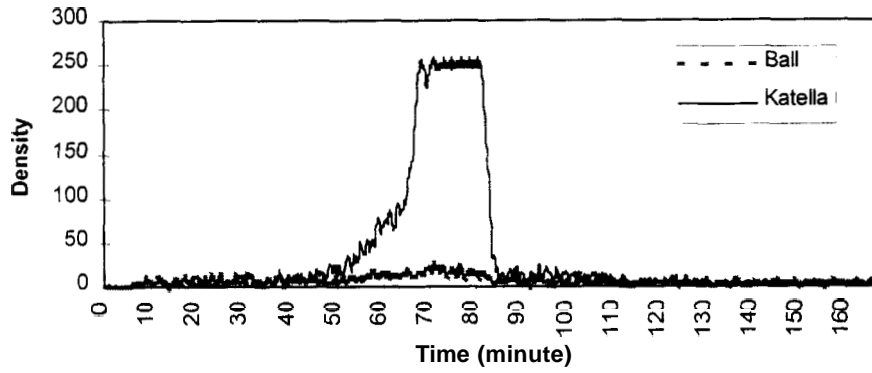


Figure 4.6 Arrival Pattern to the Arena

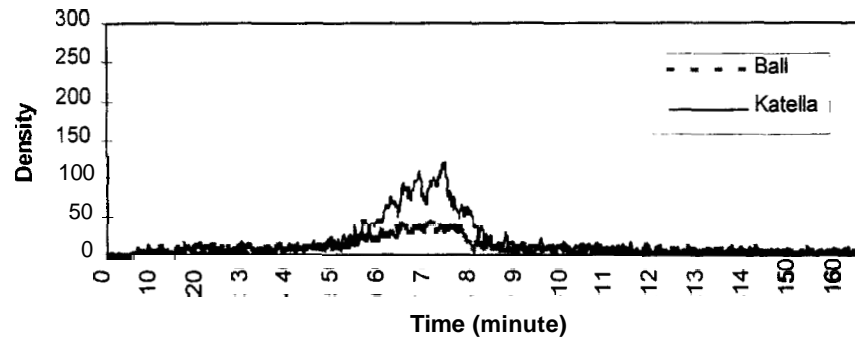
In new CMS routing case, network performance varies depending on the driver's compliance rate to the message. Figure 4.7 shows density changes between two alternative street guided by the CMS. In case of current information system, Katella Avenue reaches almost jam density while the alternative route, Ball Road, remains at low density. When 40% of compliance is assumed, density on Katella Avenue drops to lower than half. When 100% of compliance is assumed, levels of density on Ball Road becomes higher than Katella Avenue, but the difference between two is tiny. In addition, the comparison of densities between two alternative streets shows that CMS guidance is effective only during peak 30 minutes.

As noticed from the Figure 4.7, the new routing scheme is expected to show good performance by reducing congestion on Katella Avenue. However, travel distance of the route suggested by new CMS is longer than current one, and delay at a short stretch may not affect to the overall travel time. Table 4.3, Figure 4.8, and Figure 4.9 show average travel time and average travel distance for all traffic and event traffic by compliance rate. As expected, the higher compliance rate is, the longer travel distance is. It is because CMS guides drivers to avoid congested area by taking a detour. Being considered travel time for all vehicles as overall network performance measure, network condition is optimal around at a compliance rate of 40%; however, it results in longer travel time for event traffic. It is compliance rate of 40% that shows best result for event traffic. In all case except 100% compliance case, network condition improves and shows satisfactory result for both overall and event traffic case.

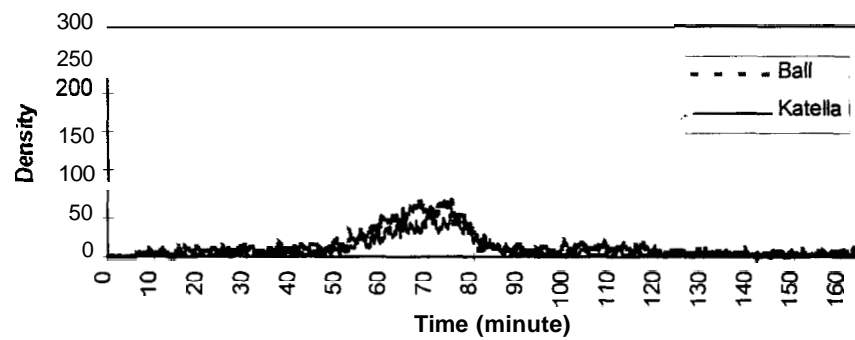
With the assumption of 40% compliance, the simulation results estimate 2% of travel time saving for event traffic although travel distance increases by 2.5% thanks to new CMS routing scheme. For all vehicles, travel time is estimated to decrease by 1%. In this simulation CMS message is assumed to be turned on during whole simulation period. When CMS is turned on only during event peak period, the benefit for event traffic is estimated to be 2.6 % of travel time saving. That is, dynamic routing is more beneficial and necessary.



