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ABSTRACT

This project 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. This study is also answering some basic questions in ATIS implementation associated with routing strategies, driver's compliance and network performance.

This research develops algorithms for static and dynamic optimal Changeable Message Signs (CMS). The optimized CMS schemes are based on performance evaluations using a traffic simulation-based evaluation model, DYNASMART (Dynamic Network Assignment Simulation Model for Advanced Road Telematics). Performance of ATIS depends on drivers' compliance behavior, and the compliance issue is addressed in this research. This study develops a framework of driver's compliance model, and incorporates it into the evaluation framework. The model includes inherent value of guidance system, and the value is analyzed via day-to-day update approach.

A limited field test is implemented for the event traffic management. 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 and heuristic algorithms proposed for use here include those for static and dynamic traffic simulation-assignment. The essential part of algorithmic research is 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.

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 advanced management systems, 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. Algorithms to find routing messages for changeable message signs (CMS) are developed as a generalized problem. To find an optimal routing scheme, static network optimization and dynamic simulation approach are used. While finding optimized routing solution, this study incorporates driver compliance behavior into optimization framework. This study also investigates effects of information reliability, which is an inherent factor of information devices, via day-to-day evolution approach.

Finally, the evaluated routing scheme for event traffic management is implemented in real world. The routing scheme is evaluated via off-line simulation tests prior to the real-world implementation, and performance of the implemented routing scheme is analyzed via on-line traffic data collection. Also drivers' responses to CMS are surveyed to analyze drivers' compliance behavior.

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 "best possible" 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 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 have been numerous researches on driver's response to information, but there are few usable behavior models capturing 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 that 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 seeking usable optimal routing schemes. 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 In-Vehicle Navigation Systems (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 that 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, due to the rather simple link travel-time functions used. The study 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 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 or 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 Types 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 an 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 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 2.1.

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 2.2. 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 modifications are needed to use such a framework on an operational framework.

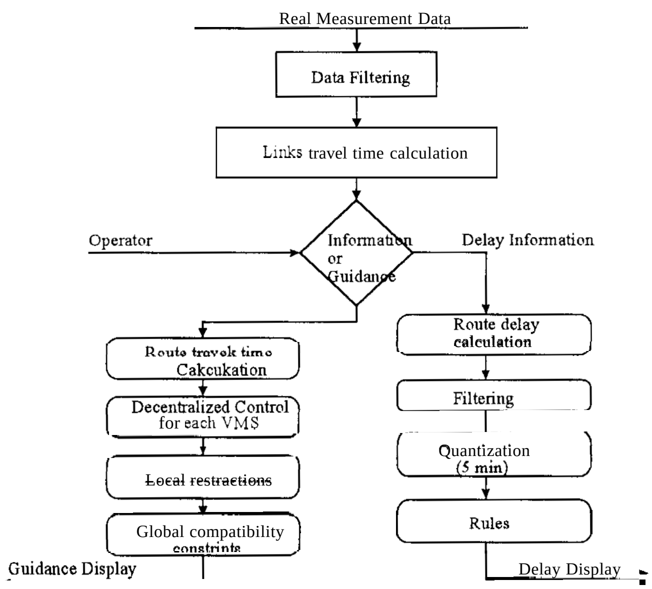

Figure 2.1 Automatic Control Software Architecture (Mammar et al, 1997)

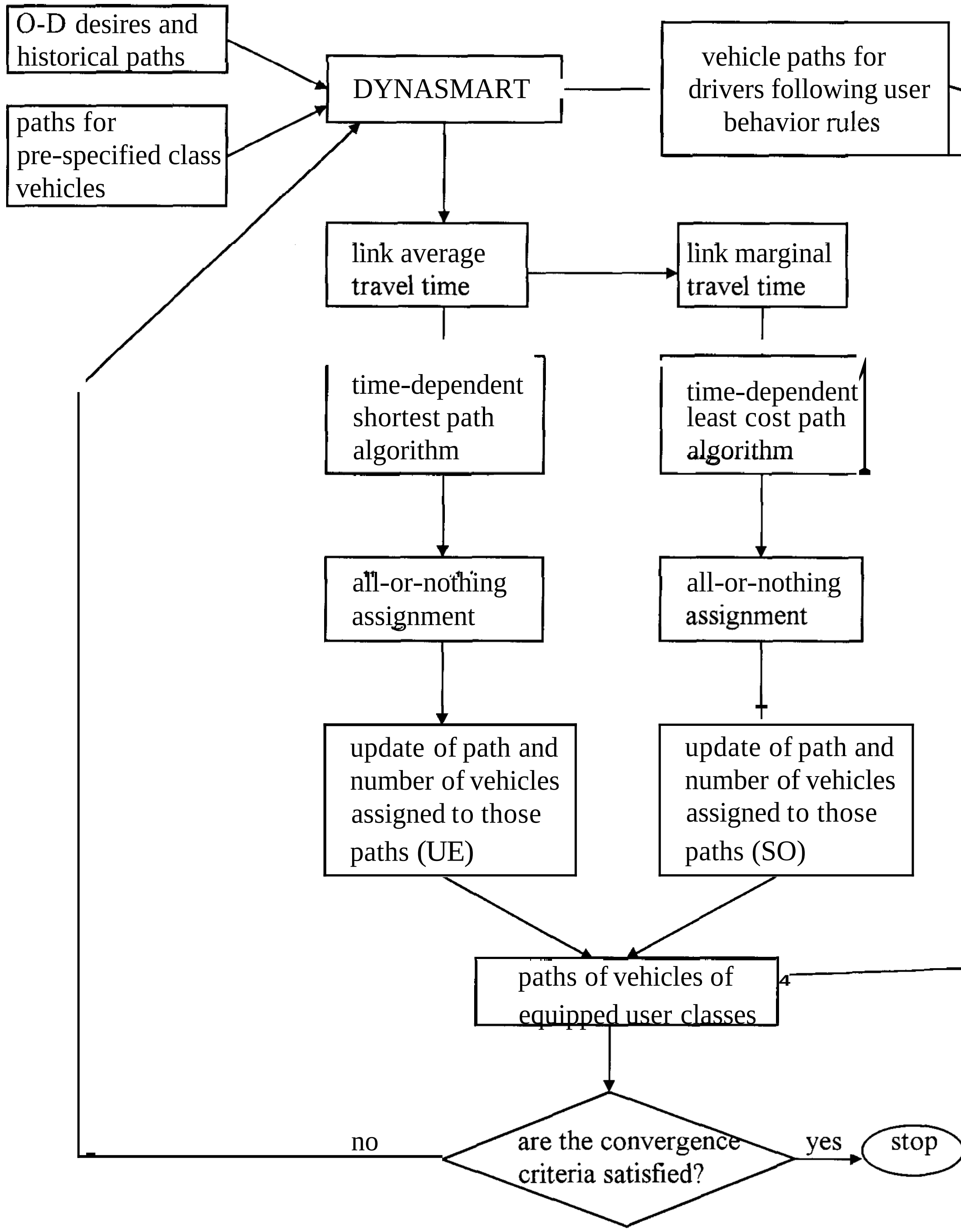

Figure 2.2 Multiple user Classes Solution Algorithm (Mahmassani and et al, 1993)

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

$$\min \quad Z = \sum_{a \in A} \int_0^{x_a} t_a(w)\, dw \tag{2.1}$$

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

$$\sum_{k \in K_{rs}} f_k^{rs} = q_{rs}, \quad \forall\, r \in R, s \in S \tag{2.2}$$

$$f_k^{rs} \geq 0, \quad \forall\, k \in K_{rs}, r \in R, s \in S \tag{2.3}$$

$$x_a = \sum_{r \in R} \sum_{s \in S} \sum_{k \in K_{rs}} f_k^{rs}\, \delta_{ka}^{rs}, \quad \forall\, a \in A \tag{2.4}$$

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 demsontrate 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 fbnction 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.

$$f_k^{rs}(n+1) = [f_k^{rs}(n) - \alpha(n) D(n) \nabla\tilde{Z}(n)]^+ \tag{2.5}$$

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 fbnction, 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 fbnction 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 $f_{\bar{k}_{rs}}^{rs}(n)$ 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 $f_k^{rs}(n)$.

$$f_{\bar{k}_{rs}}^{rs}(n+1) = q_{rs} - \sum_{\substack{k \in K_{rs} \\ k \neq \bar{k}_{rs}}} f_k^{rs}(n+1), \quad \forall\ \bar{k}_{rs}, r \in R, s \in S \tag{2.6}$$

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

$$\min \ \tilde{Z}(\tilde{f}) \tag{2.7}$$

$$\text{subject to } f_k^{rs} \geq 0, \quad \forall\, \boldsymbol{k} \in K_{rs}, \boldsymbol{k} \neq \bar{k}_{rs}, \boldsymbol{r} \in \boldsymbol{R}, \boldsymbol{s} \in S \tag{2.8}$$

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.

$$\frac{\partial \tilde{Z}}{\partial f_k^{rs}} = \frac{\partial Z}{\partial f_k^{rs}} - \frac{\partial Z}{\partial f_{\bar{k}_{rs}}^{rs}}, \quad \forall\, k \in K_{rs}, k \neq \bar{k}_{rs}, r \in R, s \in S \tag{2.9}$$

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.

$$\frac{\partial Z}{\partial f_k^{rs}} = \sum_{a \in A} t_a(x_a)\, \delta_{ka}^{rs} \tag{2.10}$$

$$\frac{\partial Z}{\partial f_{\bar{k}_{rs}}^{rs}} = \sum_{a \in A} t_a(x_a)\, \delta_{\bar{k}_{rs}a}^{rs} \tag{2.11}$$

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

$$\frac{\partial^2 \tilde{Z}}{(\partial f_k^{rs})^2} = \sum_{a \in A} t'_a(x_a)\, (\delta_{ka}^{rs} - \delta_{\bar{k}_{rs}a}^{rs})^2, \quad \forall\, k \in K_{rs}, k \neq \bar{k}_{rs}, r \in R, s \in S$$
(2.12)

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 $\boldsymbol{k}$ 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 $\boldsymbol{k}$ 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

$$f_k^{rs}(n+1) = \max\{0, f_k^{rs}(n) - \frac{\alpha(n)}{s_k^{rs}(n)}[d_k^{rs}(n) - d_{\bar{k}_{rs}}^{rs}(n)]\}, \forall\ k \in K_{rs}, k \neq \bar{k}_{rs}^{n}, r \in R, s \in S \qquad (2.13)$$

where α(n) is a scalar stepsize modifier which may be chosen by different methods. A 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 $x_a(n), \forall\ a$ 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 (n) is a scalar step size modifier, usually $(n) = \alpha = 1$ 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 $x_a(n+1), \quad \forall\ a$.
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 ($\alpha(n) = a$, for all iteration n). It can be shown that given any starting set of path flows there exists an

$\bar{a} > 0$ such that if $a \in (0, \bar{\alpha}]$ 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:

$$E = \max_{rs} \sum_{\substack{k \in K_{rs} \\ k \neq \bar{k}_{rs}}} \frac{f_k^{rs}(n)}{q_{rs}} \left(\frac{d_k^{rs}(n) - d_{\bar{k}_{rs}}^{rs}(n)}{d_k^{rs}(n)} \right) \tag{2.14}$$

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 42.3136. 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-once[1] flow update while GP updates the flow pattern one-OD-at-a-time[2]. Our results show that GP converges several orders of magnitude faster than FW.

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[1]The 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.

[2]The 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.

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.

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 fbnction, $t = t_0(1 + 0.15\,(x/c)^4)$, 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 Static 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, "KATELLA 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 compliance may be needed. In this case the corresponding message can be "ANAHEIM STADIUM / ALTERNATIVE ROUTE AVAILABLE / EXIT BALL OR KATELLA," while stronger words should be used for higher compliance. However, more empirical studies will be needed to control compliance rate. Processing CMS message requires manual work with some intelligence in the beginning. Once alternative routes are identified, then the CMS messages are stored in message library so that they can be used in need.

CMS routing is based on prepared message sets, and so messages need to be pre-defined. Routing will be between these CMS alternative paths and routes are defined from feasible path sets in the network. Feasible path sets connecting a CMS to target destinations can be prefixed. A CMS message is composed of four arguments as follows.

Destination Designation Argument (Optional)

Sub-Path Argument

Action / Description Argument

Cause Argument (Optional)

Two arguments, such as Sub-Path and Action/Description, are essential components of a message, while Destination Designator and Cause are optional components. Let's consider a full message, "ARROWHEAD POND / USE BALL / KATELLA CONGESTED / DUE TO ACCIDNET." The first argument specifies the destination, and the last argument explains cause of the delay. The second and third terms include Sub-Path are Action/Description information. BALL and KATELLA would be regarded as Sub-Path arguments, and USE and CONGESTED are Action / Description arguments to recommend whether to take or to avoid the route.

Path information is the most common argument in any message, so message searching is done by path information. Every CMS message C_m has a prefixed sub-path set P_c associated with it. P_c is defined as

$$P_c = \{p_c(1), p_c(2), \ldots\ldots, p_c(k), \ldots\ldots p_c(j)\}$$

where, P_c = Sub-path set associated with CMS c
$p_c(k)$ = Sub-path associated with CMS c
c = Identification number for a CMS
$\boldsymbol{k}$ = Identification number of sub-path associated with the CMS message m

Each sub-path $p_c(k)$ is a set of nodes (n1, n2, ..., etc.) or links in the network. Each sub-path $p_c(k)$ normally has a literal name, such as "I-405" associated with a message, for the final translation purpose. Note that the same name of street can refer to different sub-paths for different messages if these messages apply to different CMS locations. At the same location, one literal name translates to one specific sub-path.

Action/Description arguments by sub-path can be selected based on network optimization results. In order to generalize CMS messages the argument explaining traffic information or suggestion can be interpreted as a format of value of information through the perception model which will be discussed later. For instance, a message, "CONGESTION ***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.

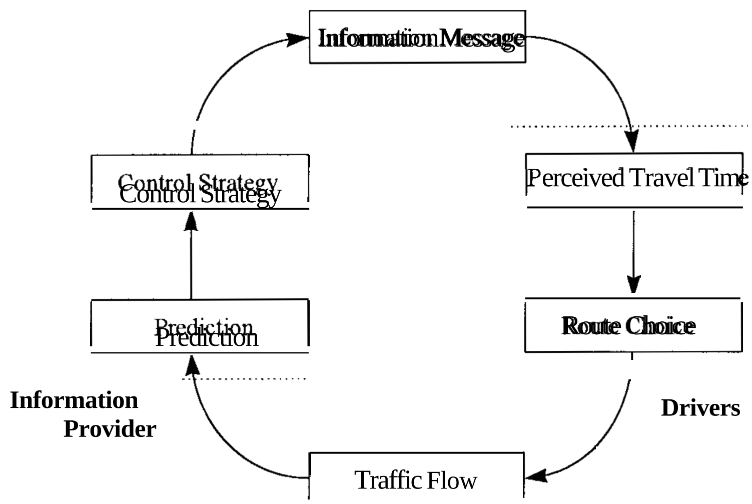


Figure 2.3 Interaction between Information Provider and Drivers

There are two decision variables in this game. One is a set of path flows 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 times 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,

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

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 he 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 Optimizationfor CMS Routing and Message Generation

While considering on-line implementation of the informatiodguidance 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, the problem is solved by evaluation of sub-paths represented by CMS messages since a CMS message cannot deliver all paths' information. 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 satisfling 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. ***An*** 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 is heavy traffic heading to the event place. Six sub-paths associated with the CMS are selected to examine.

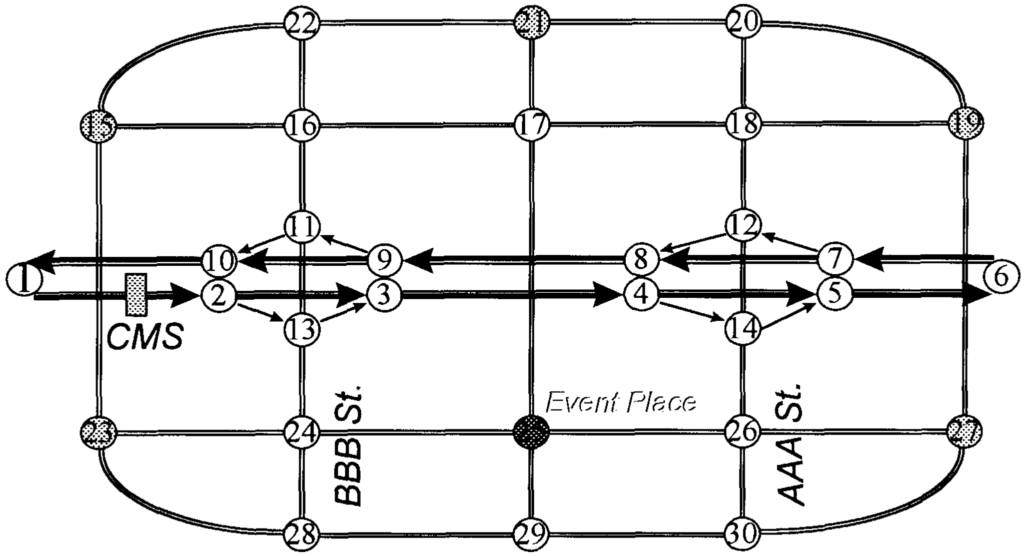


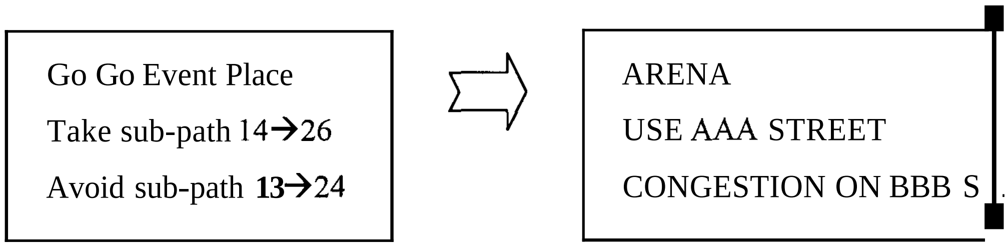
Figure 2.4 Test Network

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 the optimized results into a CMS message. **As** shown in Figure 2.5, 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 actioddescription argument and a sub-path argument. The actioddescription 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.



Result of Optimization CMS message

Figure 2.5 Translation of Optimized Results into CMS message

2.4 Dynamic CMS Routing

Even though the static optimization solution in previous section can be applied to the generation of CMS message during a time period, it cannot respond to the changes in traffic condition unless it is repeated within a short time period. To meet need of ATIS, the message should be dynamically changed every time interval. Dynamic information or dynamic network optimization solution can be obtained from dynamic traffic assignment (DTA). **As** addressed in section **2.1.3,** DTA can be classified into two groups: analytical model and simulation-based model while analytical models can be classified into several categories. In this study, a simulation-based approach is used for dynamic CMS routing.

This study uses DYNASMART (Dynamic Network Assignment Simulation Model for Advanced Road Telematics) as a dynamic assignment-simulation tool. Using DYNASMART capability, dynamic CMS routing schemes are developed. The method is based on the optimal message selection approach. That is, an optimal message is chosen out of a set of prepared messages. We adopt user optimal principle as a CMS routing objective, and seek dynamic optimal routing schemes for both instantaneous and predictive cases.

2.4.1 Simulation Tool 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 informatiodcontrol, (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. DYNAMSART 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 changeable message signs (CMS) 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 used can specify the intervals at which paths are updated at the Traffic Operation Center (TOC)

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 routes 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.

2.4.2 Dynamic Optimal Route Guidance

Route guidance systems can be classified into several classes in terms of their algorithmic structures. Their algorithmic structures are decided by adopting one of types from each of three categories such as:

- user optimal vs. system optimal
- instantaneous vs. predictive
- open-loop vs. closed-loop system

The first category is based on objective applied, user optimal principle or system optimal principle. The difference between these two objectives has been controversially discussed and experimented in many studies. A controversial argument is whether the system optimal objective can be used in route guidance since the routes produced from the system objective are not best from users' point of view. This brings a compliance issue that seems to be one of important factors for the success of ATIS.

The second category is whether or not to predict. In general, the predictive algorithms, if accurate, are known to perform better than instantaneous algorithms. In dynamic system, the dynamics traffic assignment (DTA) is regarded as a tool predicting future network condition. In a narrow sense, DTA is a way of assigning vehicles onto network under time variant system, as oppose to the conventional static assignment. However, DTA often means a traffic estimation and prediction system to meet the information needs of the various ITS subsystems. DTA in a broad sense consists of several components, such as (1) network monitoring systems, (2) route choice behavioral models, **(3)** traffic flow models, and (4) traffic information and control systems. The network monitoring systems include not only measuring network condition but also estimating O/D demand. Pure part of DTA is the capability of predicting future network conditions, which includes modeling route choice behavior (demand side) and traffic flow modeling (supply sides). While demand side models find path flow patterns, supply side models move vehicles link to link. Prediction systems for both demand and supply side respond to traffic information and control systems. Traffic information and control systems are inputs affecting vehicles' movement; however, they could also be products of DTA to be applied to real world obtained from DTA's estimation or prediction. Success of the predictive algorithms is dependent on accuracy of all these components. If one of them fails maintaining admissible level of accuracy, the algorithms might show too poor performance to use.

The third category is whether or not to adopt closed-loop feedback system. The opposite meaning of the closed-loop system is the open-loop system. The closed-loop feedback control system feeds gaps between prediction and observation back into the system, as opposed to the open-loop system. There is strong need of using closed-loop feedback system in dynamic systems where various disturbances exist like dynamic traffk control systems. There are also different types of feedback control systems depending on the ways of regulating control variable associated with disturbances, such as bang-bang system, proportional (P) feedback, proportional-integral (PI) feedback, and proportional-integral-derivative (PID) feedback. Despite presence of different types of feedback algorithms, only the bang-bang system can be applied to CMS routing since it is not possible to split traffic into certain rates via CMS.

When the second and third categories are considered, three optimal routing approaches exist as follows.

- Simple feedback approach: instantaneous travel time based feedback system
- Predictive approach: predicted travel time based open-loop system

Predictive feedback approach: predicted travel time based feedback system

Simple Feedback Amroach

The simple feedback approach seeks optimal routes based on instantaneous travel time at every instant. The control interval is dependent on capability of data processing. Main drawback of the system is that the optimal routes may not be real optimal when reviewed after trip. However, this approach does not require any other input other than link travel times. Measurement errors in network monitoring system are the only source of disturbance. Other disturbances including drivers' compliance rate are reflected to network condition. Also this approach can be applied independently without conflict with others where multiple CMS' exist. That is, advantage of this approach is not only simple and easy to implement but also robustness in application.