(a) Base Case (current information system)



(b) 40% Compliance Case with New CMS Message



(c) 100% Compliance Case with New CMS Message

Figure 4.7 Density Comparison of Two Alternative Streets by Compliance Rate

Table 4.3 Performance Measure by Compliance Rate

	Compliance Rate (%)	Average Travel Time (minute)		Average Traveled Distance (mile)	
		Overall	Event	Overall	Event
Performance Measure	0	18.153	17.500	9.5622	7.730
	20	18.088	17.280	9.5794	7.860
	40	17.965	17.140	9.5834	7.920
	60	18.002	17.310	9.6009	8.000
	80	18.024	17.500	9.5998	8.130
	100	18.026	17.630	9.5754	8.260
Benefit	20	0.065	0.220	-0.017	-0.130
	40	0.188	0.260	-0.021	-0.190
	60	0.151	0.190	-0.039	-0.270
	80	0.129	0.000	-0.038	-0.400
	100	0.127	-0.130	-0.013	-0.530

1) 0 % compliance case means current information system case.

2) Overall case includes all vehicles, while event case includes only vehicles arriving at the Arena.

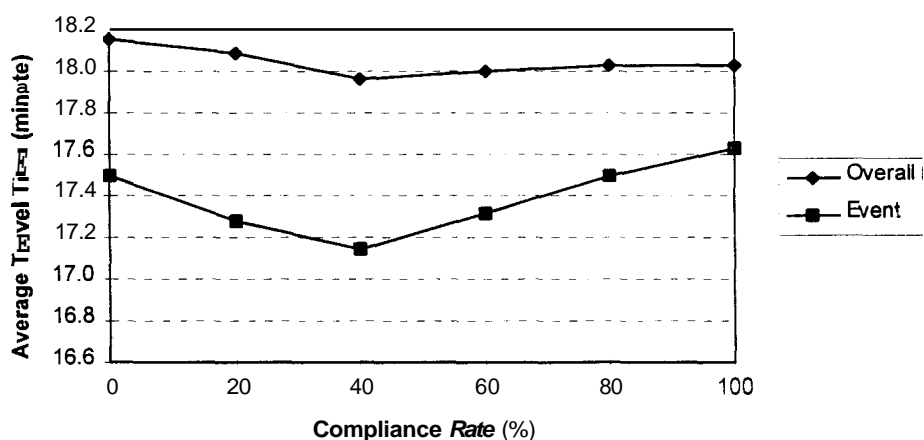


Figure 4.8 Changes in Average Travel Time by Compliance Rate

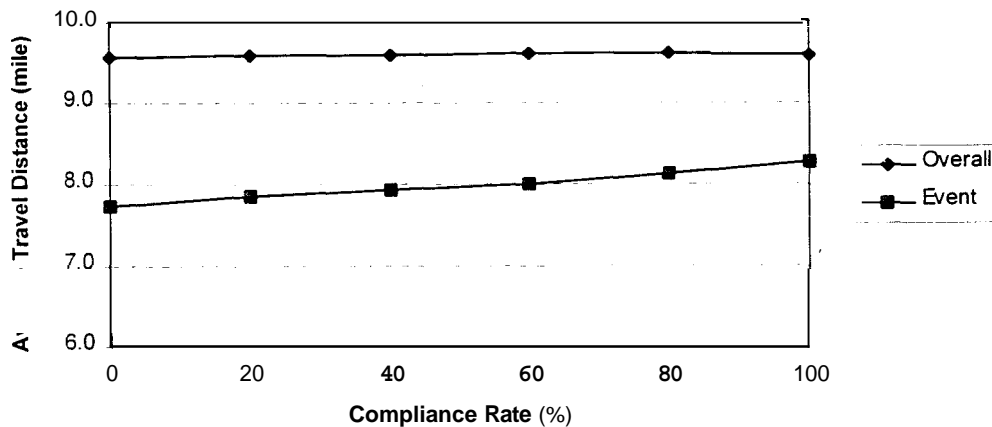


Figure 4.9 Changes in Average Travel Distance by Compliance Rate

4.4 Field Test in Anaheim

For the field test of the new CMS message three event days when were selected: November 12th and January 21st as current message cases (Before Study), and March 11th for new message case (After Study). The new messages addressed in section 4.2.2 were displayed for two hours on March 11th.

In order to monitor changes in traffic flow pattern due to the new CMS message, traffic counts and occupancy data on the freeway 57 were collected from the Caltrans-UCI ATMS research Testbed data base system. Speed data are calculated from the traffic counts and occupancy data based on assumed vehicle length (20ft). Overall traffic volume for after-case was approximately 10% higher than that of before-cases as shown in Figure 4.10.

Effects of the event on traffic pattern were witnessed from 18:50 which is 40 minutes before game start, and traffic pattern return to normal at 19:40. During this event period, influence of new CMS routing on traffic pattern was also observed. It is presumed that delays on the Katella Avenue and the Freeway 57 were reduced thank to the new CMS route guidance compared with current CMS routing even though it is not possible to measure overall performance of new CMS routing due to lack of traffic data on surface streets.

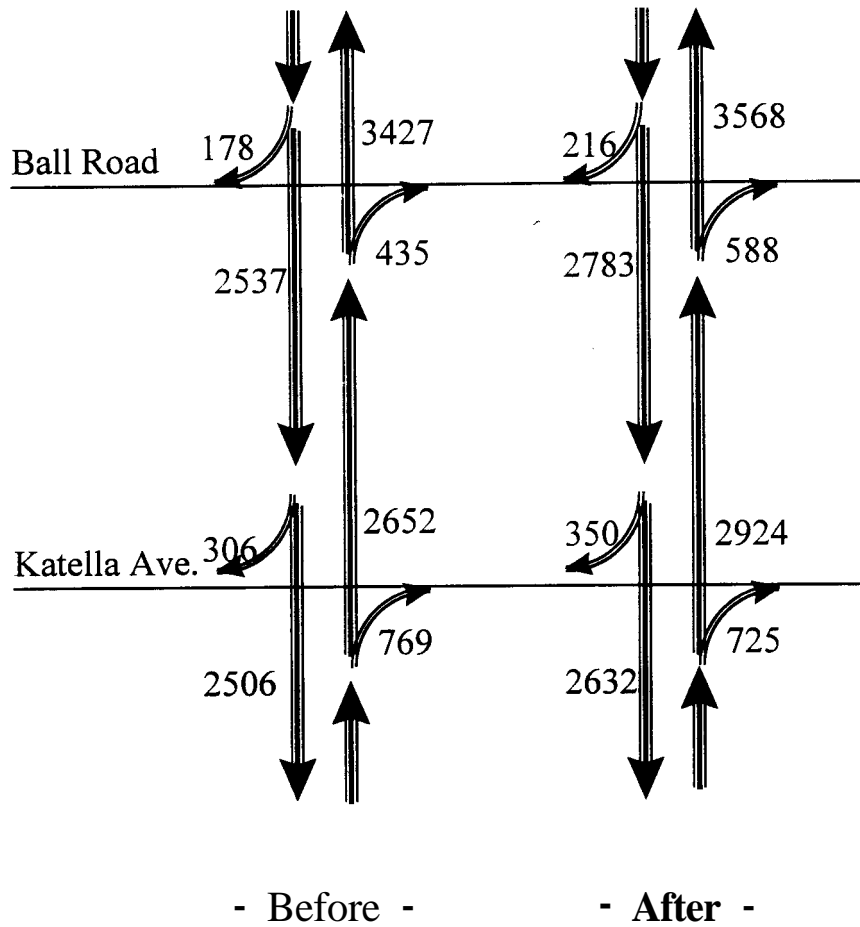


Figure 4.10 Traffic Volume on Freeway 57 During Event Period (19:00-19:30)