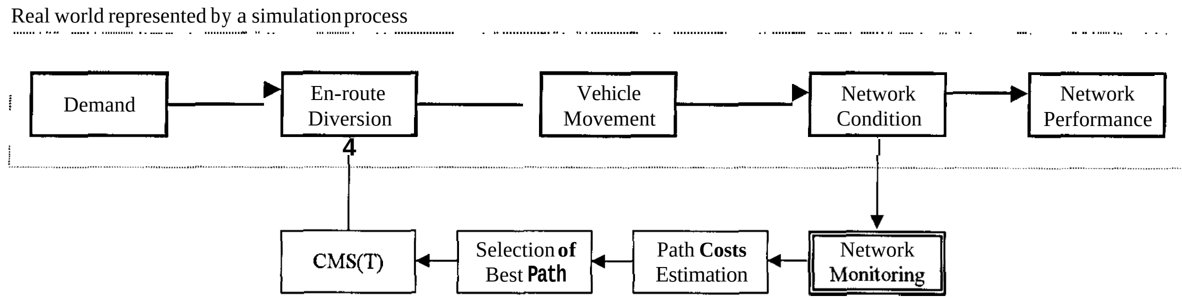


Figure 2.6 *Simple Feedback Approach*

As shown in Figure. The simple feedback approach seeks an instantaneous user optimal CMS message at the instant out of predefined messages. When multiple target destinations exist, the CMS message giving highest benefit is chose. If multiple target destinations exist and there are paths dominantly used under non-incident situation, define these paths as primary paths for the selection of most beneficial path under the multiple target destination cases. This approach reflects a decentralized feedback loop control scheme without need of prediction. The approach responds to real measurements so as to equalize costs of alternative routes. **A** heuristic algorithm of the approach is as follows:

Step 1. Construct a sub-network associated with the CMS.
Step *2.* Define target destinations associated with the CMS. Construct a set of paths connecting **CMS** to target destinations. Define primary paths associated with their target destination if exist.
Step 3. Estimate path costs by summing instantaneous link travel times at the instant.
Step 4. If there is only one target destination, select the minimum cost path as an optimal and go to Step 6. Otherwise, find the first bast path and the second best among paths with a same target destination. If the first best path is not a primary path, the second best has to be best one out of primary paths.
Step *5.* Calculate travel time difference between the first base path and the second best.

Step 6. Find a target destination whose travel time difference is greatest, and select the minimum cost path associated with the destination as an optimal.

Step 7. Display a message associated with the optimal path. Go to step 3 for next time step

Predictive Approach

The predictive approach is to optimize the network under the assumption of full knowledge. Unlike instantaneous feedback approach, this approach provides real user optimal paths. In this approach there is no feed back routine, so that this approach is classified as an open-loop system that relies on perfect prediction capability. This approach assumes that all prediction components are perfect. In fact, any imperfection of the approach may worsen the system. In reality, there exist errors in every components, such as O/D demand prediction, route choice model, compliance prediction, are network flow model. Therefore, this approach is hard to be applied in real-life that is full of stochastic nature though this approach is attractive from theoretical point of view.

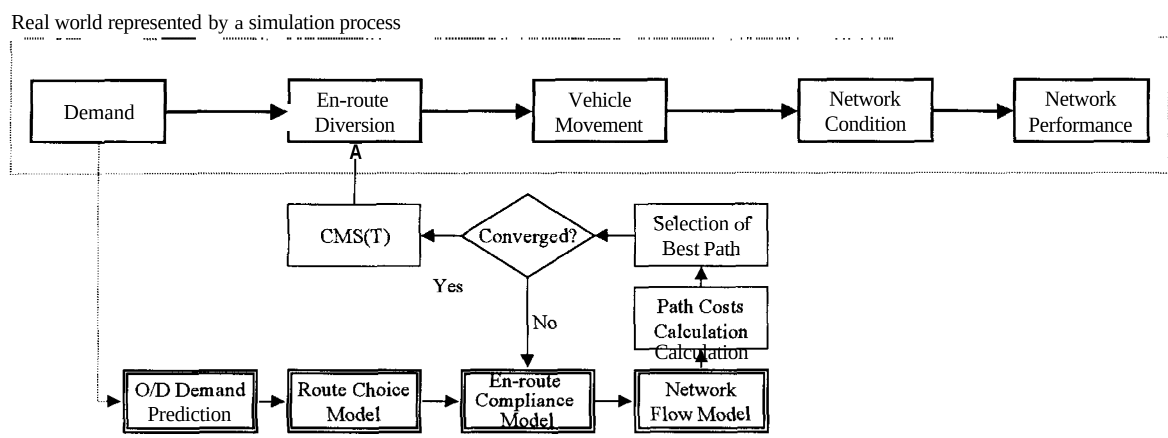


Figure 2.7 *Predictive Approach*

This approach is usually used for off-line cases like most analytical DTA models. For the on-line application of the approach, a rolling horizon framework has been proposed (Peeta *et al.*, 1995). The solution of the approach is obtained through an iterative method. Control variables are CMS messages in optimal CMS routing. The algorithm iterates until a set of optimal CMS messages is found. The set of CMS messages is a sequence of CMS messages over time. While a discrete DTA seeks a fraction of path flow for a given origin-destination pair during the discrete time interval, this algorithm seeks an optimal path for a given origin-destination pair as a representation of CMS message for the time interval (or a CMS phase). Real optimal would be a split between multiple paths for a CMS phase, but it cannot be achieved with CMS. That is, the CMS routing problem is an integer problem and ineffectiveness is unavoidable. However, such ineffectiveness is not a problem when messages are updated with very small time interval because the need is reflected immediately. The ineffectiveness exists only when time step is long to accommodate the need of message change. This is defined as *a time-lag effect* in a discrete system.

In the predictive approach, it should be noted that changes of past events affect state of present and future. Therefore, this approach essentially fixes one solution after another in order of time. That is, total number of iterations would be total number of CMS phases in the worst case when the best message alternates every time step. However, advantages of the approach are that 1) the heuristic guarantees convergence in terms of needs of CMS message change and 2) there is no need to re-run time steps whose CMS were fixed.

This predictive approach can be used for both user optimal and system optimal by applying average cost for user optimal and marginal cost for system optimal. Similarly the proposed heuristic can be used for both cases. In dynamic case, it is almost impossible to find true marginal cost due to time-dependency, so that quasi-marginal costs are calculated and used for marginal cost routing (Peea and Mahmassani, 1995).

The general iterative heuristic algorithm for the predictive approach is as follows:

Step 0. Initialization

Step 0.1 Set iteration number $i = 0$. Run a simulation without CMS information, and then store time dependent link travel times and turn movement delays.

Step 0.2 Find a best CMS message, $M^i_{c,1}$, for CMS c at time step 1 based on the time dependent network costs, and set the fixed time step, $tf_{c,1}$, equals 1.

Step 0.3 Find initial set of CMS messages, $M^i_{c,t}$, for CMS c at time step t based on the assumption that $M^i_{c,t} = M^i_{c,1}$, $\forall c \in C, t \in T$.

Step 1. Simulation

Run a simulation with a set of CMS message, $M^i_{c,t}$, and store time dependent link travel times and turn movement delays

Step 2. Selection of best messages

Calculate experienced path costs and find a new set of best CMS messages, $M^{i+1}_{c,tf}$, for CMS c at time step tf_i, based on link travel times and turn movement delays.

Step 3. Selection of messages

Update new messages, M^{i+1}_{c,tf_i+1}, for time step tf_i+1, and set $M^{i+1}_{c,t} = M^{i+1}_{c,tf_i+1}$, $\forall c \in C, t \in [tf_{c,i}+1, T]$. Find number of time steps, s, lasting same message as M^{i+1}_{c,tf_i+1}, and update new fixed time steps, step $tf_{c,i+1} = tf_{c,i} + s$.

Step 4. Stopping Criteria

Stop if the fixed time step reaches the total number of time steps ($tf_{c,i+1} = T$); otherwise, set $i = i + 1$ and go to step 1.

As noticed, the approach fixes time by time. Therefore, the algorithm can directly applied to real-time case by providing the predicted optimal message for the instant. This is a version of rolling horizon approach in a sense that the message for next time period **is** determined based on the prediction for the time period that the demand for next time arrives at the target destination. The algorithm for the rolling horizon version of predictive approach is as follows:

Step 1. Do a simulation for next time period [t, t+Δt] based on the assumption that current CMS message lasts during the period, and store time dependent network costs.

Step 2. Calculate CMS path costs based on predicted time dependent network costs.

Step 3. Select the best CMS message associated with the best path.

Step 4. Display the message for At and go to Step 1.

The method is a valid when At is short to maintain optimal condition; however, a set of multiple messages for At is needed if At is too long to keep optimal condition. For this case, a set of message can be found by using the regular predictive algorithm instead of step2 and **3** in the rolling horizon approach.

Predictive Feedback Amroach

The predictive feedback approach is similar to the rolling horizon version of predictive approach in the sense that it seeks an optimal solution for demand during a time interval via iterative method. However, unlike the predictive approach, this predictive feedback approach optimizes parameters of each model components. This approach brings a lot of issues with respect to on-line model calibration and interaction between model components. Main issue of the approach is how to reflect stochastic nature of the system into the prediction model. Some model parameters may need on-line adjustment while some of them can be adjusted later. Difficulty of the adjustments arises from the fact that the observed errors are mixture of each model components' errors. Basically aim of the approach is to minimize the gap between simulation model and real world.

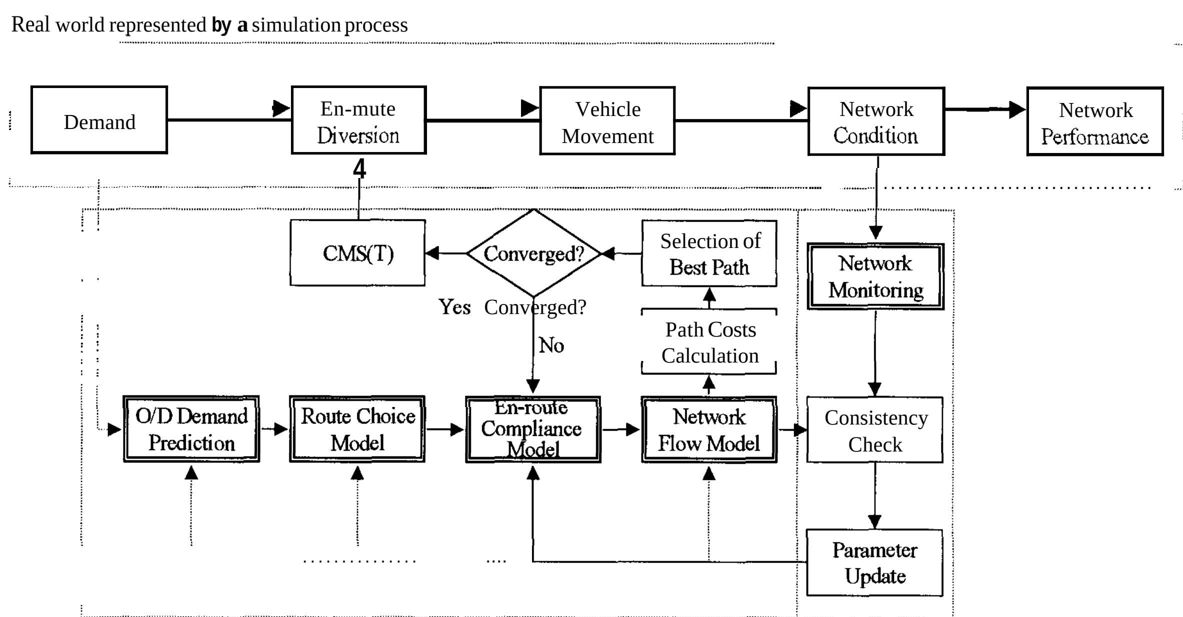


Figure 2.8 *Predictive Feedback Approach*

Based on the assumption that the traffic flow model embedded in the simulation model is considerably accurate, three demand side issues, such as *O D* demand, path flow, and en-route compliance behavior, are remaining tasks. *O D* demand or path flow pattern can be estimated based on observed traffic variables on network, which must be one of the hardest problems in DTA implementation. Associated with CMS routing, there is another disturbance factor, driver's compliance behavior. Compliance rates are usually assumed to be known in predictive approach; however, admittedly there could be large gaps between the assumed compliance rates and actual observed ones. These disturbances need to be adjusted because of two reasons. They are (1) to maintain simulation variables consistent with the real observed ones, *(2)* to minimize prediction error occurring due to compliance assumption. These need to done for the real-world application of predictive approach. However, the routine checking consistency and updating model parameters are out of this research scope to be further studied.

2.4.3 Examples of Dynamic Optimal CMS Routing

This section shows examples of dynamic optimal CMS routing. Two different routing approaches, a simple feedback approach and a predictive approach, are tested, and four different update intervals, such as 0.1, 1, and 3 minute, are used in order to examine time lag effects in dynamic route guidance. 0.1 minute update system is included to find theoretical optimal condition rather than a practical point of view. In this example, a 100% compliance rate is assumed.

A test network used in this section is same as one used for static optimized CMS routing. Heavy event demand is assumed as before. Three alternatives are predefined as shown in Figure 2.9. The first path is a primary route most often used while the second and third paths are alternatives to avoid congestion either on free exit or main entrance of event place.

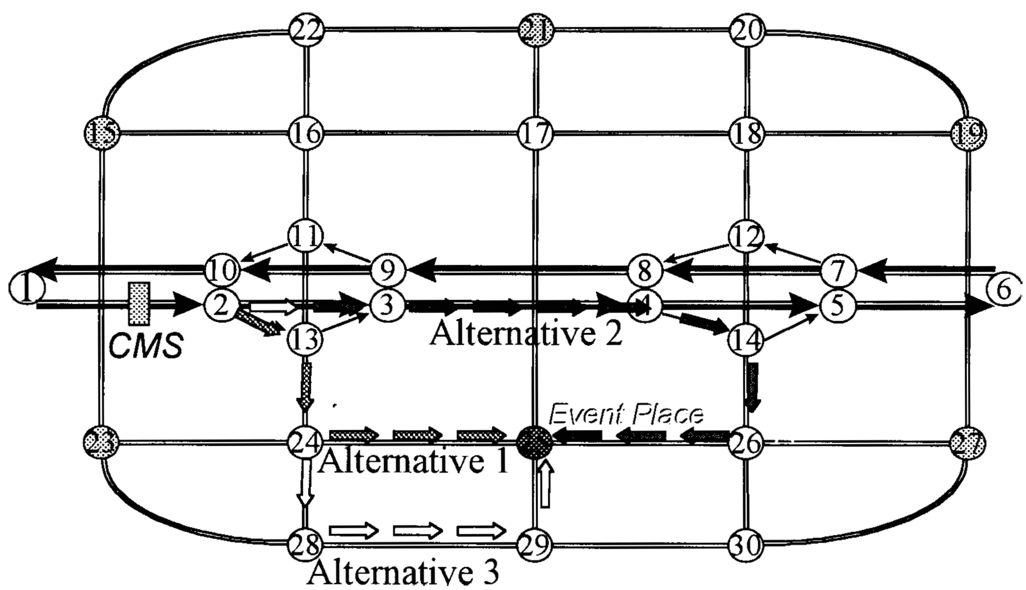
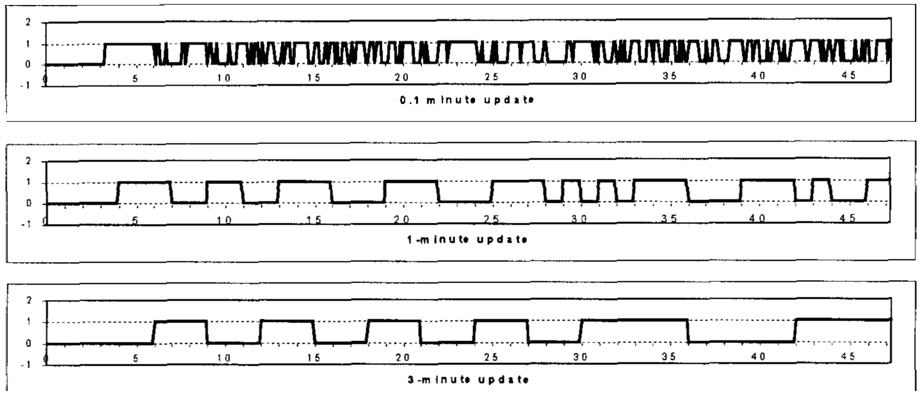
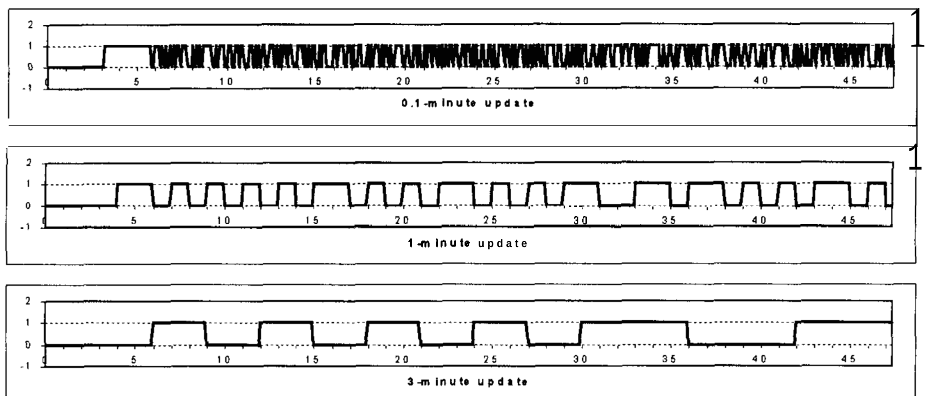


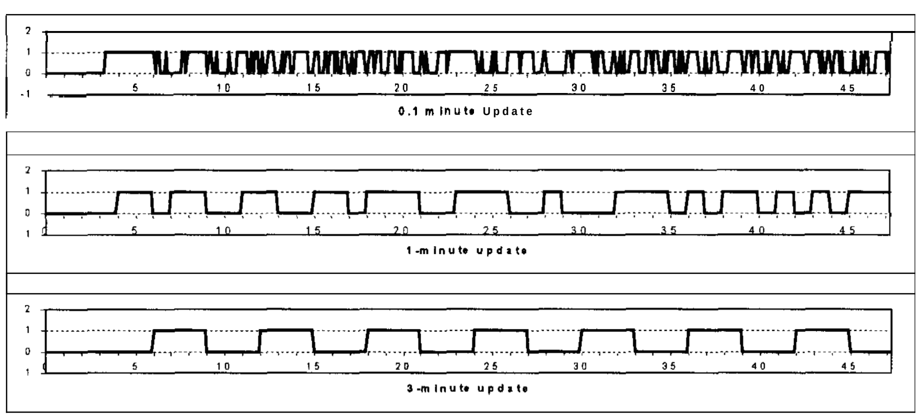
Figure 2.9 *Test Network and Alternative*



(a) Feedback Approach



(b) Predictive – Average Cost Routing



(c) Predictive – Marginal Cost Routing

Figure 2.10 Dynamic Optimal CMS Guidance Scheme

* 0 indicates alternative **1, 1** indicates alternative 2

The dynamic optimal route guidance for CMS has found using algorithms addressed in previous section. Even though three alternatives are considered in the CMS, only alternative one and two are used. Hence, the CMS guidance is a bang-bang system in terms of control strategy. Since a 100% compliance rate is assumed, the optimal route tends to alternate every short time interval. The shorter update interval is used, the more often the optimal route switches. The dynamic optimal route guidance for the CMS is shown in Figure 2.10. The optimal guidance solutions found from the feedback approach shows similar pattern as ones from predictive approach. It may be because the distance from CMS to target destination is not long enough to show difference between approaches.

Distinct performance difference was revealed with respect to update time interval as shown in Table 2.4. Expectedly, CMS routing with shorter update interval performed better. It is because of time-lag effect induced from inability of optimal guidance during the time interval. The case of 0.1-minute update was selected as a benchmark. Compared other cases with the benchmark case, average time costs increase by 5 – 12%.

In the feedback approach, optimal routes are selected based on instantaneous travel time at the instant while the predictive approach is based on experienced travel time. Therefore, the optimal routes found from the feedback approach do not necessarily optimal when the routes are evaluated after trip. As shown in Table 2.4, the predictive approach with average cost routing performed better in general. However, there is little difference between two approaches in the case of long update time interval like 3-minute update. That is because advantage was lessened due to time lag-effect. It should be noted that the time lag-effect here might be exaggerated due to short length from CMS to destination. In the larger network case, it is expected that the benefit would be even greater for the predictive approach.

We also test a marginal cost routing as a predictive approach. However, performance is not better than that of average cost routing due to lack of ability in calculating true marginal costs in the dynamic system and in reflecting marginal cost effects in the heuristic approach.

Table 2.4 ***Performance Comparison of Dynamic CMS Routing***

Approach	Indices	Update Interval (minute)		
		0.1	1.0	3.0
Feedback	Avg. Cost (Event Traffic), min	6.89 (1.00)	7.35 (1.07)	8.07 (1.17)
	Avg. System Cost, min	6.57 (1.00)	6.92 (1.05)	7.23 (1.10)
Predictive (average cost routing)	Avg. Cost (Event Traffic), min	6.54 (1.00)	7.52 (1.15)	8.07 (1.23)
	Avg. System Cost, min	6.47 (1.00)	6.77 (1.05)	7.23 (1.12)
Predictive (marginal cost routing)	Avg. Cost (Event Traffic), min	6.93 (1.00)	7.60 (1.09)	8.07 (1.16)
	Avg. System Cost, min	6.69 (1.00)	6.75 (1.01)	7.23 (1.08)

* Values in ( ) indicate relative values with respect to the case of 0.1 update interval

In predictive approach, an iterative method is used, so here we compare convergence performance with respect to update interval. In order to evaluate convergence, a value representing level of equilibrium between alternatives is used as a measure of effectiveness. The equilibration index value is calculated as follows.

$$Z = \frac{\sum_t \sum_a (tt_{a,t} - tt_{o,t})^2}{T} \qquad \forall\, a \in A,\ t \in T$$

where A = a set of alternatives associated with a CMS
T = total number of time steps
$tt_{a,t}$ = travel time of alternative a at time step t
$tt_{o,t}$ = travel time of optimal route at time step t

As shown in Table 2.5, a shorter update interval requires more number of iteration. To reach a converged solution, the 0.1-minute update requires almost 20 times iterations than 3-minute update because it considers 30 times more detail in terms of time step use. When the shorter time interval is applied, the larger and more frequent oscillations are observed during early iteration as shown in Figure 2.11. However, the case with shorter update interval results in much better equilibrium state. The equilibration index for predictive average cost routing with 3-minute update shows more than 6 times higher than that of 0.1- minute update.

Table 2.5 ***Convergence Comparison***

Approach	Indices	Update Interval (minute)		
		0.1	1.0	3.0
Feedback	Equilibration Index Value* (relative value)**	1.58 (1.00)	3.84 (2.43)	7.10 (4.49)
Predictive (average cost routing)	Number of Iterations (Total simulation time steps)***	249 (474)	37 (486)	13 (507)
	Equilibration Index Value (relative value)**	1.13 (1.00)	2.94 (2.60)	7.10 (6.28)
Predictive (marginal cost routing)	Number of Iterations (Total simulation time steps)	209 (473)	26 (501)	15 (502)
	Equilibration Index Value (relative value)**	2.66 (1.00)	4.44 (1.67)	11.25 (4.23)

* A 0.1 minute of time interval is used for the calculation of equilibrium index value.
** Values in ( ) indicate relative values with respect to the case of 0.1 update interval.
*** Total number of simulation time steps required to clean total demand.

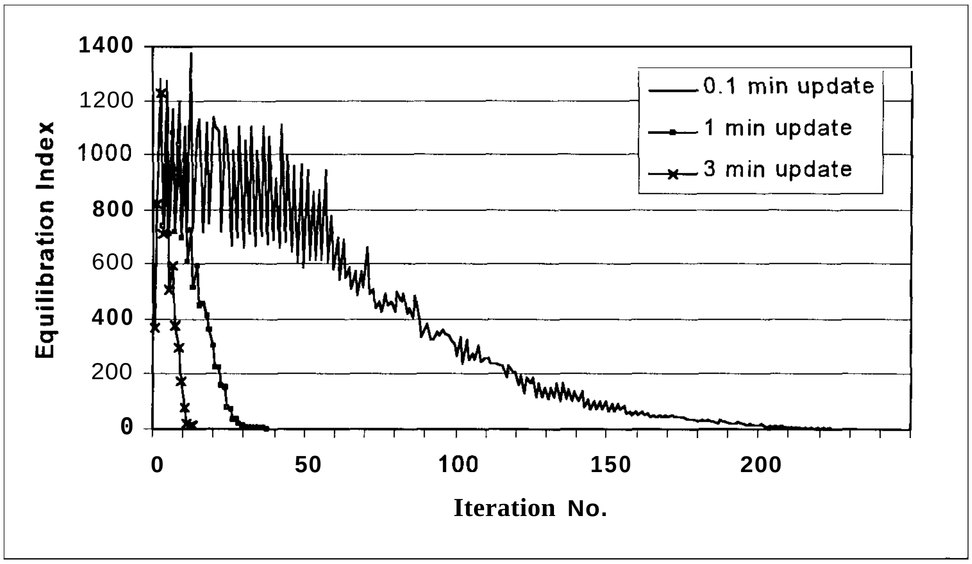


Figure 2.11 *Convergence of Predictive Model*

2.5 Summary and Conclusion

In this chapter, various optimized **CMS** routing approaches have been introduced. We have been discussed on limitation of each approach and other factors affecting performance of routing scheme, such as time-lag effect and predictability. Performance comparison of these methods has also been provided.

The first method, a static path-based network optimization technique, is a fastest and simplest approach to be applied for event traffic management. Static assignment models are theoretically robust and stable; however, they are unrealistic for short-term analysis since they cannot capture traffic dynamics. In case of scheduled events where overall traffic condition including O-D demand could be predicted to some extend, the static optimized solution could be applied, at least as an early stage of **CMS** application, though it cannot reflect traffic variations induced from stochastic nature of traffic demand and network flow.

Dynamic optimal routings have great benefit compared to static routing. Especially for the incident traffic management, the feedback approach is an effective way to improve traffic condition by directly reflecting traffic dynamics into traffic rerouting strategies. However, the feedback approach relies on instantaneous traffic information that is not necessarily optimal when reviewed after trip. That is, this approach may result in misleading drivers in some cases especially when there are drastic changes in traffic condition in near future. Therefore, this approach would be an effect way for short-trip traffic management where only minor changes in traffic condition is expected while traveling on the area.

The predictive approach must be attractive in the sense that the route guidance reflects future traffic condition. This chapter has shown two different objective routings, an average cost routing and a marginal cost routing. The average cost routing aims at accomplishing user optimal network condition, while the marginal cost routing aims at system optimum. However, there is limitation in achieving the true system optimal with the heuristic approach introduced here. It is because of lack of ability in calculating true marginal costs in dynamic system and in reflecting marginal cost effects in proposed heuristic approach. More research is needed to apply the system optimal routing.

An issue of this approach is predictability of the network condition. Even though this approach is expected to give greatest benefit theoretically, this approach may cause an absurd situation when applied with inaccurate prediction. That is, power of the prediction model is the core of the approach. One way of powering the predictability is to incorporate the feedback approach into the predictive approach. The predictive feedback approach is based on on-line prediction models that updates previous prediction errors and parameters for next prediction. Overall framework of the approach has been addressed, but detailed algorithms and applications are out of this study scope.

CHAPTER 3: MODELING OF DRIVER'S COMPLIANCE BEHAVIOR

The candidate CMS messages need to be evaluated within the simulation framework prior to real-world implementation. The evaluation framework is based on a traffic assignment-simulation model, 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 informatiodcontrol system configurations for urban traffic networks with Advanced Traffic Management and Information Systems (ATMIS). For the completion of the evaluation simulation model, a tool analyzing driver's compliance behavior model needs to be incorporated. This chapter investigates driver's response to information, and a model framework is introduced.

3.1 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:

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

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 $\hat{T}^{\tau u}_{mjk(u)}$ and $\hat{T}^{\tau u}_{mjk(u)^*}$ 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)
Familiaritv 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				

3.2 Modeling Approach

3.2.1 Two Step 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.

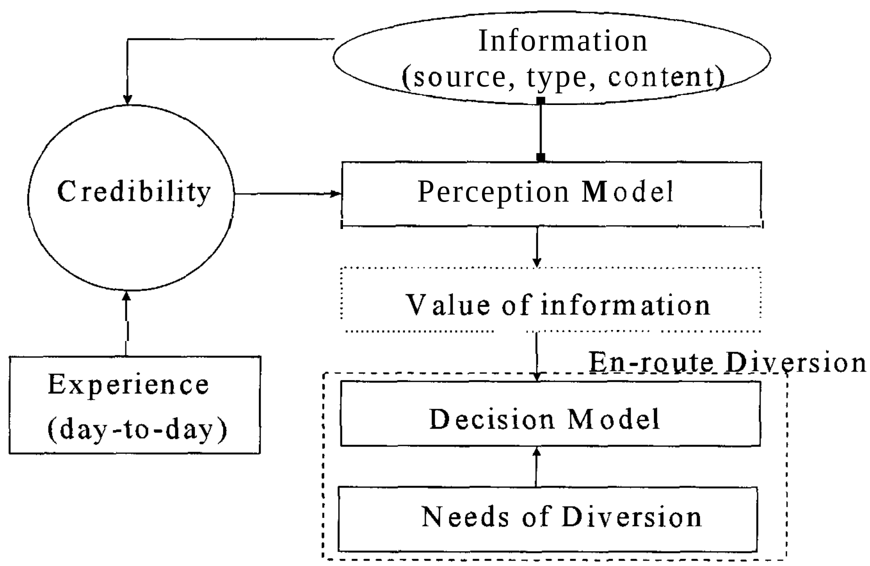


Figure 3.1 A General Structure of En-route Diversion Model

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 update approach is necessary because reliability is a product from past experience. Questions on reliability will be discussed more with the other issue, such as 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, what is the relative value of delay with respect to the travel time if the value of travel time information is 1.0? 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.

The second part, the decision model, is more general. This model also may have two-step effects: one is driver's needs of diversion (for instance, level of congestion on current route), and the other is the perceived relative value of current route or alternative route. In order to reflect the drivers' heterogeneity in the model, each driver's characteristic can be incorporated, such as socio-demographic information characteristics and network knowledge. 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.

This research is intended to construct overall framework for information design and ATIS evaluation. Even though models need to be calibrated and validated for real application, developing a model framework itself is also meaningful. Furthermore, data acquisition is not possible currently because such ATIS infrastructure is not available yet.

3.2.2 Reliability Issue in Behavior Modeling

Credibility of information in driver's mind is a product learned from the process of experience and post evaluation of information. Drivers will have better experience from reliable information, which results in better evaluation. From the evaluation, they will accumulate their credibility on the system. That is, reliability of information is an important factor directly affects driver's compliance behavior. There are many factors affecting to reliability of information devices. Most of them result from the capability of information devices, such as accuracy of traffic monitoring system, capability of relaying information timely, future prediction capability, etc. Besides them, there is another factor associated with system manager's objective.

While the capability of information devices can be easily understood, the routing object involves somewhat complicated nature. System managers want to optimize the total system; however, it is questionable if the system optimality can be obtained through the ATIS. It is because the objective to minimize the total system cost is not necessarily same as drivers' objective. ATIS is regarded as a soft control tool from a traffic manager's point of view due to the lack of enforcement. That is, the routing objective is another factor influencing driver's credibility. These credibility factors are accumulated from long-term experience. In modeler's perspective, such credibility can be investigated via day-to-day update approach as shown Figure **3.X.** Issues on routing policy and day-to-day dynamics of driver's credibility are more investigated in Chapter 5 and Chapter 6.

Following is a simple example of interaction between routing policy and driver's behavior. This example compares user costs and system costs with respect to routing policies.

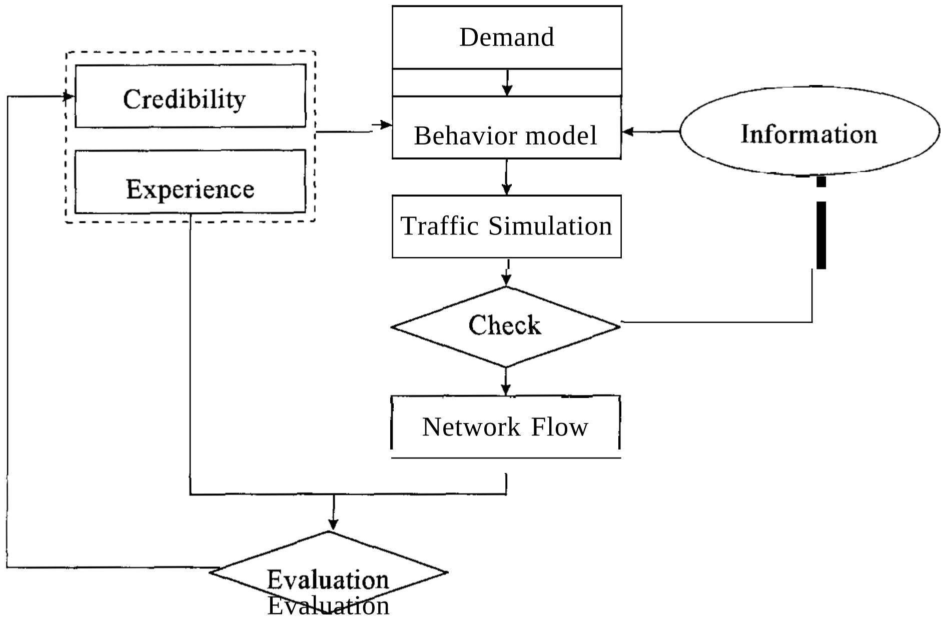


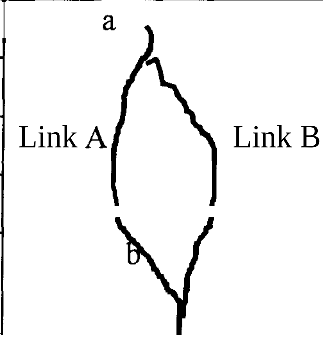
Figure 3.2 Framework for day-to-day credibility update

<u>Simple example in static case</u>

Network condition associated with driver behavior or route guidance strategies 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 based on their perceived travel costs.

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 (a 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 (veh/min)	100		
Link performance function	$t = t0 * \{1 + 0.15\ (V/C)4\}$		
Route choice model	P(i) = U(i) / {U(A) + U(B)}		
Utility function	$U(i) = -0.15 *$ travel time(i)		

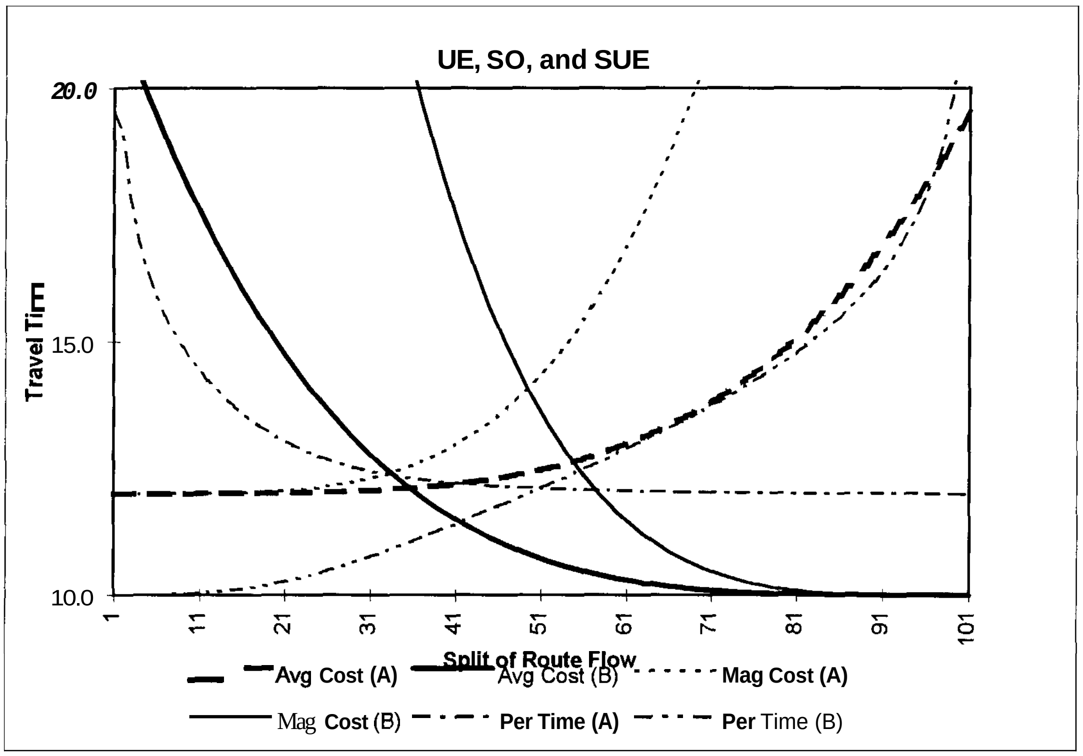


Figure 3.3 ***User Equilibrium, System Optimal, and Stochastic User Equilibrium***

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 3.2 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.

3.3 Model Framework for Driver's En-route Diversion

This section introduces a model framework to capture driver's compliance behavior. The model is based on the conceptual framework addressed previous section. The model includes basic variables affecting driver's decision associated with CMS. The model framework is a logit-type model that assumes Gumbel distibution for the error components. In the model, three different types of variables are taken into consideration as follows:

Driver's knowledge on network

Representing current traffic condition

Inherent value of CMS

In this model, travel times or detailed traffic conditions on alternative routes are not included to avoid modeling additional processes for expected travel times. CMS are considered as devices providing prescriptive route guidance rather than descriptive information. In the sense, drivers make their decisions depending on their evaluation of information source. That is, the evaluation is an inherent factor in driver's mind, affecting their compliance. This inherent variable is a compound of strength of message and reliability. The message, "ACCIDENT AHEAD / HEAVY CONGESTION" will be stronger than the simple message, "DELAY POSSIBLE'. That is, there exists relative strength of message, and the strength is represented by a inherent variable with reliability of information. This inherent factor for the information source for a driver is obtained from the driver's long-term experience. From modeler's point of view, the value can be captured via day-to-day update approach.

There are also other factors affected by driver's characteristics. One of important driver's characteristics associated with en-route diversion behavior is driver's knowledge on network. Many researchers have pointed out this as an important factor affecting driver's en-route decision. That is, drivers familiar with network may switch their route more often than those who are not familiar. Drivers unfamiliar with an area tend to stick on their initial route due to fear of losing their ways. Current traffic condition is also another factor affecting driver's en-route decision. Usually driver's needs to divert increases in heavy traffic condition, especially those who are familiar with the area or those who are late for their schedule. As a representative variable for current traffic condition, a ratio of current speed with respect to free flow speed is used in the model.

Of course, there are more factors affecting driver's en-route decision. The model framework proposed here is a binary logit model, deciding whether or not to divert. The probability that a driver, n, follows the guidance from CMS, c, at the link, a, is expressed as equation (3.1). Table **3.4** shows an example of the model including parameters and possible range of variables. Figure 3.3 shows changes of compliance rates interacting with changes of other variables. The values in the table are an example for demonstration purpose, so the model parameters need to be calibrated for the application of real world.

$$P(n) = \frac{1}{\exp(\alpha + \beta \cdot LOF_n + \gamma \cdot LOC_a + \delta \cdot CMS_c)} \quad (3.1)$$

where, LOF_n = Level of network familiarity for driver n

LOC_a = Level of congestion on link a represented by speed / free speed.

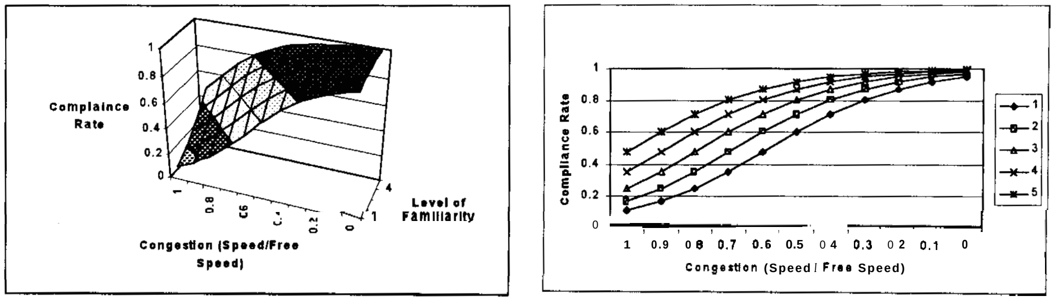
CMS_c = Reliability value for CMS c

Table 3.4 ***Example of En-route Diversion Model for CMS***

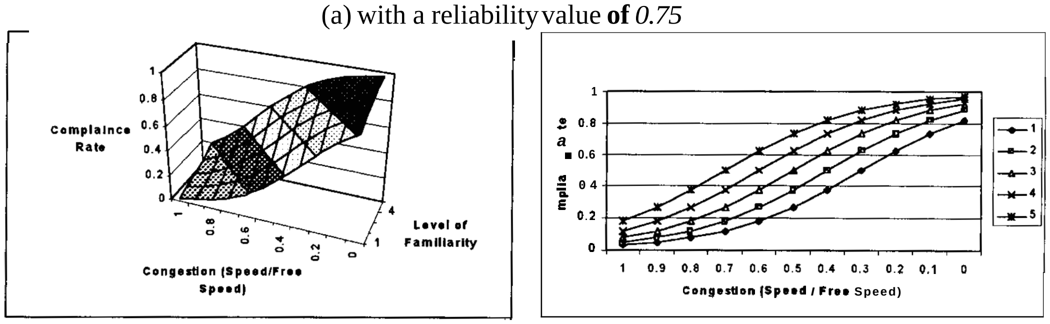
Variables	Constant	Level of Familiarity	Congestion Level	Reliability Value
Parameters	**1.8**	-0.5	5	-5.6
Possible Range of Variable	1	1 - 5	0.0 – 1.0	0.0 – 1.0

3.4 Dynamic Changes in Compliance Model

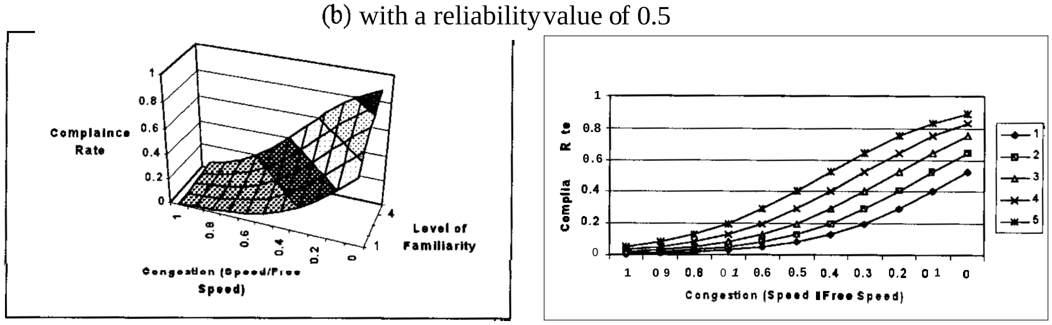
In chapter **2,** various CMS route guidance approaches have been introduced and algorithms were tested based on 100% compliance assumption. This section incorporates the proposed en-route diversion model framework into DYNASMART simulation program. **A** system reliability value of 1.0 is used instead of 100% compliance, so as for the simulation model to reflect dynamic en-route diversion decision. That is, current traffic condition and individual driver's network knowledge are involved in their decision making process as well as information system reliability. Dynamic changes in driver compliance rate are demonstrated in Figure 3.5. The example shows driver's compliance rate with respect to the CMS from guidance predictive model with 1-minut update.