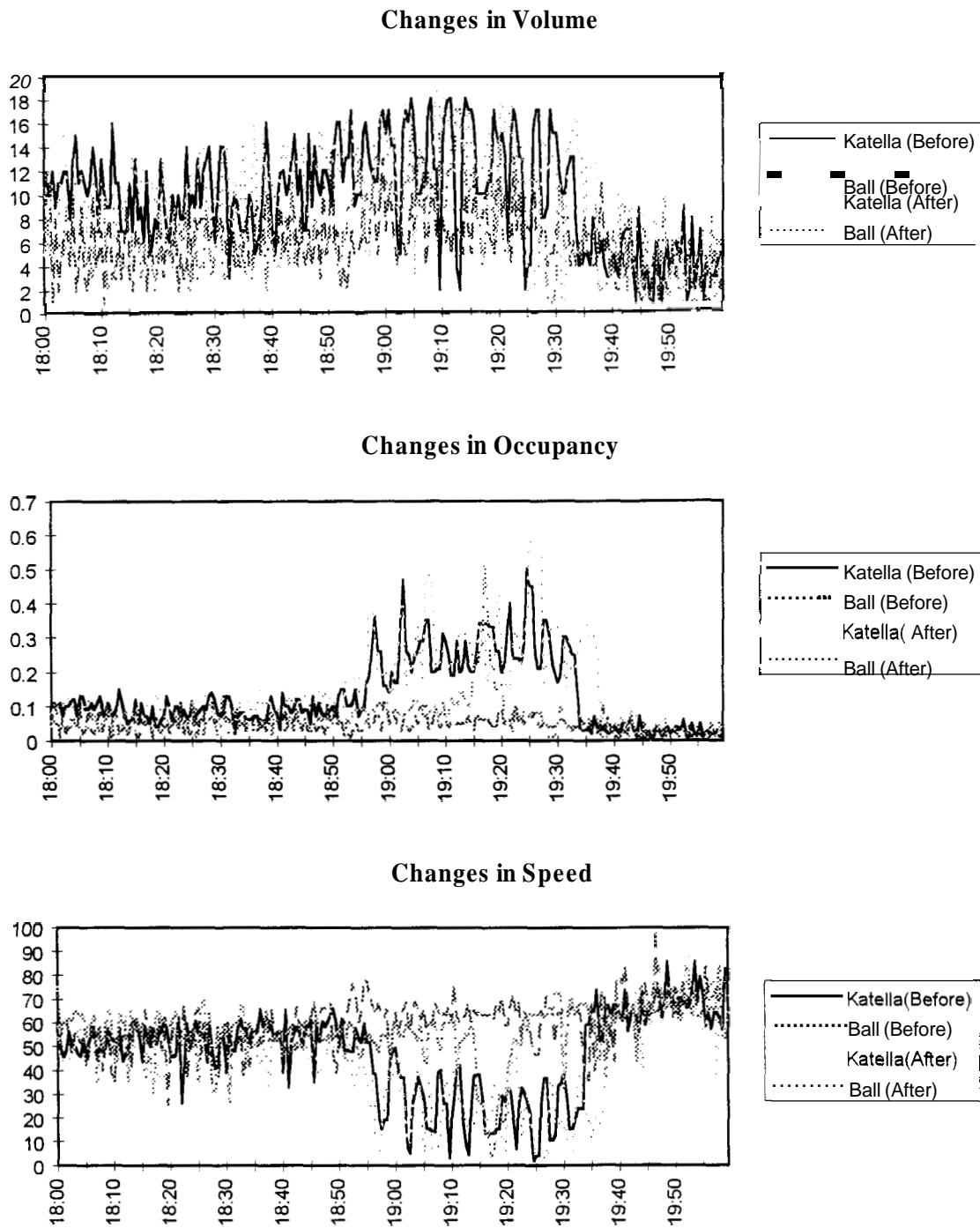


Figure 4.11 Comparison of Traffic Condition on Alternative Exit Ramps

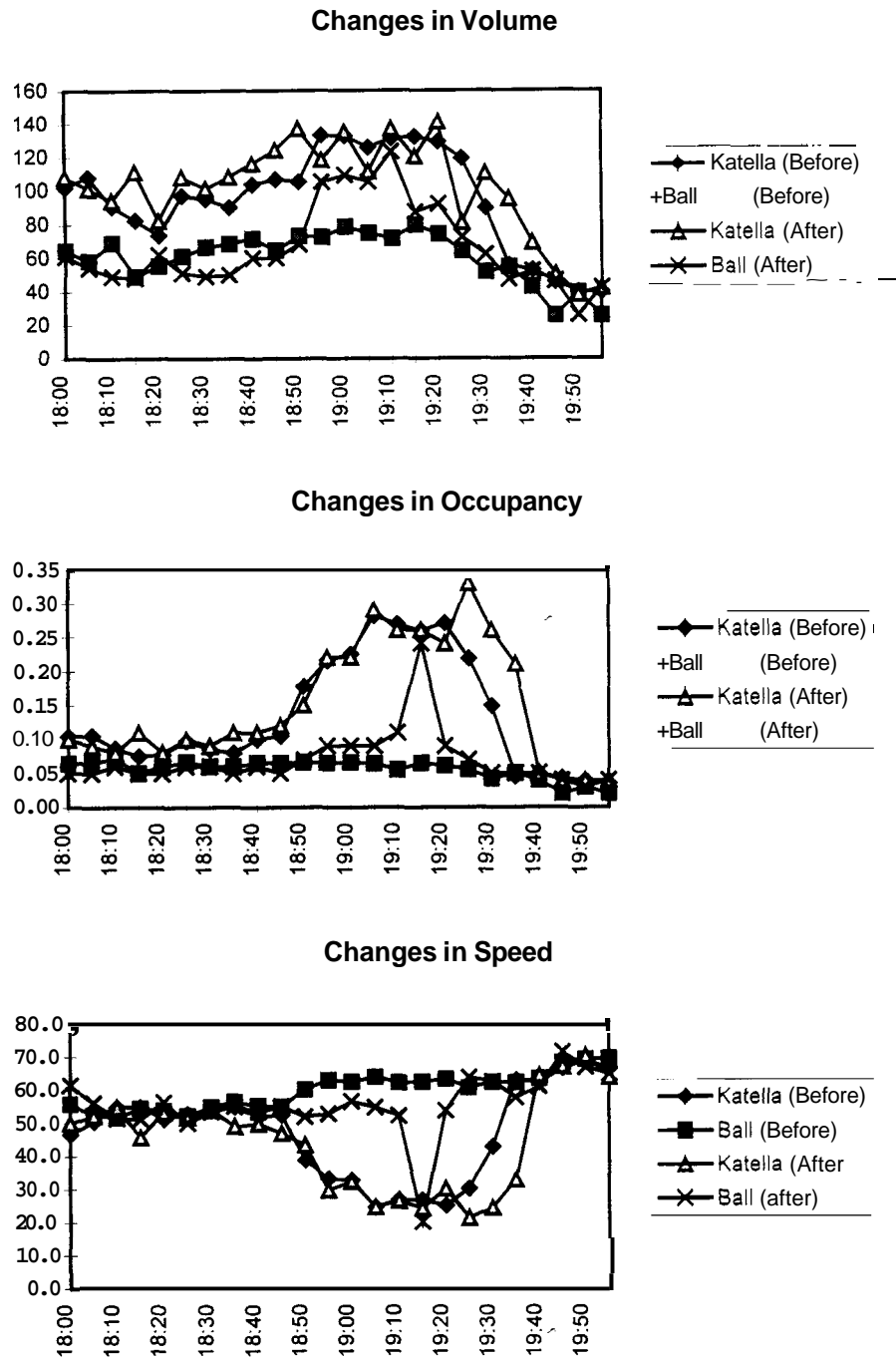


Figure 4.11 Comparison of Aggregated Traffic Condition on Alternative Exit Ramps

Table 4.4 Comparison of Freeway Traffic Condition

• Katella → Ball (Main)

Time Interval	Before			After			Changes (%)		
	Vol	Occ	Speed	Vol	Occ	Speed	Vol	Occ	Speed
18:00 - 18:15	1536	0.29	27.1	1628	0.23	33.8	6.0	-19.5	24.5
18:15 - 18:30	1478	0.26	30.8	1634	0.25	31.4	10.6	-4.1	2.0
18:30 - 18:45	1546	0.18	40.3	1563	0.26	30.5	1.1	45.3	-24.4
18:45 - 19:00	1503	0.11	57.9	1619	0.24	32.4	7.8	128.3	-44.1
19:00 - 19:15	1370	0.10	58.7	1548	0.16	46.9	13.0	68.0	-20.2
19:15 - 19:30	1282	0.10	58.5	1376	0.10	59.4	7.4	4.9	1.5
19:30 - 19:45	1100	0.08	62.2	1183	0.09	62.2	7.6	11.7	0.0
19:45 - 20:00	909	0.07	63.8	1045	0.08	62.6	15.0	13.4	-1.8
Total	10722			11596			8.2		