(a) with a reliability value **of** *0.75*



(b) with a reliability value of 0.5



(c) with a reliability value of 0.25

Figure 3.4 ***Driver's Compliance Model***

Numbers in legend box indicate levels of familiarity

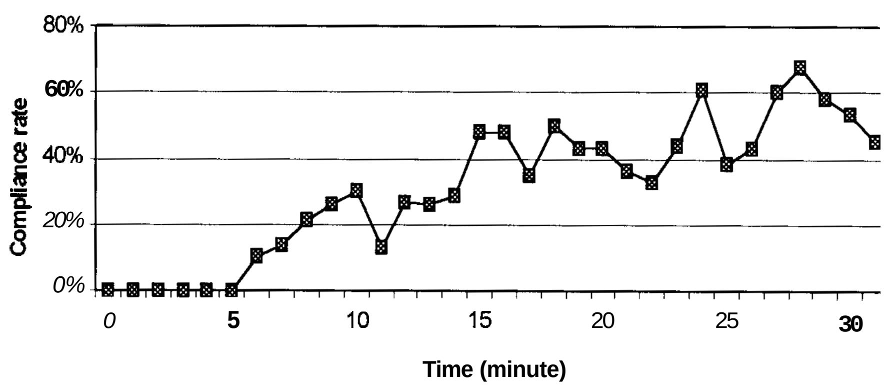


Figure 3.5 ***Dynamic Changes in Driver Compliance Rate***

3.5 Summary and Conclusion

In this chapter a model framework has been introduced for driver's en-route diversion behavior. The model framework includes three factors, such as individual driver's characteristics, driver's needs of diversion, and inherent reliability value of information devices. In order to account for these factors, the model includes three major variables: driver's knowledge on network, current traffic condition, and inherent value of CMS. Impacts of variables to driver's decision has illustrated and discussed. The model here gives better explanation on driver's diversion behavior by reflecting network conditions and driver's characteristics. This study has emphasized on the reliability of information as a major factor influencing driver's decision. More analyses on the reliability issue will be shown in Chapter 5 and Chapter 6. The model proposed here is incorporated into DYNASMART, a simulation program for **ATIS** evaluation.

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. Candidate ATIS strategies, such as CMS and HAR messages, are studied in the Advanced Testbed lab prior to the real implementation, so that a subset of strategies are 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. The field tests mainly focus on availability of data and driver's reaction to the new CMS message. This chapter reports overall field test results and addresses limitation of CMS routing implementation revealed from field tests.

4.1 Site Description

4.1.1 General Description

The site for 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, covering a total land 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 modes of 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 at 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, and 55) are located within a five-mile radius.

There are 6 CMS's on freeways which are used for route guidance 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 signboard guiding to these sport facilities are located along the surface roads connecting from freeways to the facilities.

4.2 Description of First 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 the northbound traffic, and the other for the southbound traffic. Usually CMS messages are displayed from two hours before game start for inbound traffic. Messages currently used are shown in Figure 4.1.

ARROWHEAD POND EXIT KATELLA AVE.	ARROWHEAD POND EXIT BALL ROAD
North Bound 57 at Champman	South Bound 57 at Wagner

Figure 4.1 Current CMS messages for Arrowhead Pond 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 is using Douglas entrance on Katella Avenue via freeway 57, while audience from north area is using 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.

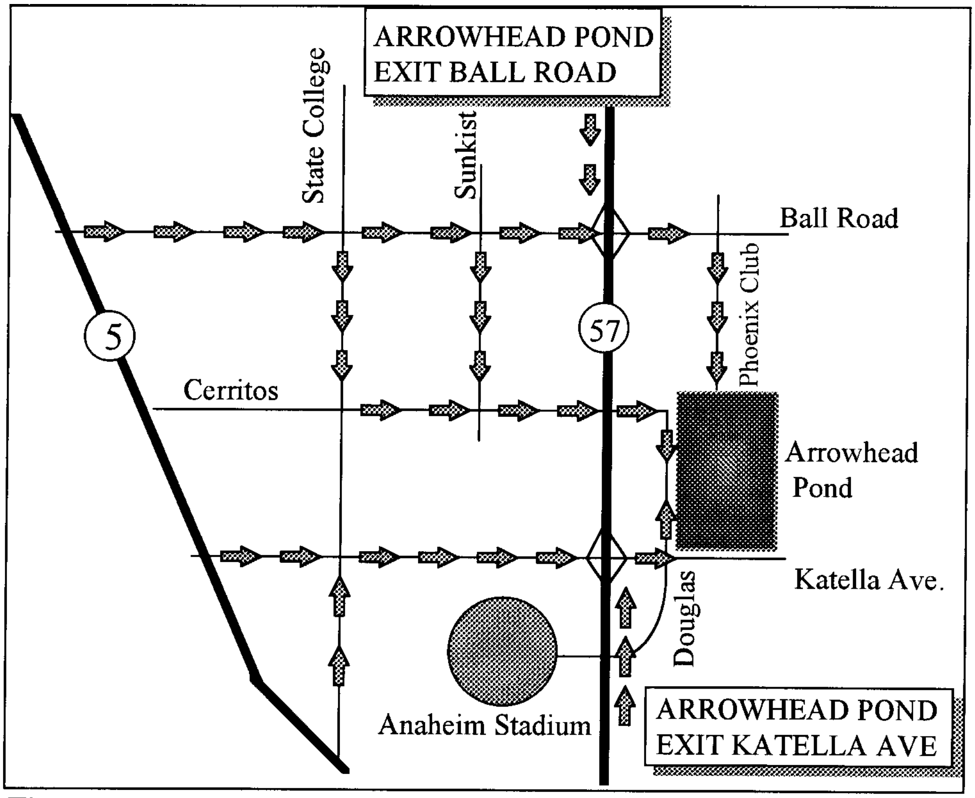


Figure 4.2 ***Current Routing Scheme for Event Traffic***

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.

ARROWHEAD POND EXIT BALL ROAD	ARROWHEAD POND EXIT BALL ROAD
Northbound 57 at Champman	Southbound 57 at Wagner

Figure 4.3 New CMS messagesfor Arrowhead Pond Traffic

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 purpose of the test is to observe driver's compliance behavior and to investigate data collection methods, the new messages were 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.

4.3 Off-line Simulation Study

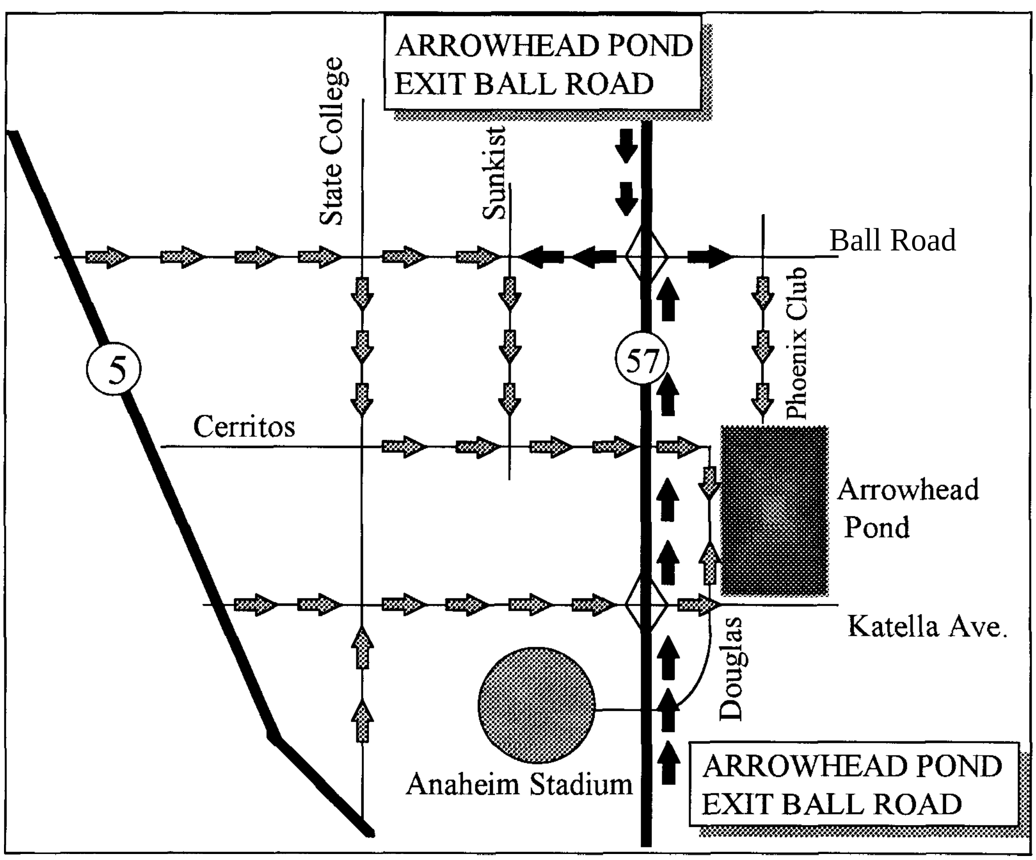


Figure 4.4 New Routing Scheme for Event Traffic

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 zones, 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 Gammar 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.

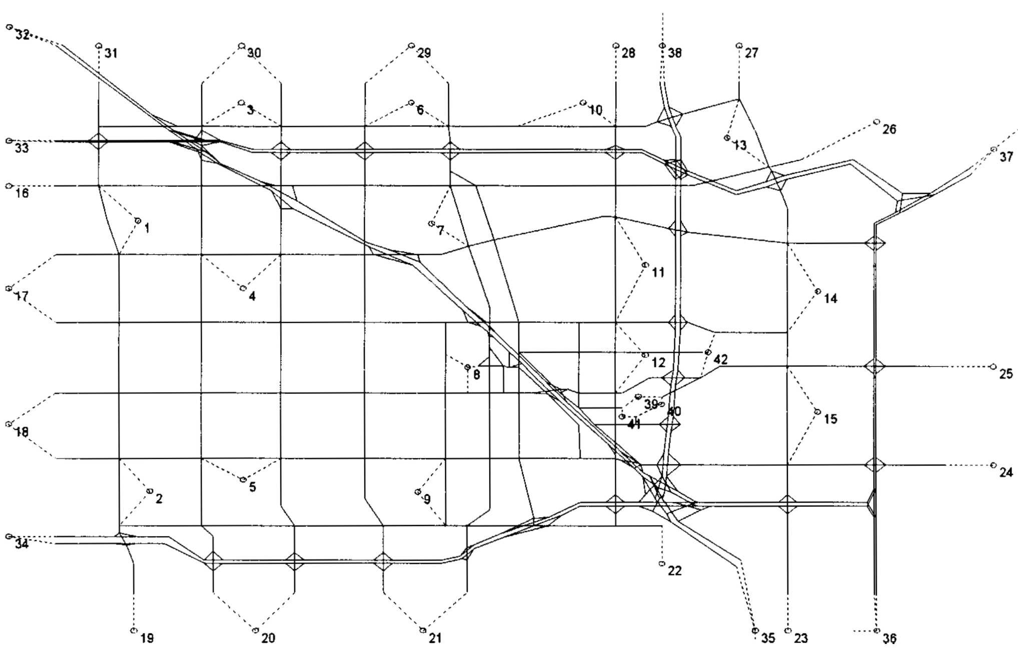


Figure 4.5 Anaheim Transportation Network

4.3.2 Simulation Results

In this study, multiple simulations are performed based on various fixed compliance rates. 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 vehicles tagged for statistics and average travel time per vehicle is 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 loner 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.

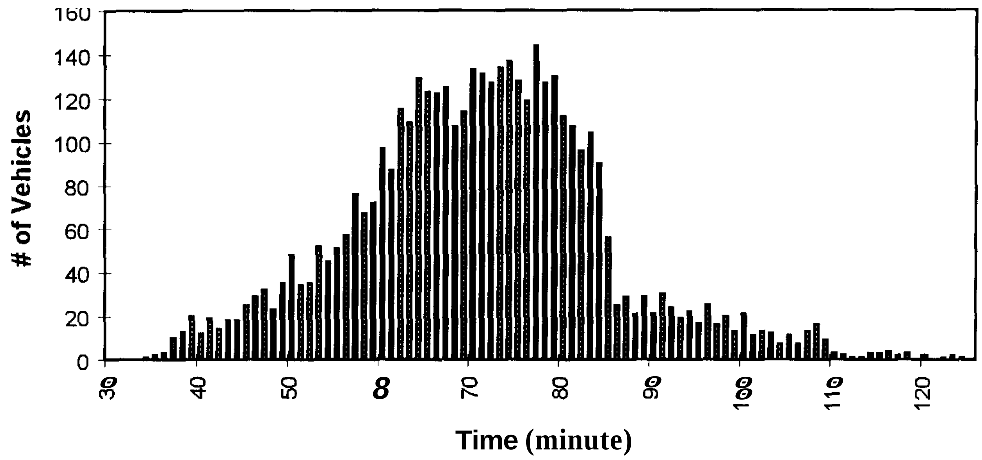
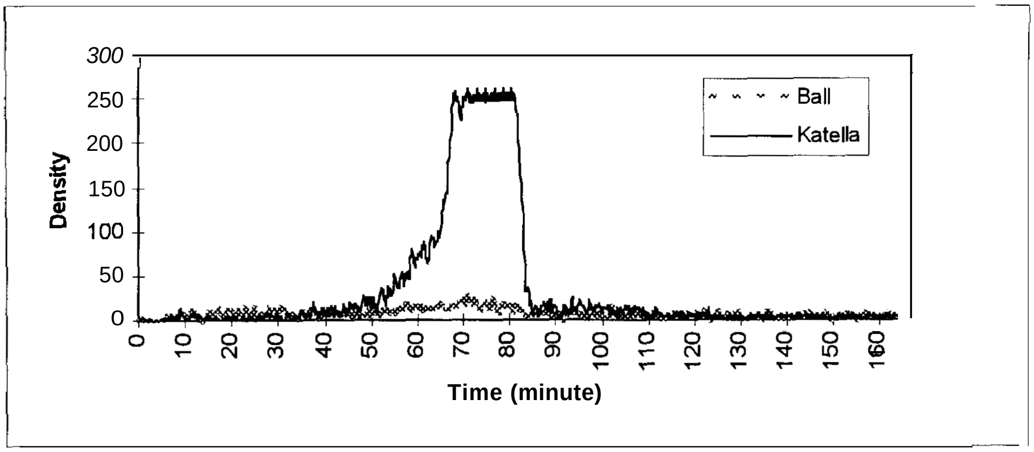


Figure 4.6 Arrival Pattern to the Arena

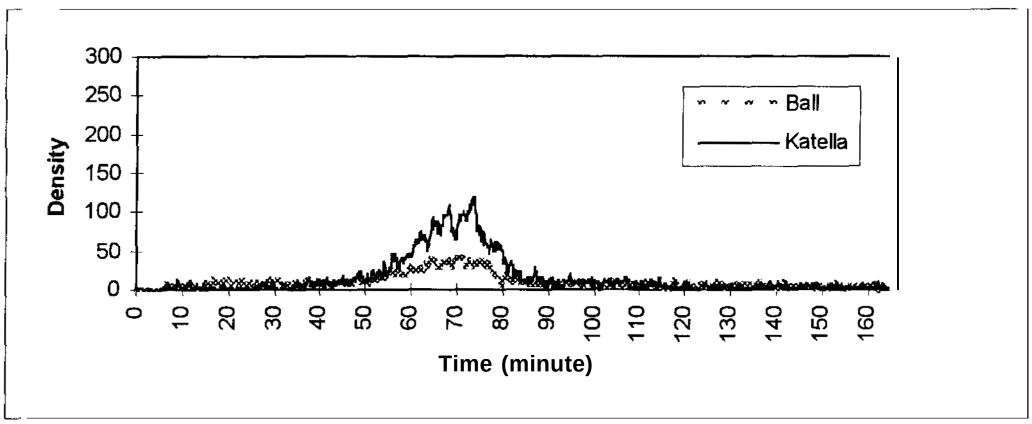
In new CMS routing case, network performance varies depending on the driver's compliance rate to the message. Figure 4.7 shows density changes between two alternative streets guided by the CMS. In case of current information system, Katella Avenue reaches almost jam density while the alternative route, 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 the case of 100% compliance rate, network condition improves and shows satisfactory result for both overall and event traffic case.

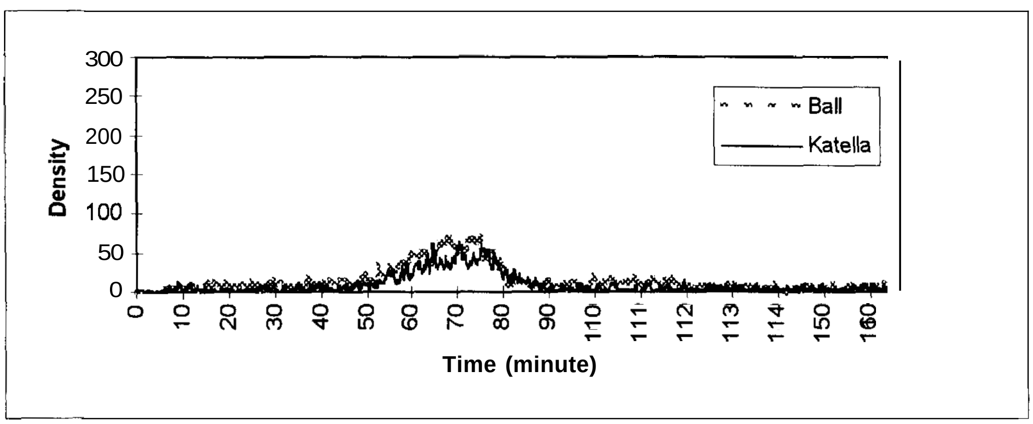
With the assumption of 40% compliance, the simulation results estimate 2% of travel time saving for event traffic although travel distance increases by 2.5% thanks to new CMS routing scheme. For all vehicles, travel time is estimated to decrease by 1%. In this simulation, it is assumed that CMS message is 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, it tells that 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[2]	Event[2]	CMS	Overall	Event
Performance Measure	0[1]	18.153	17.50	4.06	9.5622	7.730
	20	18.088	17.28	3.54	9.5794	7.860
	40	17.965	17.14	3.30	9.5834	7.920
	60	18.002	17.31	3.56	9.6009	8.000
	80	18.024	17.50	4.06	9.5998	8.130
	100	18.026	17.63	4.24	9.5754	8.260
Benefit	20	0.065	0.22	0.52	-0.017	-0.130
	40	0.188	0.26	0.76	-0.021	-0.190
	60	0.151	0.19	0.50	-0.039	-0.270
	80	0.129	0.00	0.00	-0.038	-0.400
	100	0.127	-0.13	-0.18	-0.013	-0.530

0 % compliance case means current information system case.
Overall case includes all vehicles, while event case includes only vehicles arriving at the Arena.

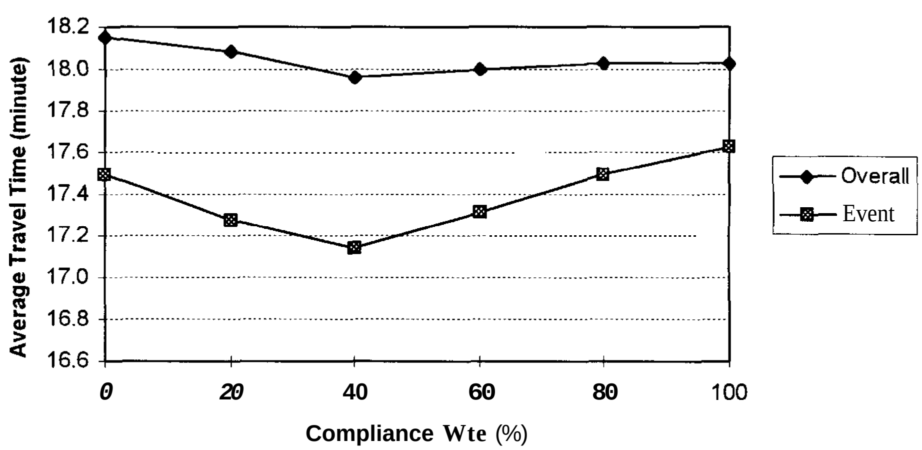


Figure 4.8 Changes in Average Travel Time by Compliance Rate

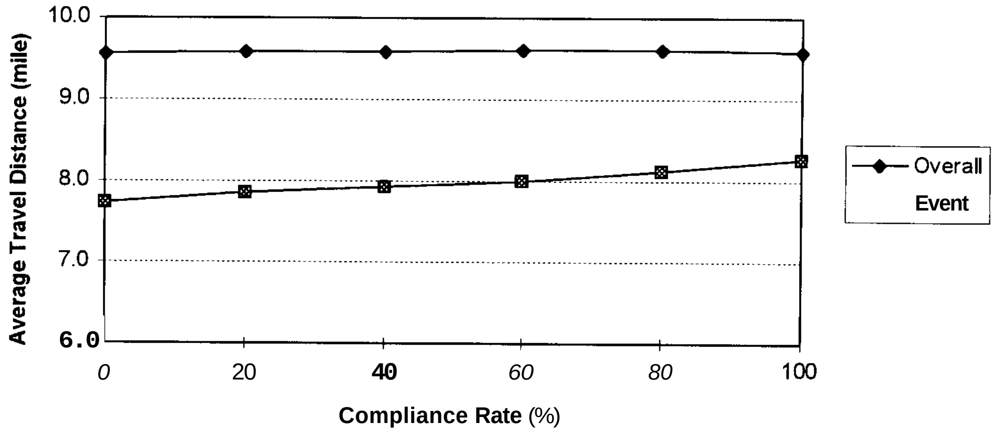


Figure 4.9 Changes in Average Travel Distance by Compliance Rate

Direct benefit of CMS routing is obtained from re-routed event traffic. Expected travel time saving for this traffic varies from -4.4% to **18.7%** depending on compliance assumption as shown in Figure 4.10 and Table **4.3.** In the 100% compliance assumption, negative benefit is expected due to the over-reaction problem. From this analysis, two important factors are revealed. First, compliance rate is the most important factor affecting overall performance of CMS routing. Second, dynamic route guidance is needed not only to achieve better performance but also to prevent overreaction problem.

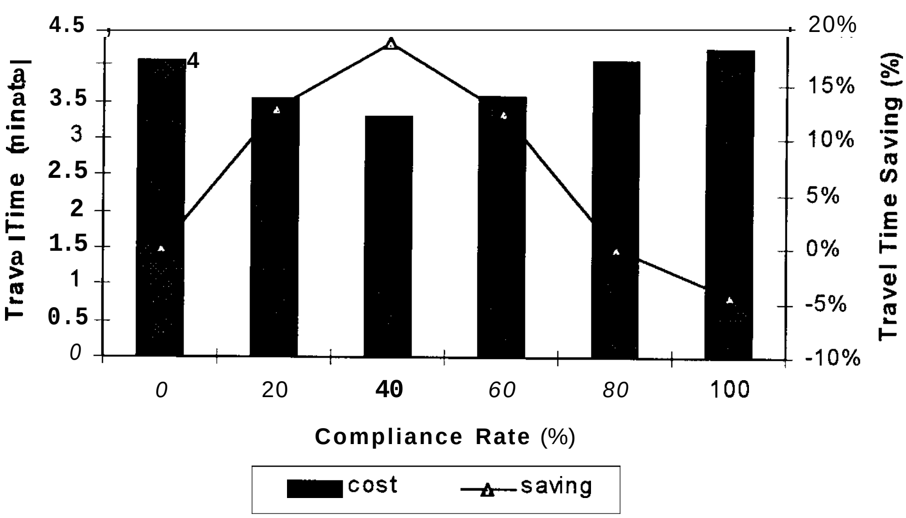


Figure 4.10 Travel Time Saving for the Traffic Guided by CMS

4.4 First Field Test in Anaheim

Three event days 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 database system. Speed data are calculated from the traffic counts and occupancy data based on vehicle length assumption (20ft). Overall traffic volume for after-case was approximately 10% higher than that of before-cases as shown in Figure 4.11.

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.

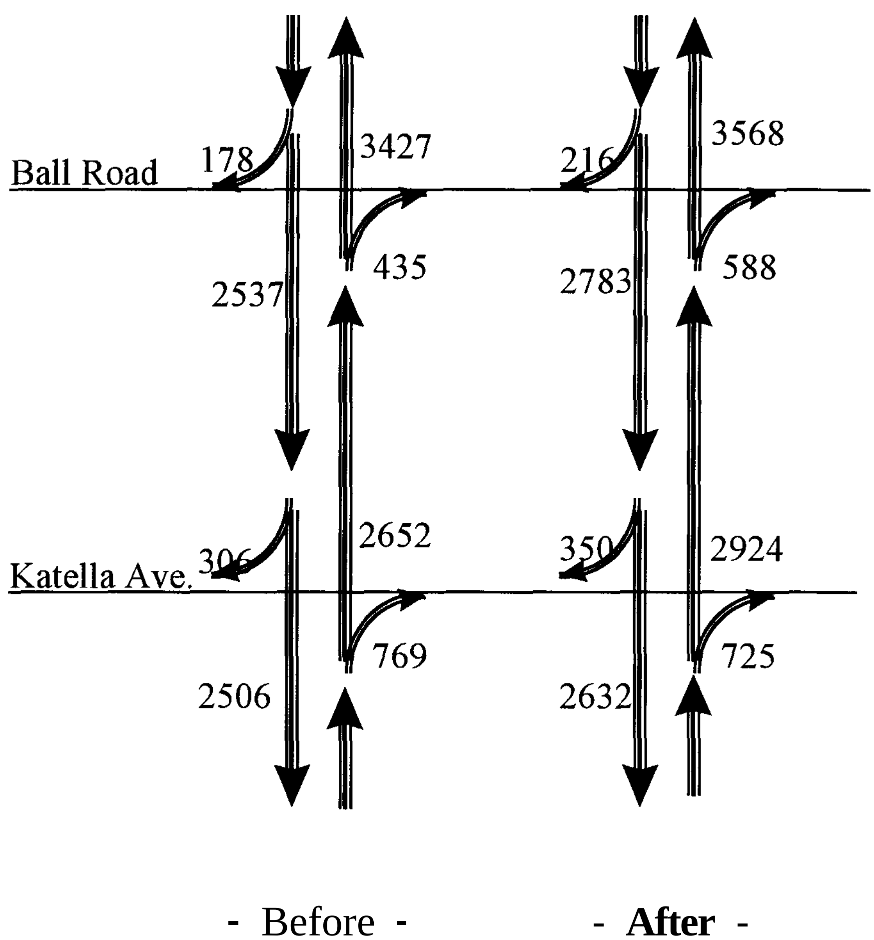


Figure 4.11 Traffic Volume on Freeway 57 During Event Period (19:00-19:30)

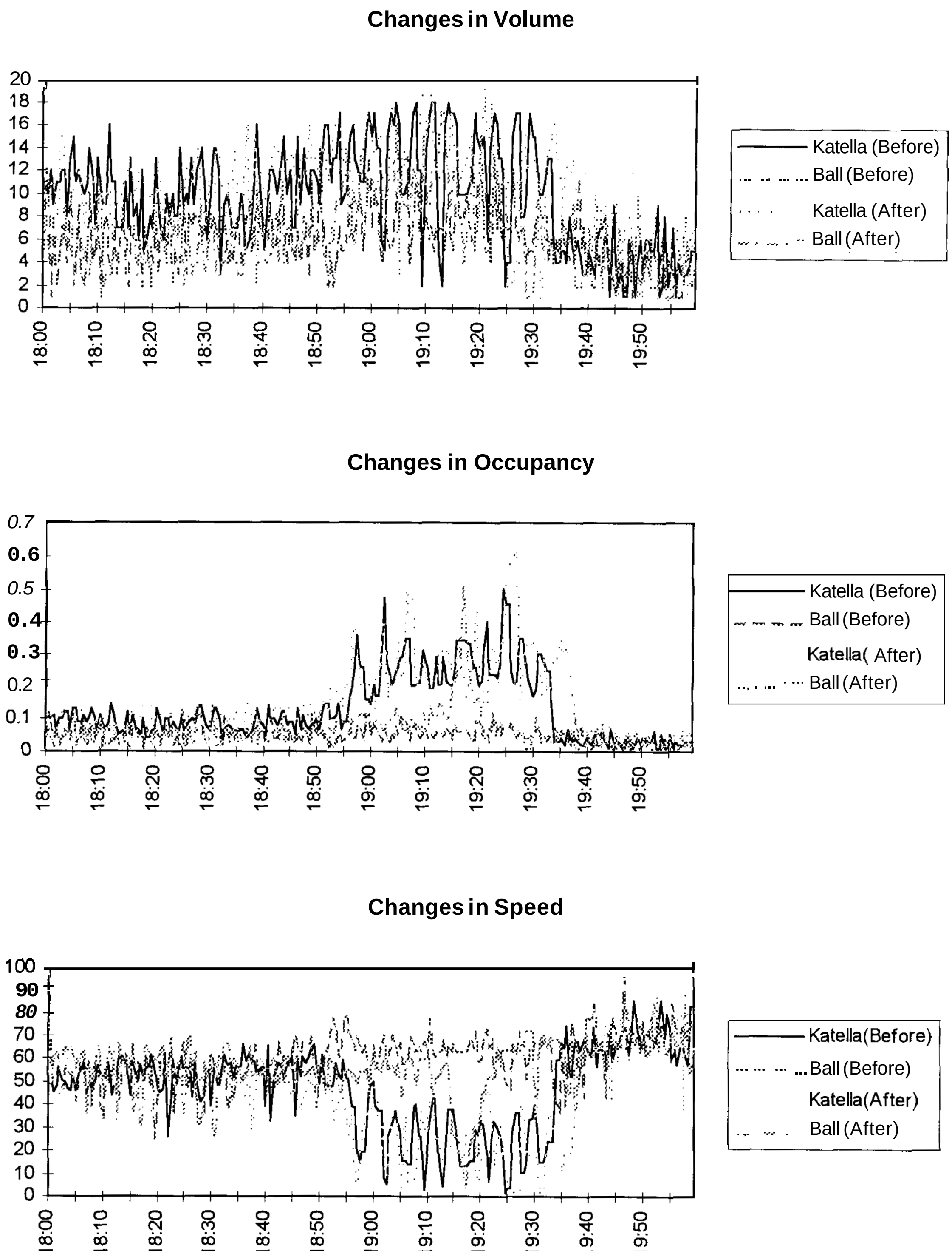


Figure 4.12 Comparison of Traffic Condition at Alternative Exit Ramps

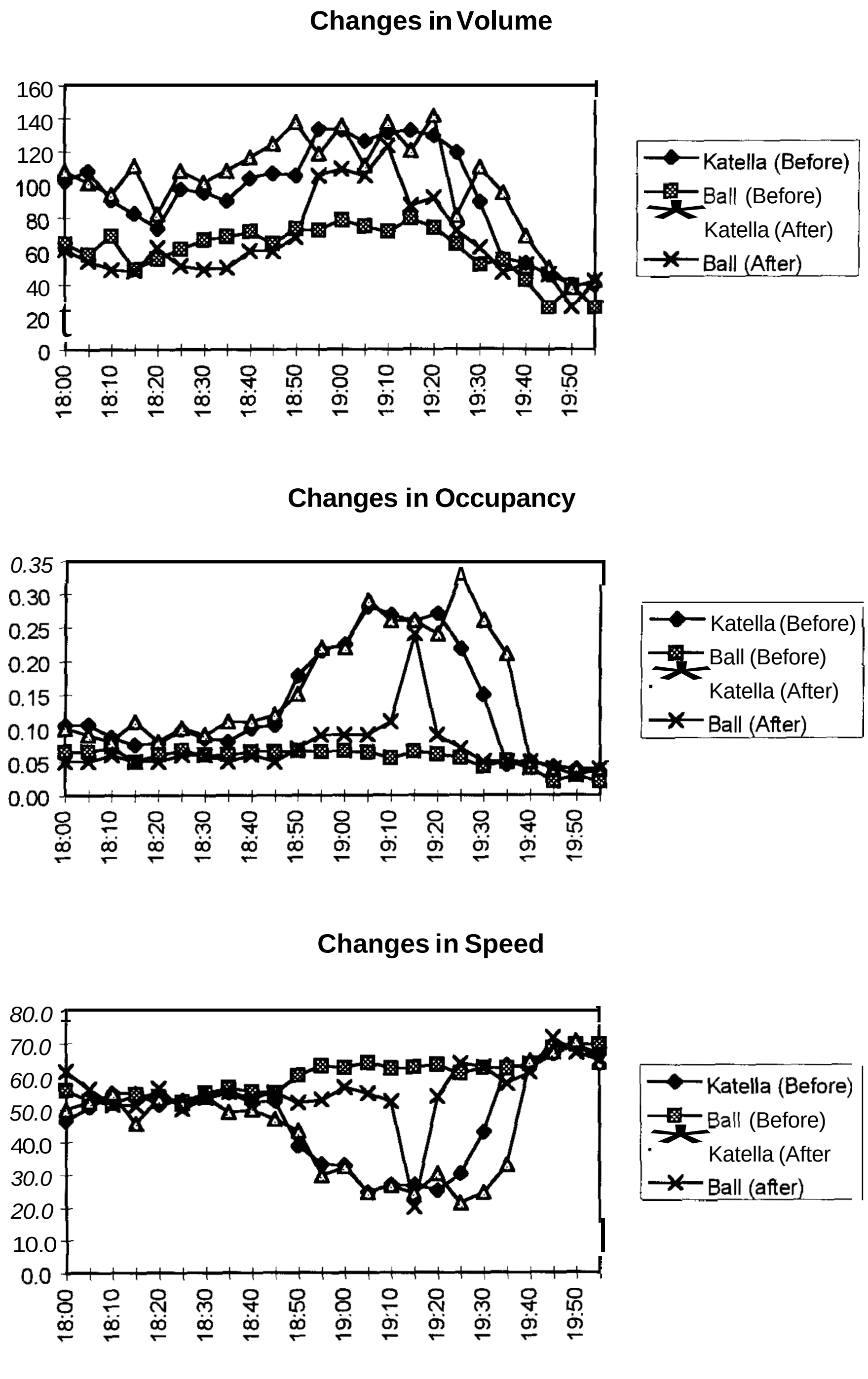


Figure 4.13 Comparison of Aggregated Traffic Condition at Alternative Exit Ramps

Table 4.4 Comparison of Freeway Traffic Condition

Katella → Ball (Main)

Time Interval	Before Vol	Before Occ	Before Speed	After Vol	After Occ	After Speed	Changes(%) Vol	Changes(%) Occ	Changes(%) Speed
18:00 - 18:15	1536	0.29	27.1	1628	0.23	33.4	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 Vol	Before Occ	Before Speed	After Vol	After Occ	After Speed	Changes (“A) Vol	Changes (“A) Occ	Changes (“A) 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 Vol	Before Occ	Before Speed	After Vol	After Occ	After Speed	Changes (“A) Vol	Changes (“A) Occ	Changes (“A) 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	67.0	4.4	13.1	-0.6
Total	2278			2437			7.0		

Exit to Ball (North Bound)

Time Interval	Before Vol	Before Occ	Before Speed	After Vol	After Occ	After Speed	Changes (%) Vol	Changes (%) Occ	Changes (%) 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 Comvarison of Traffic Volume between Alternative Exits

Time	*Total*[1)]	*Exit Katella*					*Exit Ball*				
Interval	Volume	Before	%	After')	%	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	-10	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

Total volume is sum of exit volume both Katella and Ball.
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 4.14 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.

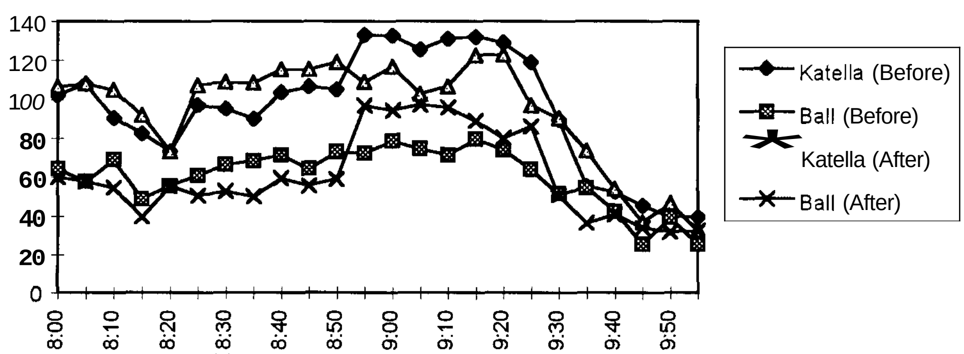


Figure 4.14 Changes in Volume at Alternative Exit Ramps

4.5 Second Field Test

We observed importance of driver compliance from the first field test. The performance of the information system is dependent on the fraction of complied drivers. Therefore, we focus on observing driver's compliance behavior in the second field test. The purpose of the test is to observe driver's response to CMS information as well effects of information.

4.5.1 Description of Event and Routing Scheme

In the second test, the event was held at the Edison International Field (home stadium of Anaheim Angels). The stadium is located next to the Arrowhead Pond Area, event place of the first field test. Total stadium area is 140 acres, and the stadium can accommodate 45,050 people with a parking capacity of 15,000 vehicles. The event on the test day (September 22, 1998) is a baseball game of Anaheim against Texas.

On the event day, all five CMS' around the stadium are turned on for 45 minutes from 6:20 p.m. to 7:05 p.m. Usually two CMS' on freeway *57* were used to guide freeway exits to the stadium indicating the closest exit to the stadium, which have induced left turn movements. Unlike ordinary messages, the new routing scheme aimed to avoid left turns at the intersections. The routing scheme was discussed and decided at the event meeting where related agencies are participating, such as City, Caltrans, police department, and event facility management agencies. CMS messages displayed for the test are shown in Table 4.6, and overall routing scheme for the event traffic is shown in Figure 4.15.

Table 4.6 CMS messages for the 2nd Test

	Location	Message
CMS 1	SR-57 SB at Wagner	EDISON FIELD EXIT ORANGEWOOD
CMS 2	SR-57 **NB** at Chapman	EDISON FIELD EXIT KATELLA
CMS 3	SR-22 WB at Tustin	EDISON FIELD USE FWY 57 N EXIT KATELLA
CMS 4	SR-22 EB at Harbor	EDISON FIELD USE ST. COLLEGE
CMS 5	1-5 **NB** at 17 St.	EDISON FIELD USE FWY 57 N EXIT KATELLA

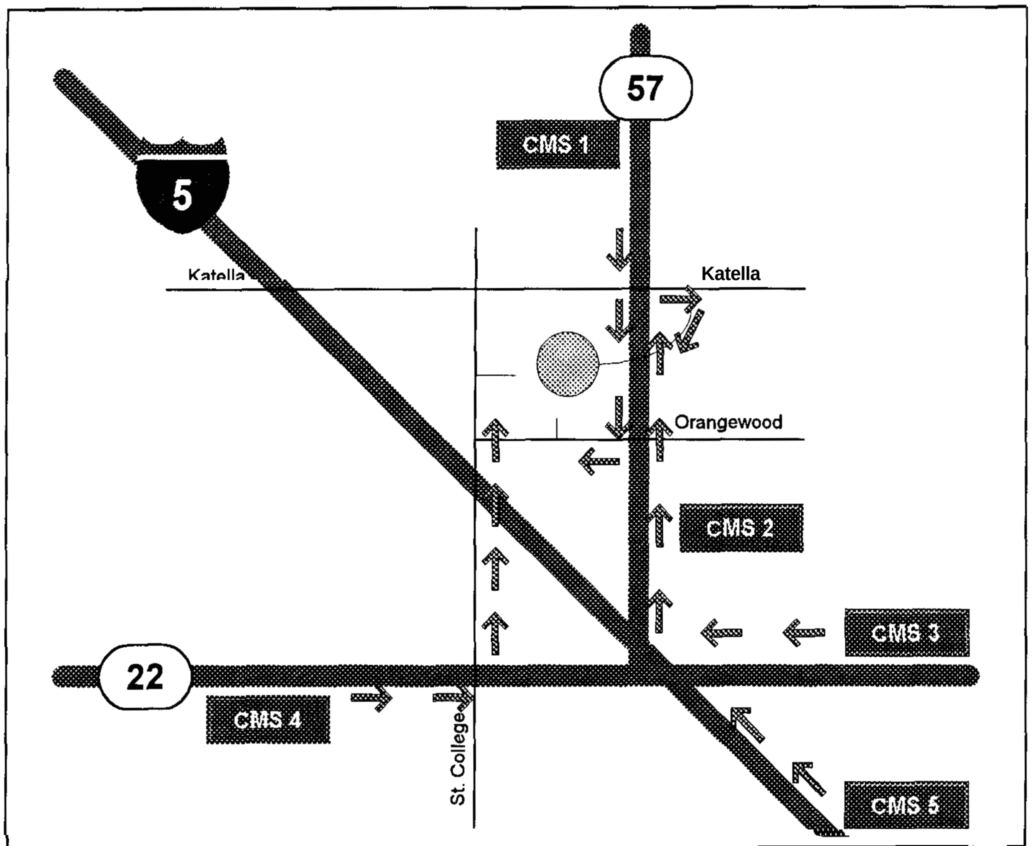


Figure 4.15 *Routing Scheme of the 2nd Test*

4.5.2 Data Collection and Survey Results

In the second test, one of the main purposes is to observe drivers' responses to the CMS. The most direct way to observe drivers' responses is to do a one-to-one interview. We surveyed drivers' responses to the CMS at the entrances of the stadium. Figure 4.16 shows overall procedure of interview.

Figure 4.17 shows distribution of drivers by access roads. According to the survey, more than 50% of attendee use either Orangewood or Katella Exit on SR-57. This tendency for drivers to use closest exit to the destination reveals drivers' freeway use preference. ***An*** interesting observation of the survey is that only half of drivers remember the CMS route guidance information. The survey reveals that a 58% of drivers recognizes presence of **CMS** and an 86 % of drivers remembers the guidance messages out of drivers who recognized the presence of **CMS.** That is, approximately only half of all attendee recognized CMS as a source of traffic information. This implies that CMS re-routing has not been a useful source of information at least from driver's point of view. Though this is a little disappointing number, the rate tends to increase as the event start time closes by. That is, this reveals driver's behavior seeking information and switching their routes in case of heavier congestion.

CMS Field Test Questionnaire

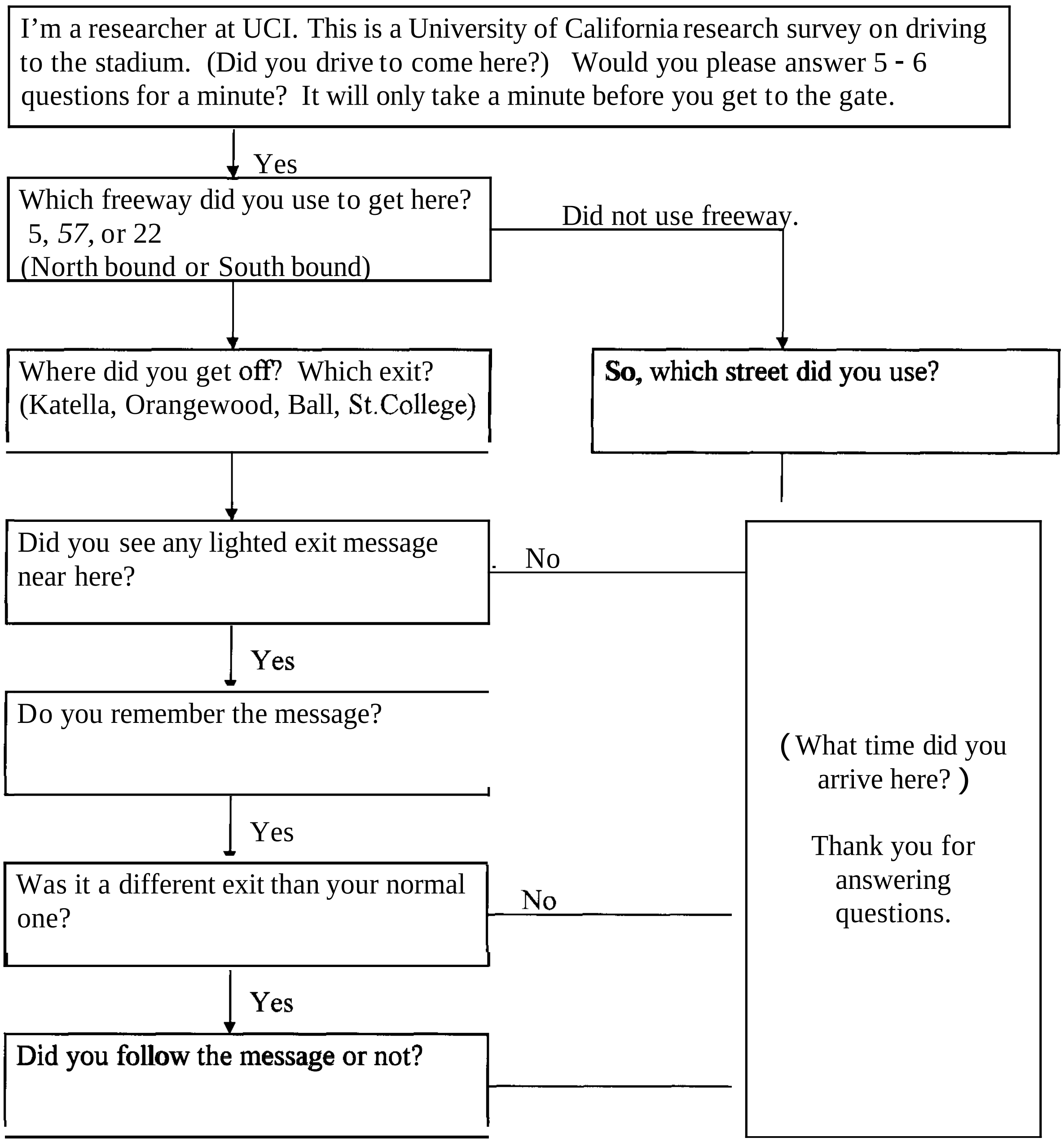


Figure 4.16 ***Field Survey Questionnaire***

Table 4.7 Number of Vehicles by Access Road

	Tot	Katella	Orage	St. Col	Ball	Other
Total	269	101	86	48	19	15
FWY	206	75	75	36	14	6
57	151	64	74	1	9	3
NB	60	14	45	0	1	0
SB	91	50	29	1	8	3
5	38	11	1	19	5	2
NB	9	3	1	5	0	0
SB	29	8	N/A	14	5	2
22	17	N/A	N/A	16	N/A	1
EB	15	N/A	N/A	14	N/A	1
WB	2	N/A	N/A	2	N/A	0
Surface Street	63	26	11	12	5	9