• Ball → Lincoln (Main)

Time Interval	Before			After			Changes (%)		
	Vol	Occ	Speed	Vol	Occ	Speed	Vol	Occ	Speed
18:00 - 18:15	1758	0.43	18.8	1749	0.42	20.4	-0.5	-1.7	8.5
18:15 - 18:30	1746	0.41	20.7	1750	0.42	19.3	0.2	2.0	-6.6
18:30 - 18:45	1794	0.39	22.4	1740	0.42	18.8	-3.0	8.6	-16.1
18:45 - 19:00	1732	0.28	32.7	1784	0.39	22.3	3.0	41.8	-31.8
19:00 - 19:15	1752	0.25	38.8	1908	0.27	36.4	8.9	8.0	-6.1
19:15 - 19:30	1675	0.21	43.8	1660	0.24	39.6	-0.9	13.9	-9.5
19:30 - 19:45	1435	0.19	43.0	1448	0.18	45.6	0.9	-7.6	6.1
19:45 - 20:00	1202	0.16	47.4	1418	0.22	41.0	18.0	41.8	-13.6
Total	13094			13457			2.8		

• Exit to Katella (North Bound)

Time Interval	Before			After			Changes (%)		
	Vol	Occ	Speed	Vol	Occ	Speed	Vol	Occ	Speed
18:00 - 18:15	301	0.10	50.5	303	0.09	52.1	0.8	-5.6	3.2
18:15 - 18:30	253	0.08	53.0	301	0.10	49.9	19.0	23.1	-5.9
18:30 - 18:45	289	0.09	53.6	325	0.10	50.8	12.7	11.1	-5.1
18:45 - 19:00	345	0.17	40.9	379	0.16	40.3	10.0	-4.7	-1.4
19:00 - 19:15	389	0.26	28.3	383	0.25	28.2	-1.5	-3.8	-0.3
19:15 - 19:30	380	0.25	27.4	342	0.27	26.1	-10.0	8.4	-4.9
19:30 - 19:45	198	0.09	53.8	274	0.19	37.6	38.7	112.3	-30.1
19:45 - 20:00	125	0.04	67.4	130	0.04	67.4	4.4	13.1	-0.6
Total	2278			2437			7.0		

• Exit to Ball (North Bound)

Time Interval	Before			After			Changes (%)		
	Vol	Occ	Speed	Vol	Occ	Speed	Vol	Occ	Speed
18:00 - 18:15	192	0.07	53.2	164	0.05	56.7	-14.4	-23.7	6.5
18:15 - 18:30	166	0.06	53.3	161	0.05	52.8	-2.7	-9.1	-1.0
18:30 - 18:45	207	0.06	55.5	159	0.06	53.9	-23.0	0.0	-2.9
18:45 - 19:00	210	0.07	59.5	233	0.08	53.1	11.0	22.4	-10.7
19:00 - 19:15	225	0.06	62.9	337	0.10	54.4	50.1	66.7	-13.5
19:15 - 19:30	218	0.06	62.3	251	0.14	45.1	15.4	133.3	-27.6
19:30 - 19:45	149	0.05	62.7	161	0.05	60.7	8.4	10.1	-3.2
19:45 - 20:00	90	0.03	69.1	114	0.04	68.0	26.7	33.3	-1.6
Total	1454			1580			8.7		

Even though it is not possible to estimate exact compliance rate because of the daily variation in traffic condition, rough estimation can be made by adjusting traffic volumes based on fraction between the alternative exits, Katella and Ball. It is estimated that about 13% of drivers among those who used Katella Avenue before diverted to Ball Road thanks to new CMS guidance during 30 minutes before game start.

Table 4.5 Comparison of Traffic Volume between Alternative Exits

Time Interval	Total ¹⁾ Volume	Exit Katella					Exit Ball				
		Before	%	After ²⁾	%	Change	Before	%	After ²⁾	%	Change
18:00 - 18:15	492	301	61.1	319	64.9	19	192	38.9	173	35.1	-19
18:15 - 18:30	419	253	60.5	273	65.2	20	166	39.5	146	34.8	-20
18:30 - 18:45	495	289	58.3	332	67.1	44	207	41.7	163	32.9	-44
18:45 - 19:00	555	345	62.1	343	61.9	-1	210	37.9	211	38.1	1
19:00 - 19:15	614	389	63.4	326	53.2	-63	225	36.6	287	46.8	63
19:15 - 19:30	598	380	63.6	345	57.7	-35	218	36.4	253	42.3	35
19:30 - 19:45	346	198	57.1	218	63.0	20	149	42.9	128	37.0	-20
19:45 - 20:00	215	125	58.0	114	53.3	-11	90	42.0	100	46.7	10
19:00 - 19:30	1227	769	62.7	671	54.7	-98	442	36.0	540	44.0	98

1) Total volume is sum of exit volume both Katella and Ball.

2) Volume for after case is adjusted based on before-case volume

The CMS message guiding vehicles to take Ball Road instead of Katella Avenue was turned on from 18:00; Figure 4.12 shows, however, that distinct changes in traffic counts between before and after case actually began from 18:55 when congestion due to event occurs. Even though overall network performance was not compared in this field study, it is concluded that the route guidance with CMS was very effective during the event period in this Anaheim field study.

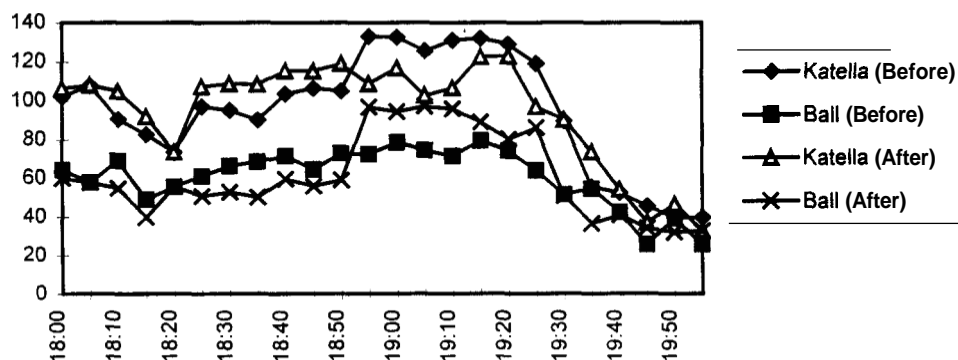


Figure 4.12 Changes in Volume on Alternative Exit Ramps

Chapter 5

CONCLUSION AND FURTHER RESEARCH

This research project is developing a comprehensive ATIS evaluation framework. This evaluation framework is utilized in setting up optimized routing strategies and generating concrete information that can be directly to drivers for optimal routing. In this research CMS routing is main concern, and the routing scheme for event traffic has been implemented in real world. This research is expected to play an important role in advancing ATIS to real world implementation by completing major components which are still under development.

For on-line real time implementation of optimal routing strategies faster algorithm to find optimal routing scheme is required. This research is trying to adapt static network optimization, and innovative “gradient” concept is under development. The main benefit from static assignments is that they are fast by orders of magnitude over the dynamic assignment algorithms which exists now, and thus are very attractive for real-time application. The disadvantage, on the other hand. is that they do not capture network congestion dynamics very well, thanks to the rather simple link travel time functions used. This research project attempts coordinating static and dynamic assignments in such a way that the computational benefits are gained from the static assignment while the inaccuracies from the results are minimized.

In this research an ATIS evaluation framework is constructed based on dynamic simulation tool, DYNASMART (Dynamic Network Assignment Simulation Model for Advance Road Telematics). Driver’s behavior model is under development for completed version of the evaluation tool within which captures driver’s compliance problem as well. Using current evaluation framework with fixed compliance rate to CMS messages, off-line simulation for Arrowhead Pond Arena event was conducted as a preliminary test. This test shows that dynamic optimal routing is necessary and CMS messages should be well designed to achieve certain level of compliance resulting optimal condition.

As a real world implementation, a new CMS message tested in off-line simulation was actually operated during event traffic hours. According to traffic data, it was witnessed that the new CMS message induced changes in traffic pattern. Rough estimation of compliance rate was 13% which is higher than expectation even though exact compliance rate could not be estimated due to lack of data. This field test showed that CMS routing can be used a useful tool for event traffic management.

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