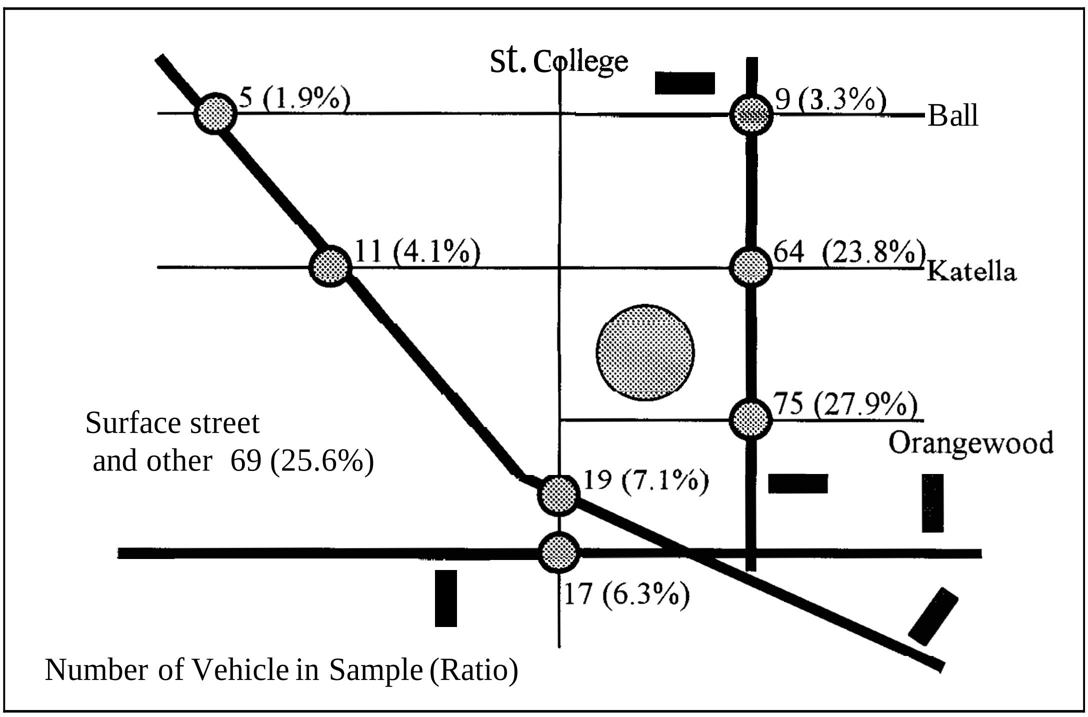


Figure 4.17 Fraction of Number of Vehicles by Approach

Table 4.8 ***Resvonse to CMS bv Exits (Freewav 57 users)***

		Number of Drivers					Ratio (%)				
		Tot	CMS	Rem	Conf	Comp	CMS	Rem	Conf	Com	Div
Total		151	88	76	39	18	58	86	51	46	12
NB Total		60	34	29	8	6	57	85	28	75	10
	Katella	14	5	4	3	1	36	80	75	33	7
	Orange	45	29	25	5	5	64	86	20	100	11
	Ball	1	0	0	0	0	0	-	-	-	0
SB Total		91	54	47	31	12	59	87	66	39	13
	Katella	50	31	26	13	11	62	84	50	85	22
	Orange	29	19	17	14	1	66	89	82	7	3
	Ball	8	4	4	4	0	50	100	100	0	0
	Other	4	0	0	0	0	0	-	-	-	0

Ratio of CMS: percentage of drivers watching CMS among all drivers passing CMS
Ratio of Rem : percentage of drivers remembering message among drivers watching CMS
Ratio of **Conf** : percentage of drivers whose routes are different from the route the CMS suggests among those who remember CMS message
Ratio of **Comp** : percentage of drivers complying CMS message among drivers whose route are different from the route the CMS suggests
Ratio of Div : percentage of drivers who divert from their routes to one that the CMS suggests among all drivers heading to the stadium

It was surveyed that 46% of drivers complied out of drivers whose original routes were different from the one suggested by CMS. When classifying those who ignored presence of CMS as non-complied drivers, the actual compliance rate is estimated about 20%. Overall diversion rate is estimated about 12% when considered all drivers. Though high compliance rate is not expected, this compliance rate is enough to improve traffic condition as we analyzed before. In fact, very high compliance rate may just cause congestion at the alternative routes.

Table 4.9 ***Response to CMS by Arrival Time (Freeway 57 users)***

		Number of Drivers					Ratio (%)				
		Tot	CMS	Rem	Conf	Comp	CMS	Rem	Conf	Com	Div
Total		151	88	76	39	18	58	86	51	46	12
-	5:45	24	7	4	1	0	29	57	25	0	0
5:45	6:00	21	10	7	5	1	48	70	71	20	5
6:00	6:15	25	14	13	9	4	56	93	69	44	16
6:15	6:30	34	25	23	13	7	74	92	57	54	21
6:30	6:45	21	12	12	4	3	57	100	33	75	14
6:45	7:00	18	13	12	6	2	72	92	50	33	11
7:00	-	8	7	5	1	1	88	71	20	100	13

4.6 Summary and Conclusion

We implemented two field tests. The first test was to observe performance of CMS routing, and the second test was to survey drivers' responses to CMS routing. Large gap was found between laboratory research level and practical implementation level through two field tests.

Dynamic optimal routing schemes can be found and applied within laboratory; however, there were many obstacles in applying these approaches. Technically, there is no direct connection between traffic monitoring systems and CMS information systems. It is partly due to low reliability of current traffic monitoring systems. Even though loop detectors are installed both freeways and surface streets, it is not possible to measure correct travel times through data from loop detectors. There are also institutional issues. Traffic management agencies are reluctant directly providing alternative guidance due to the lack of confidence on their decision. This is not only due to unreliable monitoring systems but also due to responsibility that they have to take when they mislead drivers.

In the first field test, we monitored traffic condition on both freeways and surface streets. We could compare traffic conditions via data from exit ramps. However, reliable traffic measurements were not obtained for performance evaluation. It is mainly because of difficulty in monitoring traffic condition on surface streets. Even tough detectors are available on surface streets, their data are usually used for signal control and lost. In fact, there is strong development need for a network-wide traffic monitoring system on surface streets.

In the second test, drivers' responses were surveyed. Even for the event traffic management, the CMS' were not very useful in terms of drivers' recognition and compliance. Out of all event traffic, only 50% drivers recognized presence of CMS information. This result reflects low drivers' expectancy of CMS information. That is, drivers do not expect much benefit from CMS. Their expectations are results of their experience and evaluation. When CMS provide the more reliable and beneficial information, the higher drivers' expectation would be expected.

CHAPTER 5: PARAMETRIC EVALUATION FRAMEWORK WITH ENDOGENOUS DRIVER COMPLIANCE

5.1 Introduction

Research evaluating the effect of ATIS takes a multiple user class traffic assignment approach (Kanafani *et al.*, 1991; Ben-Akiva *et al.*, 1991; Van Vuren et al, 1991; Peeta *et al.*, 1995). For the evaluation of ATIS, the crucial part is modeling route choice behavior for both guided and unguided drivers. Previous research using static analysis methods have used user equilibrium (UE), system optimal (SO), and stochastic user equilibrium (SUE) traffic assignment for this problem. In most studies, guided drivers are modeled to use the UE routes or the SO routes and the route guidance strategies are assumed to be available to achieve SO or UE driving pattern. Kanafani and Al-Deek (1991) estimated the benefits of ATIS by comparing costs of UE and SO. Peeta and Mahmassani (1995) classified drivers into classes, and used a dynamic traffic assignment framework to study drivers under three different types of guidance information-- instantaneous, UE, and SO. Ben-Akiva *et al.* (1991) and Koutsopoulos and Lotan (1990) employed a mixed UE and SUE traffic assignment in which the guided drivers follow the UE routes while unguided drivers follow the SUE routes.

Though in static analysis of ATIS the above two basic routing objectives (UE and SO) have been considered, many studies argued that ATIS should not be viewed as a way of achieving a system optimum (Arnott *et al.*, 1991; Hall, 1993). It is mainly because drivers will not trust the information systems if they recognize that they have been guided to use longer routes than other drivers. However, no research has shown how much the SO routes deteriorate overall performance due to reduced compliance to the guidance.

Most previous studies focused on the evaluation of ATIS benefits. One of the most important findings in these studies is that higher market penetration might lead to overreaction and lower performance (Mahmassani and Jayakrishnan, 1991; Arnott et al., 1991; Ben-Akiva et al., 1991). Even though drivers' compliance is the most important factor in ATIS evaluation, most studies have investigated the benefits of ATIS by various levels of market penetration with 100% compliance assumption. Emmerink et al. (1994) first showed a framework for analyzing market penetration and Al-Deek et al. (1998) developed an evaluation framework by combining a probabilistic route diversion model and a system performance model. Recently Yang (1998) treated the market penetration of ATIS as an endogenous variable. He proposed a convex programming model and an algorithm to solve a mixed behavior equilibrium problem with endogenous market penetration that is determined by a continuous increasing function of the information benefit.

This study evaluates two different route guidance objectives (UE and SO) by employing driver's compliance model with varied level of unguided drivers' perception error and market penetration. We formulate the problem as a general parametric nonlinear programming problem. Traffic pattern and performance of route guidance system are obtained by solving the mixed equilibrium problem while demands by user class are fixed by the endogenously equilibrated compliance rates. The logit-type compliance model is based on drivers' travel time savings. The problem seeks "*sustainable*" compliance rates under given perception error for unguided drivers and given market penetration. Using such compliance rates, two route guidance objectives are evaluated. This study takes both guided drivers' travel time savings from the drivers' point of view and the total system cost from the system manager's point of view into consideration as measures of effectiveness (MOE) of ATIS. In fact, these two MOE's should be considered while evaluating the success of ATIS. Under endogenous compliance, UE route guidance can be expected to show higher rates than SO route guidance. However, it is not certain which route guidance state will show higher total system cost saving. Even though SO route guidance aims at minimizing the total system cost, SO route guidance may or may not show lower total system cost than UE route guidance due to deterioration of driver's compliance. In total system costs, the performance of SO and UE route guidance compared to current traffic condition represented as a SUE state is interesting to examine. This paper develops a framework for such analysis.

This chapter is outlined as follows. The next section explains about problem formulations and solution procedure including a driver's compliance model and a mixed equilibrium assignment model. Section 5.3 depicts the numerical experiments, and this approach is extended to dynamic case in Section 5.4. Finally Section 5.5 presents conclusion and future research.

5.2 Formulation and Solution Algorithm

The compliance problem is an intrinsic problem in evaluating route guidance strategies. It shares many common features with the endogenous market penetration problem with multiple equilibrium behaviors formulated by Yang (1989). Here we develop a similar framework to study the compliance issue in routing.

5.2.1 Performance of ATIS and Driver's Compliance

While Yang (1998) endogenously calculated market penetration via travel time saving, all equipped drivers were assumed to follow the guided route, thus ignoring the compliance issue. Here we assume the market penetration for ATIS to be known and treat compliance rate (i.e., decision to follow the advice or not) as a fbnction of expected travel time saving. From driver's point of view, the expected travel time saving represents the quality of information. That is, if drivers are equipped, their compliance can be expressed as a function of travel time saving over the unguided case.

The problem is formulated in a similar manner to (Yang, 1998). The mixed demand is regarded as a vector of parameters and the mixed equilibrium traffic assignment problem is written as a general parametric nonlinear program problem as follows:

$$\underset{x}{\text{minmize}} \quad Z(\hat{\mathbf{q}}, \mathbf{q}) \tag{5.1}$$

subject to

$$\mathbf{q} = \overline{\mathbf{q}} \cdot \rho\big(\Delta(\mathbf{x})\big) \cdot m \tag{5.2}$$

$$\hat{\mathbf{q}} = \overline{\mathbf{q}} - \mathbf{q} \tag{5.3}$$

where

$\mathbf{q}$ = guided demand

q = unguided demand

$\overline{\mathbf{q}}$ = total demand

$\mathbf{x}$ = link traffic flow pattern

m = market penetration

$\Delta(\cdot)$ = guided driver's travel time saving over unguided

$\rho(\cdot)$ = driver's complaince function

$Z(\cdot)$ = objective function for traffic assignment

5.2.2 Compliance Model and Demand Split

A schematic of the classification of user classes is proposed in Figure 5.1. In this paper, the split between guided and unguided drivers is obtained directly by analyzing driver's compliance behavior given market penetration. That is, the fraction of guided drivers is

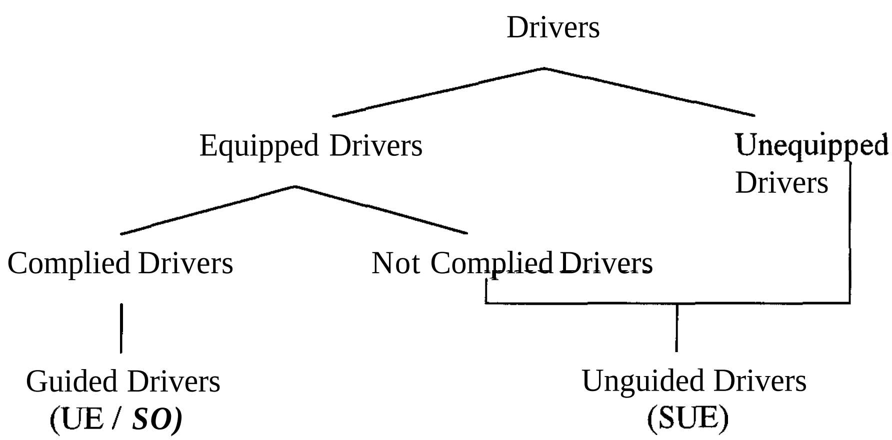


Figure 5.1 Classification of User Classes

obtained from the endogenous compliance rates and given market penetration. This study further classifies the equipped drivers into two groups: one is complied (guided), the other is not complied (unguided). Of course, the unequipped drivers fall in the unguided group. The number of guided drivers is modeled as a fknction of expected benefit (travel time saving) in this study. That is, the compliance rate is endogenously determined by the travel time difference between guided and unguided drivers. **A** logistic fknction is used for the model to reflect other factors affecting driver's compliance behavior.[3] Given market penetration for ATIS, the number of guided drivers is determined as follows:

$$q_{rs} = \frac{\overline{q}_{rs} \times m}{1+\exp(\alpha + \beta \cdot \Delta_{rs})}, \ \forall r \in R, s \in S \qquad (5.4)$$

[3] **Other functional forms are possible, but we chose the simple function as in standard discrete choice models.**

where, a, β = parameters which are common for all O-D pair

q_{rs} = guided demand from origin $r \in R$ to destination $s \in S$

$\bar{q}_{rs}$ = total demand from origin r to destination s

Δ_{rs} = travel time saving for guided demand from origin r to destination **s**

m = market penetration

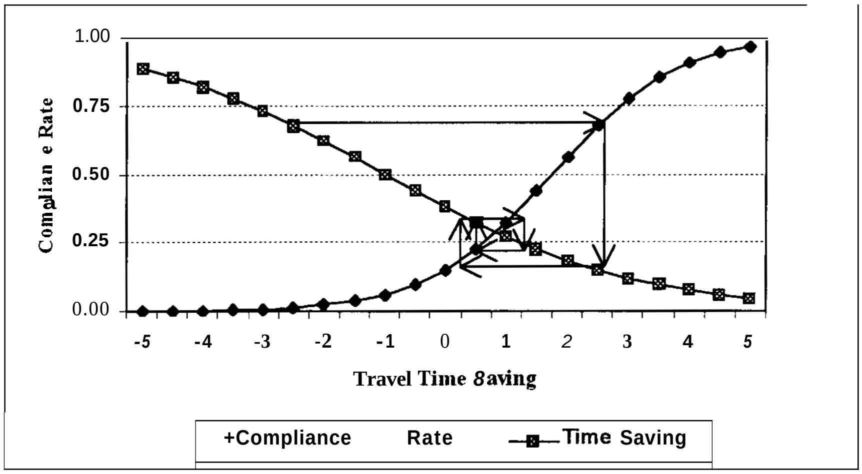


Figure 5.2 Driver Compliance Model and Sustainable Point

This type of compliance model also leaves out other factors such as inequities between route travel times experienced by drivers being guided under SO. This is a rather strong assumption. More complicated compliance models to handle any inaccuracy from this are possible, but the complication from such models were deemed outside the scope of this paper.

Figure *5.2* shows a logistic curve representing drivers' compliance rate with respect to travel time saving and a time saving curve with respect to compliance rate. The travel time saving is obtained from a mixed equilibrium assignment. While the compliance curve regarded as a demand function, the time saving curve is regarded as a supply curve. Therefore, there exists an equilibrium point between two curves. The equilibrium point is called here *a sustainable compliance rate* that is determined endogenously.

5.2.3 Mixed Behavior Equilibrium Traffic Assignment Problem

Readers familiar with the mixed equilibrium formulation and solution techniques may skip this section. The formulation discussed here is solved in the inner iterations of the solution procedure in the next section. The thrust of the paper is not on mixed assignment, but rather in incorporating it in a framework with endogenous compliance, which is handled in the outer iterations of the solution procedure.

We assume that unguided drivers make routing decisions based on perceived variables and hence their route choice behavior is assumed to result in stochastic user equilibrium. Guided drivers' travel pattern is according to user equilibrium (UE) or system optimum (SO) depending on the applied routing scheme. Therefore, the assignment problem is a mixture of either UE or SO with SUE.

Mixed behavior equilibrium formulations can be found in several previous studies (Harker, 1988; Hicks, 1992; Yang 1998). For the case of user equilibrium route guidance (UERG) where UE behavior and SUE behavior are mixed in the network, Yang (1988) formulated an optimization problem for the problem as:

(UE + SUE)

$$\text{minimize } Z_{\text{US}}(\hat{\mathbf{q}}, \mathbf{q}) = \sum_{a \in A} \int_0^{x_a} t_a(w)dw + \frac{1}{\theta} \sum_{r \in R, s \in S} \sum_{k \in K_{rs}} \hat{f}_k^{rs} \ln \hat{f}_k^{rs} \tag{5.5}$$

Subject to

$$\sum_{k \in K_{rs}} f_k^{rs} = q_{rs}, \ \forall r \in R, s \in S \tag{5.6}$$

$$\sum_{k \in K_{rs}} \hat{f}_k^{rs} = \hat{q}_{rs}, \ \forall r \in R, s \in S \tag{5.7}$$

$$f_k^{rs} \geq 0, \ \forall k \in K, r \in R, s \in S \tag{5.8}$$

$$\hat{f}_k^{rs} \geq 0, \ \forall k \in K, r \in R, s \in S \tag{5.9}$$

$$x_a = \sum_{r \in R, s \in S} \sum_{k \in K_{rs}} \left(f_k^{rs} + \hat{f}_k^{rs}\right) \cdot \delta_{ak}^{rs}, \ \forall a \in A \tag{5.10}$$

where t_a = travel time on link *a*

θ = parameter of driver's perception

f_k^{rs} = flow on route ***k*** connecting ***r*** to ***s*** for the guided drivers

$\hat{f}_k^{rs}$ = flow on route ***k*** connecting ***r*** to ***s*** for the unguided drivers

x_a = flow on link *a*

δ_{ak}^{rs} = 1 if the route ***k*** between ***r*** and ***s*** uses the link *a*, or 0 otherwise.

Unlike the mixed behavior equilibrium model for the UERG case, the equivalent optimization formulation for the mixed SO and SUE case (system optimal route guidance, SORG) cannot be obtained due to the nonseparablility of the cost fbnction. Instead, a variational inequality approach is employed (Harker, 1988; Hicks, 1992). Harker (1988) showed a single variational inequality (VI) formulation for a mixed behavior network equilibrium problem (UE + SO). By replacing UE behavior with SUE, the VI formulation can be employed for the SORG case as follows:

(SUE + SO)

$$c^u(x^*) \cdot (x^u - x^{u*}) + c^g(x^*) \cdot (x^g - x^{g*}) \geq 0 \tag{5.11}$$

or

$$\sum_{a \in A} \left[c_a^u(x_a^*), c_a^g(x_a^*)\right]^T \cdot \left[(x_a^u; x_a^g) - (x_a^{u*}; x_a^{g*})\right] \geq 0 \tag{5.12}$$

where x_a^g = the link flow of guided drivers on link *a*

x_a^u = the link flow of unguided drivers on link *a*

x_a^* = the optimal link flow of the problem
c_a^u = the perceived travel cost for unguided drivers
c_a^g = the marginal travel cost for guided drivers

Both the above formulations fit the class of formulations for which diagonalizations have been found applicable. For the UE/SUE problem, Yang (1998) used a diagonalization type algorithm with convex combinations. We employ this solution algorithm for SO/SUE also. While we have not established convergence of this algorithm to the SO/SUE state due to the lack of an equivalent mathematical program for the VI formulation, we have found that the solutions obtained were indeed in SO/SUE by evaluating the marginal costs across used paths at convergence. The algorithm forms the inner iterations in the solution procedure given next.

5.2.4 Solution Procedure

The procedure for solution is classified into two routines. The outer routine is to find equilibrated compliance rate and corresponding demand by user class-- guided and unguided. The outer routine iterates until achieving equilibrated compliance rates. The inner routine is to solve a mixed equilibrium traffic assignment problem. In inner routine traffic flows are updated by using method of average success **(MSA).** Figure 5.3 depicts overall procedure of the solution algorithm.

Outer Iteration: Compliance update and demand determination.

Step 0: Initialization.

Set iteration number i = 0.

Set an initial value of compliance rate, $\rho_{rs}^{(0)}, \forall r \in R, s \in S$, and determine demand for both guided and unguided.

$$q_{rs}^{(i)} = \overline{q}_{rs} \cdot \rho_{rs}^{(i)} \cdot m \; , \; \forall r \in R, \; s \in S$$
$$\hat{q}_{rs}^{(i)} = \overline{q}_{rs} - q_{rs}^{(i)} \; , \; \forall r \in R, \; s \in S$$

Step 1: Mixed equilibrium traffic assignment.

Obtain average travel times $\hat{c}_{rs}^{(i)}$, $c_{rs}^{(i)}$, $\forall r \in R, \; s \in S$ for both guided and unguided by performing traffic assignment algorithm.

Step ***2:*** Update demand.

Update compliance rate and demand for both guided and unguided using guided driver's travel time saving $\Delta_{rs}^{(i)}$.

$$\rho_{rs}^{(i+1)} = \frac{1}{1+\exp(\alpha+\beta\cdot\Delta_{rs}^{(i)})}, \; \forall r \in R, s \in S$$
$$q_{rs}^{(i+1)} = \overline{q}_{rs} \cdot \rho_{rs}^{(i+1)} \cdot m \; , \; \forall r \in R, \; s \in S$$
$$\hat{q}_{rs}^{(i+1)} = \overline{q}_{rs} - q_{rs}^{(i+1)} \; , \; \forall r \in R, \; s \in S$$

Step 3: Convergence check.

Stop if convergence is achieved, otherwise set i = i + 1 and go to Step 1.

Inner Iteration: Mixed UE (SO) and SUE equilibrium assignment algorithm

Step 0: Initialization.

Set iteration number i = 0.

Generate a set of link flows $x_a^{(i)}$, $a \in A$ by performing all-or-nothing assignment for $\mathbf{q}$ and a stochastic network loading for $\hat{\mathbf{q}}$ based on a set of initial free-flow time t_a^0.

Step 1: Update.

Update link cost $t_a^{(i)} = t_a(x_a^{(i)})$, $a \in A$.

Step 2: Direction finding.

Find auxiliary link flow pattern $y_a^{(i)}$, $a \in A$ by performing all-or-nothing assignment for $\mathbf{q}$, based on the current set of (marginal) link flow time $t_a^{(i)}(\tau_a^{(i)})$, $a \in A$ and a stochastic network loading for $\mathbf{q}$ based on the current set of link travel time $t_a^{(i)}$, $a \in A$.

Step 3: Move.

Find the new flow pattern by setting $x_a^{(i+1)} = x_a^{(i)} + \alpha^{(i)}(y_a^{(i)} - x_a^{(i)})$, $a \in A$.

Step 4: Convergence check.

Stop if convergence is achieved, otherwise set i = i + 1 and go to Step 1.

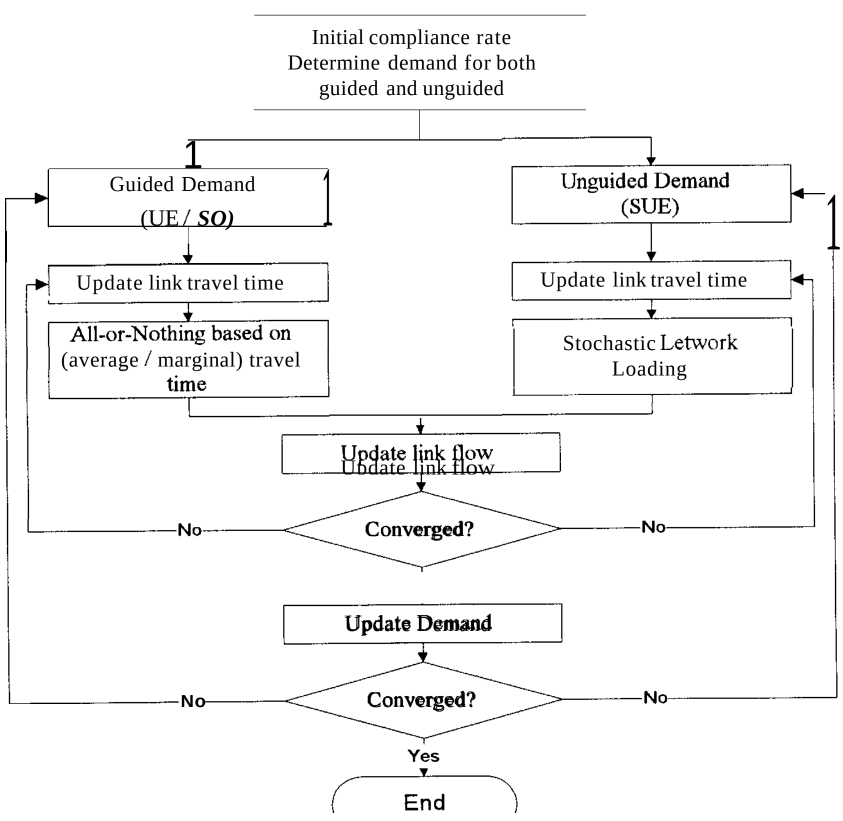


Figure **5.3** ***Solution Procedure***

5.3 Numerical Examples

5.3.1 Test Network

We use a simple network with 12 nodes and 17 links as shown in Figure 4 for the simple test. The BPR (Bureau of Public Road) link performance fbnction is used as shown in equation (13), and network input data including free-flow travel time (t_a^0) and link capacity (c_a) are shown in Table 1. Here we assume that there is only one commodity connecting origin 1 to destination 12, and total demand is 1500. The parameters for the compliance model (equation 4) are assumed to be $\alpha = 1.75$ and $\beta = -0.50$.

$$t_a = t_a^0 \cdot \{1 + 0.15 \cdot (x_a / c_a)^4\},\ a \in A \qquad \textbf{(5.13)}$$

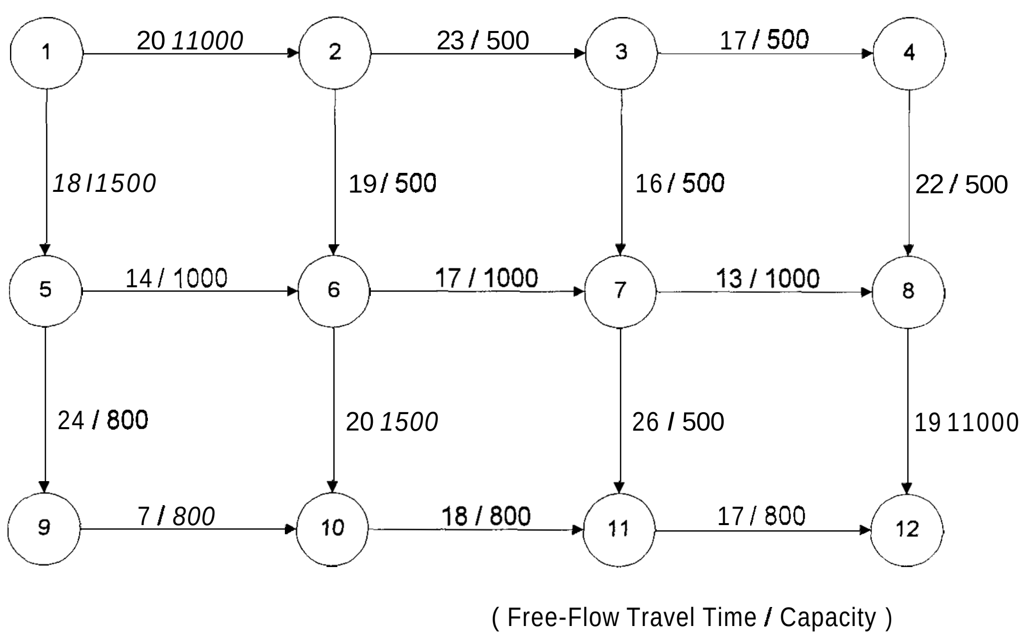


Figure 5.4 ***Test Network***

5.3.2 Comparison of Total System Costs

First, we compare total system costs of three route choice behavior models. This analysis is not yet the mixed equilibrium case but with single driver groups (SUE, UE and SO). Total system cost of the stochastic user equilibrium behavior model is varied depending on level of drivers' perception error (θ in equation 5) while UE and SO are independent from the perception error. Here smaller values mean higher perception error; so the SUE model with very large θ value is equivalent to the UE behavior model. **As** shown Figure 5, the system cost of the SUE approaches that of UE. The figure also shows that the total system cost from UE routing could be higher than that of unguided traffic (SUE) when unguided drivers' perception error is smaller than certain level. From this comparison, we learn that the UERG may lead higher system cost, which the system manager does not want. This implies that route guidance for users may not be an effective way of improving the total system for some cases, especially when driver's perception error is small. That is, we get a conclusion, which is not surprising, that an important factor affecting the benefit from information is the level of the unguided drivers' perception error. It is, however, not easy to measure θ from a practical point of view.

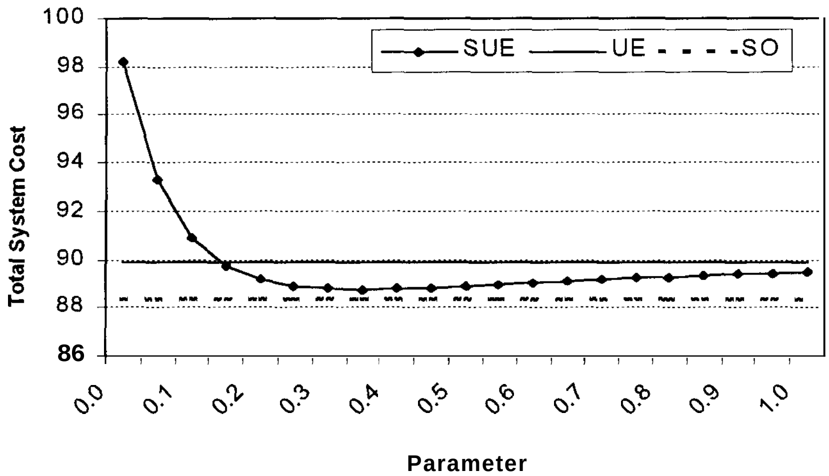


Figure 5.5 Comparison of Total System Cost

Parameter θ is unguided drivers' perception error
(higher θ means smaller perception error).

5.3.3 Performance of ATIS and Driver's Compliance Behavior

Secondly, we investigate the user travel time and total system cost by varying fractions of guided drivers and different levels of perception error. In this test, 100% market penetration is assumed, so the fraction of guided drivers is same as the compliance rate. Figure *5.6* shows changes of user travel time and total system cost. This investigation expands the results from the previous section by introducing a compliance curve into the analysis. Note that we select three value of θ (0.1, 0.15, and 0.3) which are essentially values at and on both sides of where the SUE curve intersects the UE line in Figure 5.5.

<u>Guided drivers' travel time savings over unguided drivers (upper figure in Figure 5.6)</u>

First, consider the curves excluding the superposed compliance line. Guided drivers' travel time savings are decreasing as their fractions increase except for the case of SORG with SUE perception error parameter $\theta = 0.3$ (i.e., base-case drivers know network conditions well) as shown in the upper figure. When the driver's perception error is higher, the larger user travel time saving is obtained as expected. It is found that the level of driver perception error is the dominant factor affecting the guided drivers' travel time saving.

Interestingly, guided drivers' travel time saving for SORG with perception parameter of 0.3 reveals that drivers need to sacrifice substantial amount of individual travel time to improve

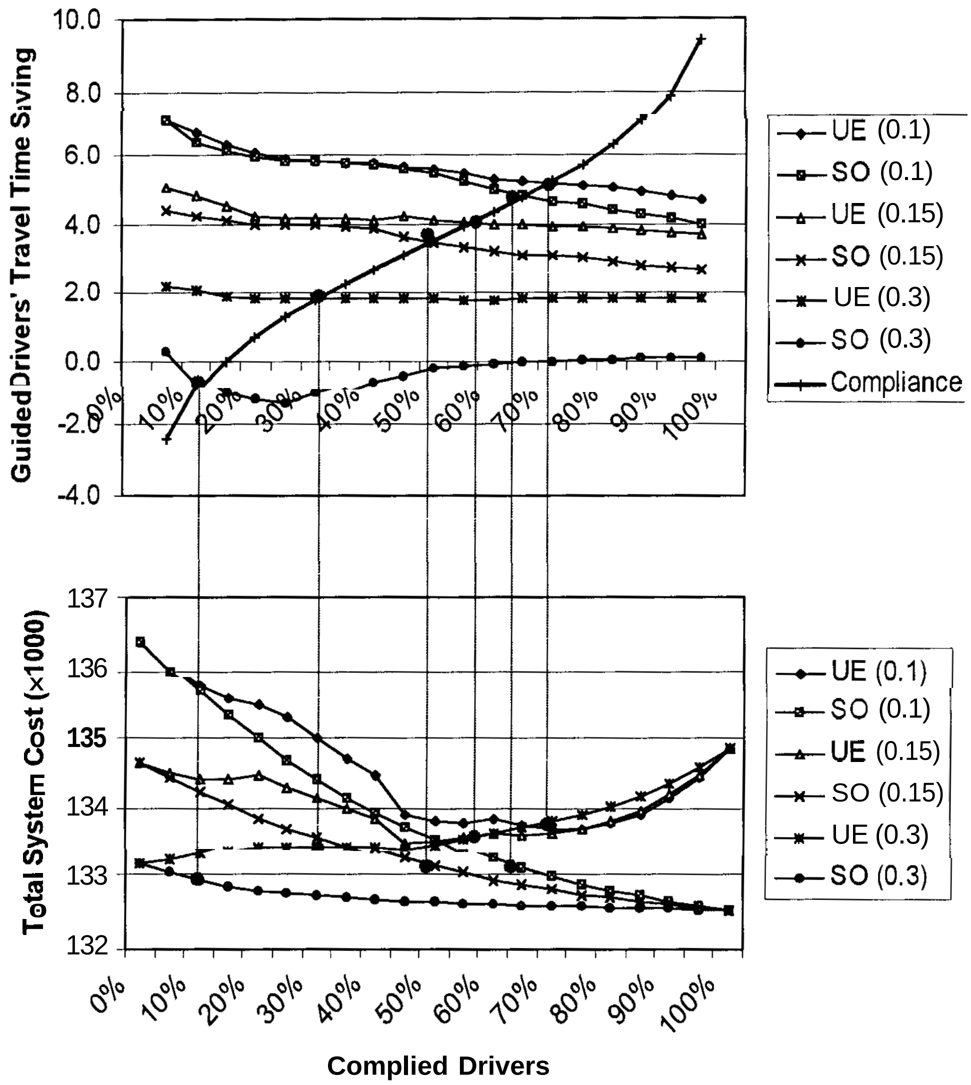


Figure 5.6 Cost Comparison by Fraction of Guided Drivers.
* The values in the brackets represent level **of** driver's perception error (θ). **A** smaller value means higher perception error.

the total system especially at low compliance rates. The amount of individual drivers' sacrifice decreases as compliance rate increases since more drivers share the burden for the total system.

Total system costs (lower figure in Figure 5.6)

The lower figure shows changes of total system costs. **As** expected, SORG with 100% compliance results in the lowest total system cost. In all SORG cases, total system costs are decreasing as fraction of guided drivers increases regardless of levels of driver's perception error. In the cases of UERG, however, total system costs increase from when guided drivers are more than certain amount even though guided travel times are reduced. Especially for the case of $\theta = 0.3$, the total system cost increases as guided drivers increase. This result shows that the UERG may result in increase of total system cost, thus showing that the results in figure 5 for higher θ hold for various fraction of guided traffic as well. That is, if the unguided drivers are well-versed with the network, higher guided fractions may only make it worse.

Endogenously determined compliance rate

Next we take driver's compliance behavior into consideration using the superposed compliance curve. An endogenous compliance rate can be found as follows. There is only one compliance rate satisfying the guided travel time saving shown for each of the six curves in Figure *5.6* (top). The fractions of guided drivers (or compliance rate at 100% market penetration) are determined by the six points where the compliance curve intersects the other six curves. Other points on the six curves cannot be achieved under the endogenous compliance framework. The total system costs corresponding to the compliance rates are found from the corresponding six points in the lower graph.

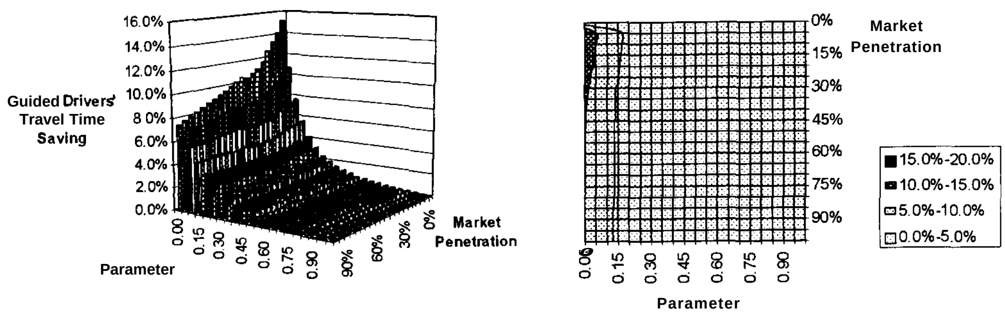
Interestingly, this experiment shows that SORG can result in lower total system cost when the compliance rate is endogenously found. The driver's compliance rate of SORG is lower than that of UERG, but not as low as we expected. This result conflicts with the general consensus that the information should not be used for achieving system optimum. Instead, this result shows that SORG may in some cases be used for lower total system cost, though it will still be under low compliance rates.

Here we get three points for SO and three for UE (for the three θ values). It is easy to compute a continuous set of points for each case for a full range of θ values which give the complete set of cost values for "sustainable" compliance rates. This technique of endogenously finding compliance rates based on a compliance curve is a significant part of the analysis framework that we propose. Other forms of the compliance curve may be used if such curves are calibrated with real data, and the framework still applies.

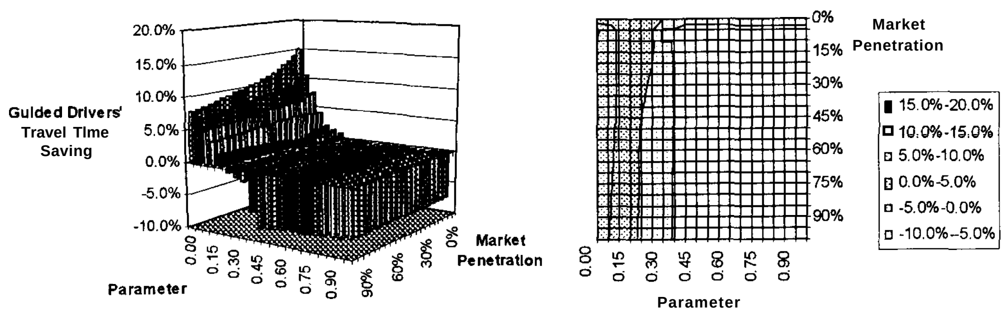
5.3.4 Performance Comparison under Endogenously Determined Compliance Rate

While the previous two sections analyzed the problem by fixing the market penetration and compliance rates at first and then superposed the compliance rates endogenously to find sustainable compliance rates, the next task is to include market penetration also into the framework. That is, the guided traffic fraction is now the fraction of *equipped* drivers who complied. Sustainable compliance rates can be formed in the same manner as above for various market penetrations.

Figure 7 compares guided travel time savings for the selected network under UERG and SORG states with sustainable compliance. **As** shown in the Figure 7-a, the UERG always gives positive travel time saving, showing highest benefit at the low market penetration and higher perception error (smaller **0).** The SORG shows negative values in guided travel time saving when θ is greater than 0.3 - 0.4 as in Figure 7-b. This is the case where guided drivers sacrifice for the system benefit. Note that the number of such drivers is very low, which would be clear from examining the compliance rates corresponding to these cases. We have left out those results here.



(a) User Equilibrium Route Guidance



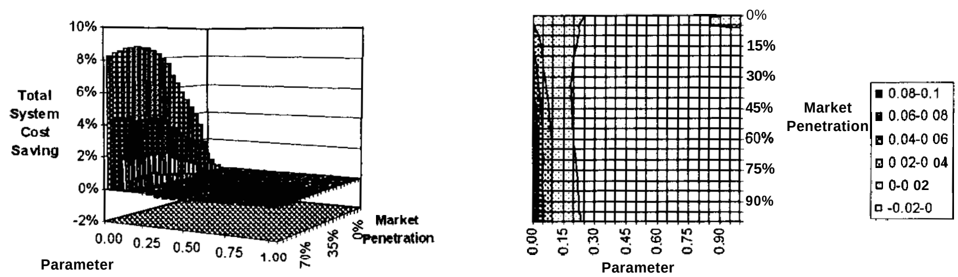
(b) System Optimal Route

Figure 5.7 Comparison of Guided Drivers' Travel Time Saving at the Sustainable Compliance Rate

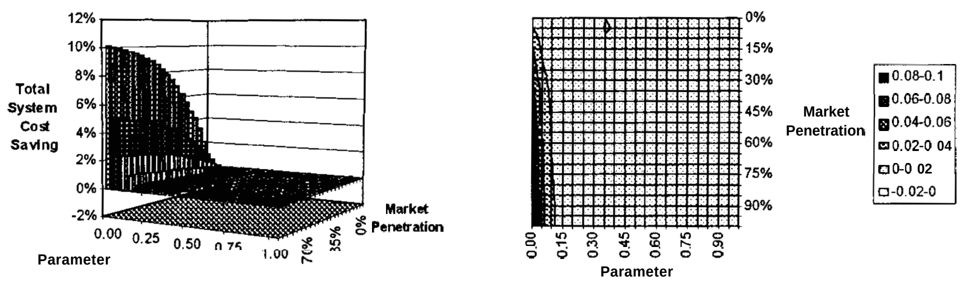
***The right side figure** shows **contour map of the left-side 3 dimensional graph**

Figure 5.8 shows a comparison of total system cost saving. In contrast to the comparison of guided travel time saving, UERG results in negative values in total system cost saving when the level of perception error is higher than 0.2 while SORG shows positive saving. Unlike guided travel time saving, the total system cost saving increases as the market penetration increases.

It is possible to look further using this framework into measures such as percentage differences between SORG and UERG travel time saving, etc, for various levels of market penetration and SUE perception errors. We leave out such analysis, as the network used is just an illustrative one, and the results may not be generalizable anyway.



(a) User Equilibrium Route Guidance



(b) System Optimal Route Guidance

Figure 5.8 Comparison of Total System Cost Saving at the Sustainable Compliance Rate
***The right side figure shows contour map of the left-side 3 dimensioal graph**

5.3.5 Performance Comparison on general urban network

Previous section has compared performance between UERG and SORG at the sustainable compliance rates, but the simple grid type network with a single origin-destination (O-D) demand cannot represent general urban network. This section compares performance using more general network with multiple O-D demand. We test a Sioux Falls network as a general urban network example. The Sioux Falls network shown in Figure 5.9 includes **24** nodes, 76 arcs, and 196 O-D pairs.

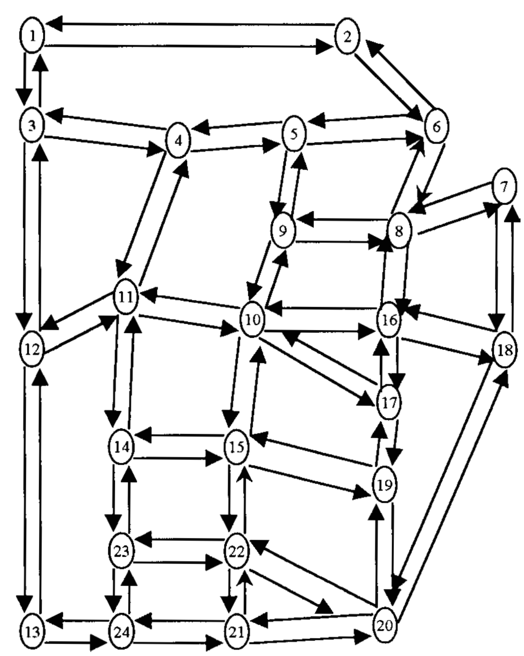


Figure 5.9 Sioux Falls network

First sustainable compliance rates are evaluated with respect to market penetration and unguided drivers' perception error. **As** shown left side in Figure 5.10, UERG results in higher compliance rates than SORG, especially at high perception error (small θ) and high market penetration. With respect to total system costs, the UERG shows better performance than SORG as well. This result implies that the performance of SORG is worse than that of UERG due to the characteristics of SORG lowering compliance rates. While SORG showed better performance (lower system costs) in many cases when analyzed with the simple grid network example, the general network example clearly shows better performance of SORG. Even though it is not possible to make a general conclusion that the UERG performs better than the SORG, it seems that UERG more like to perform better and attractive to drivers.

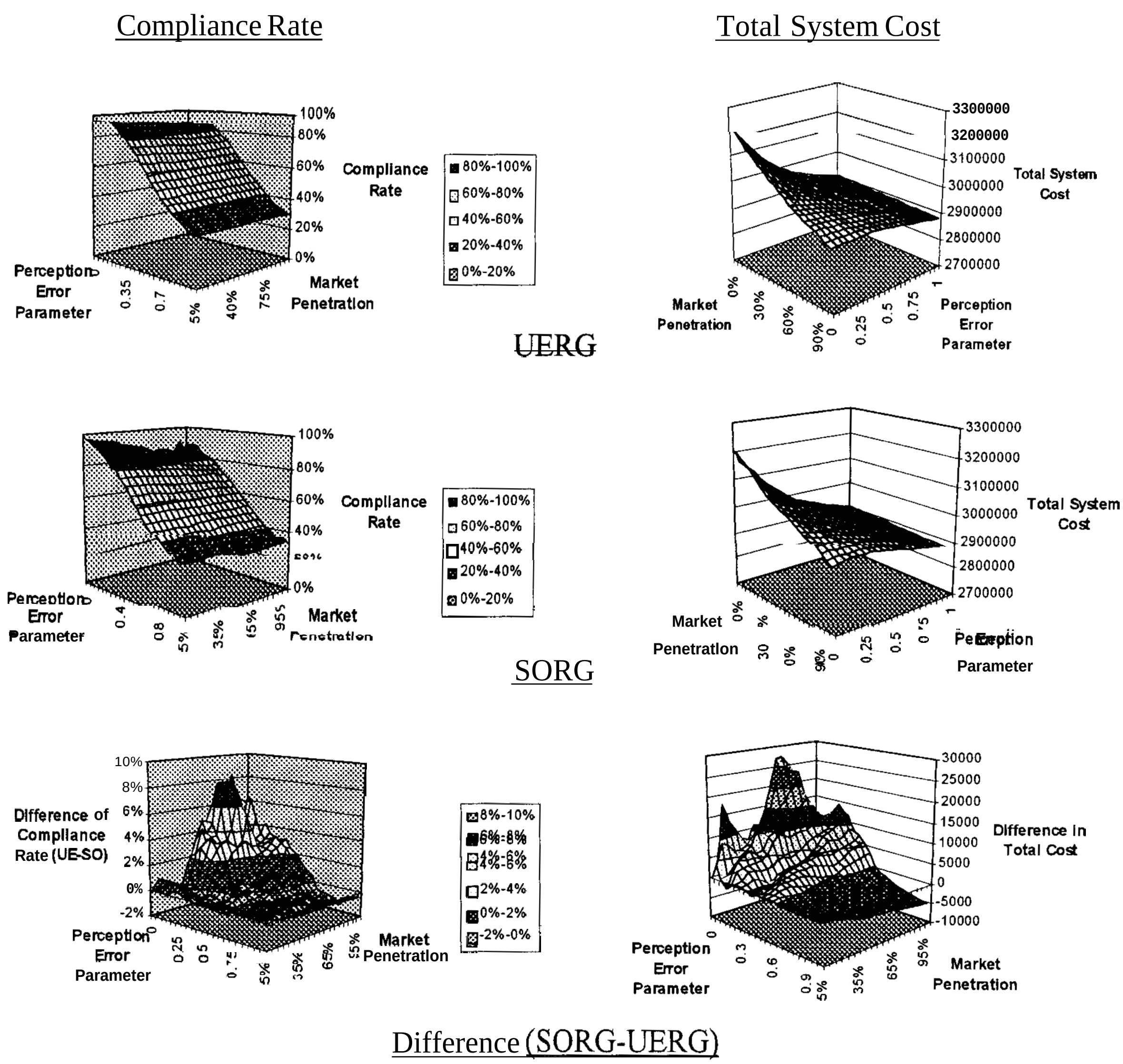


Figure 5.10 Performance Comparison (Sioux Falls Network)

5.4 Extension of Endogenous Compliance Model to Dynamic Systems

5.4.1 Overview

In previous sections we developed a parametric evaluation framework of route guidance systems with endogenously determined driver compliance. This framework is extended to dynamic route guidance systems in this chapter. While the previous chapter emphasized on the evaluation of route guidance objectives, this chapter emphasizes more on characteristics of information devices from long-term evaluation perspective.

Since the system evaluation here is based on long-term effect, the characteristics of information devices are dealt from a standpoint of system reliability that directly affects driver's compliance behavior. There are many factors affecting to system reliability, such as accuracy of traffic monitoring system, capability of relaying information timely, future prediction capability, etc. Of course, the route guidance objective is one of them as addressed in previous chapter. Influence of these factors is analyzed at the system level by modeling driver's credibility dynamics.

In this section, driver's credibility dynamics is modeled using a similar framework as in static cases. The modeling approach is same in a sense that drivers are classified into two user classes (complied and non-complied) based on their previous experience and the split is determined endogenously. This day-to-day update approach shows how drivers react to the information reliability and provides overall performance at the sustainable state.

5.4.2 Evaluation Framework

In this dynamic approach, DYNASMART is used as a dynamic traffic assignment-simulation tool. Overall feature of DYNASMART is addressed in section 2.4.1. DYNASMART uses a dynamic stochastic assignment in selecting initial routes for unguided drivers by taking drivers' level of network familiarity into account. Therefore, overall structure becomes a multiple user class problem when portions of drivers are guided by route guidance devices. Unlike the previous mixed equilibrium assignment where guided drivers are assumed to follow UE or SO pattern without other considerations on information devices, the dynamic system explicitly take information devices' characteristics into account. That is, this evaluation framework reflects detailed characteristics of information devices that affect to the information reliability. As final results of dynamic traffic assignment with an information/route guidance device, not only network performance but also drivers' post trip evaluation is of interest.

The drivers' post evaluation of their trips associated with route guidance systems is reflected to drivers' credibility that influences their next decisions. Credibility can be an endogenous variable within a day-to-day dynamics framework. This study investigates how to measure and update the credibility of information with driver behavior analysis. Figure 5.11 shows the overall framework for drivers' credibility update associated with day-to-day dynamics under the ATIS. The framework is designed for the case of CMS-based route guidance system.

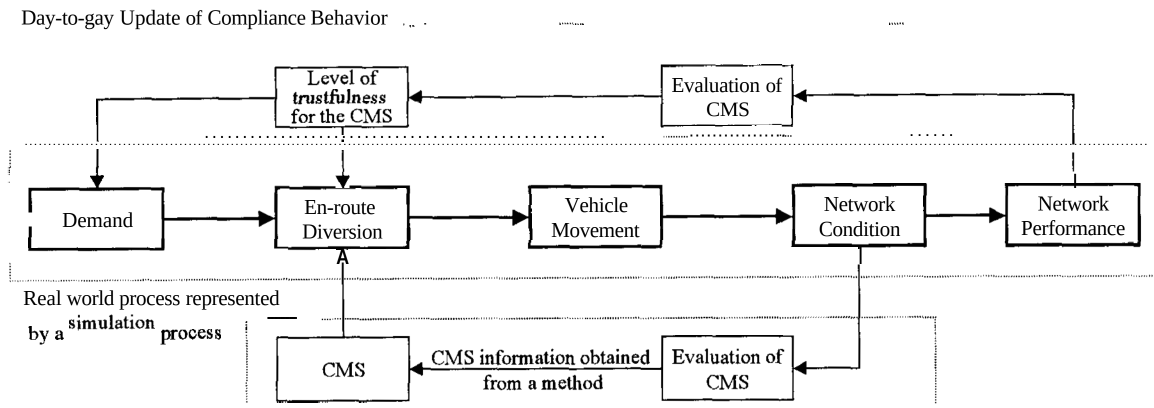


Figure 5.11 Evaluationframework with endogenous compliance behavior

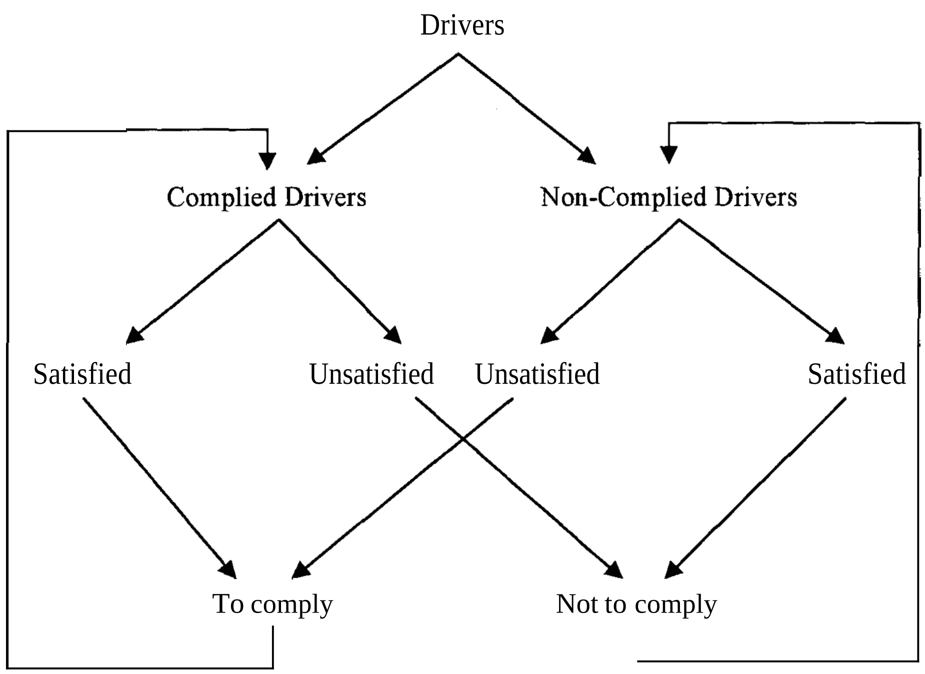


Figure 5.12 Day-to-day dynamics of driver's compliance behavior

In Figure 5.11, the upper part represents drivers' day-to-day credibility update behavior. This routine evaluates drivers' credibility from drivers' point of view. We classify four groups of drivers with respect to their compliance and satisfaction as shown in Figure 5.12. Those who have are satisfied with their decisions will stick to their decisions, while the unsatisfied will change their decisions next time. The evaluation result is represented by a system-level compliance rate calculated as:

$$CPL(i+1)=\frac{CS(i)+NU(i)}{TD(i)} \quad (5.14)$$

where, $CPL(i)$ = *Evaluated compliance rate for day i*

$CS(i)$ = *Number of drivers satisfied when complied on day i*

$NU(i)$ = *Number of drivers unsatisfied when not complied on day i*

TD(i) = Total number of drivers who made decisions on day i

Drivers' satisfaction is determined by their post evaluation. Drivers are classified into the satisfied if their travel times are not certain percentage (say, 10%) longer than the optimal ones; otherwise, they are classified into the unsatisfied. The percentage reflects indifference band as in the boundedly rational behavioral model (Mahmassani and Jayakrishnan, 1991). In this study, the system level compliance rate is updated day-to-day using method of successive average (MSA) in order to ensure convergence of the system as in Equation (5.15).

$$UCPL(i+1)=\alpha\cdot UCPL(i)+(1-\alpha)\cdot CPL(i+1) \quad (5.15)$$

where, $UCPL(i)$ = *Updated system-level compliance rate for day i*

$CPL(i)$ = *Evaluated compliance rate for day i*

α = *step size* $\left(i/_{i+1}\right)$

The compliance update is repeated until it produces the stabilized system level compliance rate. The stabilized compliance rate reflects overall reliability of the information device. The higher stabilized UCPL implies the more reliable informatiodguidance system. That is, the UCPL represents inherent value of the information device affecting to drivers' compliance rate. Overall performance of a system should be evaluated at the sustainable point only since others may be invalid conditions or interim products.

Even though UCPL is assumed directly to be a compliance rate for next day, UCPL can also be regarded as an inherent value of the system reliability that is one of variables used in the en-route diversion model as in Chapter **3.** In this case, the UCPL will be a representative value representing inherent characteristics of the guidance system. Of course, the actual compliance rates in the case are products of the compliance model rather than direct results of the UCPL.

5.5 Numerical Example

In this example, we use the same network used for the test of dynamic optimal CMS routing in Chapter **2** to keep consistency of analyses. In this example, we compare overall performances and obtained sustainable compliance rates between static CMS, feedback CMS and predictive CMS for both average cost routing and marginal cost routing.

The first example is to directly update drivers' compliance rate day to day. Table 5.1 shows overall comparison of routing methods. The case of 100% assumption is compared as a benchmark. Expectedly, the predictive average cost routing method results in highest compliance rate when same update interval is applied. While feedback approach results in 62% of sustainable compliance rate, the predictive average cost routing is expected to result in 92% of compliance rate. It is because the route guidance method is best from drivers' perspective.

Table 5.1 Converged sustainable state with respect to compliance rate

Routing Method	Update Interval	100% compliance CMS[1]	Total[2]	LOE[3]	Converged sustainable state CMS	Total	LOE	CPL[4]
Do-Not	--	7.10	6.63	2.45	9.19	8.74	392.43	--
Static	--	18.47	9.40	1276.85	7.76	6.65	5.85	41.50
Feedback	0.1	6.89	6.57	1.58	7.13	6.68	1.43	62.32
	1.0	7.35	6.92	3.84	7.33	6.79	2.25	61.27
	3.0	8.07	7.23	7.10	7.79	6.93	8.74	67.57
Predictive Average Cost Routing	0.1	6.54	6.47	1.13	6.66	6.52	1.16	92.01
	1.0	7.52	6.77	2.94	7.21	6.57	2.69	74.78
	3.0	8.07	7.23	7.10	7.57	6.80	8.26	68.97
Predictive Marginal Cost Routing	0.1	6.93	6.69	2.66	7.10	6.63	2.45	79.59
	1.0	7.60	6.75	4.44	6.92	6.86	20.98	63.66
	3.0	8.07	7.23	11.25	7.44	6.70	15.02	63.61

Average cost for vehicles receiving CMS information
Average cost of the total system
Level of equilibrium representing travel time deviation between alternative routes
Sustainable compliance rate (%)

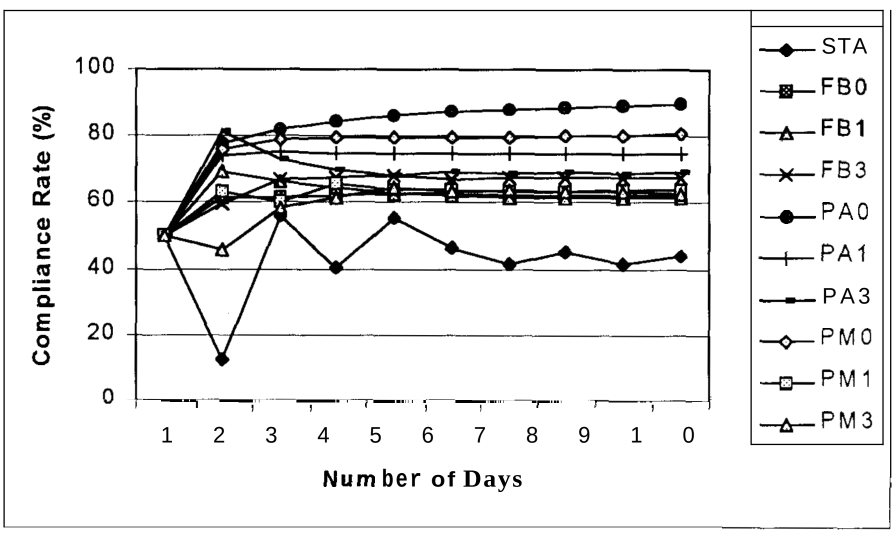


Figure 5.13 Equilibration of Compliance Rate

In the second example, we incorporate drivers' compliance model represented by Equation 5.16 as addressed in Chapter 3. Our main interest in the model is reliability value of CMS which is treated as an inherent value for the CMS. Unlike previous example, the value of reliability is updated day to day.

$$P(n) = \frac{1}{\exp(1.8 - 0.5 \cdot LOF_n + 5 \cdot LOC_a - 5.6 . CMS_c)} \tag{5.16}$$

where, LOF_n = Level of network familiarity for driver n

LOC_a = Level of congestion on link a represented by speed / free speed.

CMS_c = Reliability value for CMS c

In this case, the value of reliability is updated here, and the compliance rate is obtained as a result of the compliance model. Even though the value of reliability is used as a variable in the compliance model, the value is updated exactly same as previous case. That is, the value represents drivers' satisfaction.

The sustainable value of reliability is converged to a point through drivers' day-to-day equilibration procedure as shown in Figure 5.14. Similarly as sustainable compliance rates in previous example, the values of reliability are best for the predictive average cost routing and worst for the static routing. Also the predictive average cost routing shows best in overall performance as shown in Table 5.2.

Table 5.2 Converged sustainable state with respect to value of reliability

Routing Method	Update Interval	at reliability value 1.0				Converged sustainable value of reliability				
		CMS[1)]	Total[2)]	LOE[3)]	CPL[4)]	CMS	Total	LOE	VOR[5)]	CPL
Do-Not	--	6.86	7.92	152.84	0	6.86	7.92	152.84	0.0000	0
Static	--	10.44	7.47	429.17	47	8.25	6.87	26.74	0.6225	68
Feedback	0.10	7.19	6.66	1.55	84	7.74	6.70	2.47	0.7615	62
	1.00	7.27	6.52	2.71	83	7.92	6.85	2.55	0.7576	62
	3.00	7.81	6.99	9.33	86	7.91	6.85	7.44	0.7142	55
Predictive Average Cost Routing	0.10	7.04	6.68	1.14	85	7.01	6.56	1.22	0.8763	76
	1.00	6.92	6.53	2.54	83	6.87	6.69	2.85	0.8045	68
	3.00	7.81	6.99	9.66	86	7.47	6.63	8.80	0.7374	59
Predictive Marginal Cost Routing	0.10	6.98	6.57	2.64	81	7.18	6.84	3.94	0.7982	65
	1.00	7.30	6.70	4.20	83	7.35	6.86	9.10	0.7645	67
	3.00	7.81	6.99	9.66	88	7.47	6.63	8.80	0.7374	69

Average cost for vehicles receiving CMS information

Average cost of the total system

Level of equilibrium representing travel time deviation between alternative routes

Compliance rate

Sustainable value of reliability

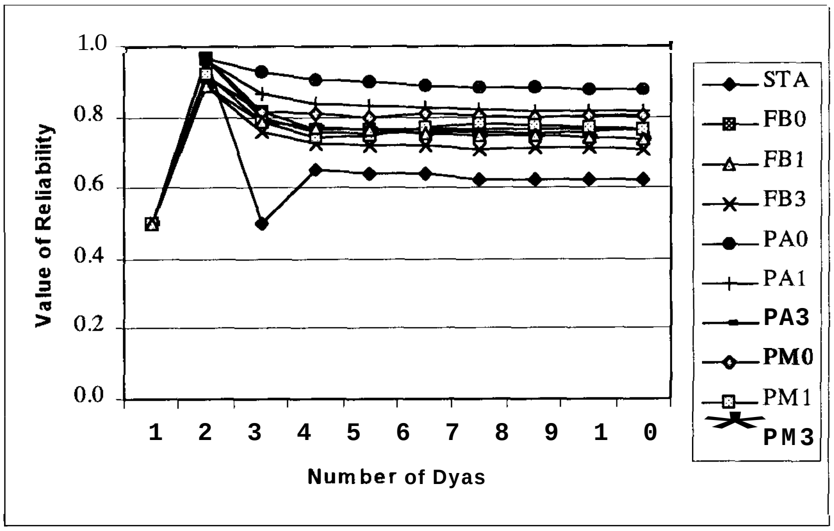


Figure 5.14 Equilibration of Reliability Value

4.6 Summary and Conclusion

This study has developed a framework to parametrically evaluate traffic networks under various converged states: the user equilibrium route guidance (UERG) and the system optimal route guidance (SORG), both with unguided traffic in stochastic user equilibrium (SUE) state. The framework explicitly models sustainable compliance by drivers. It is capable of evaluating in what condition ATIS performs well and which route guidance state performs better as the market penetration increases.

Unlike previous studies that evaluated ATIS based on externally assumed number of guided drivers with perfect compliance, this study has taken drivers' compliance behavior into consideration by treating it as an endogenous variable. The route guidance system provides prescriptive information, and drivers make their decisions whether or not to follow the route guidance based on travel time savings over unguided travel. This paper has defined the problem as a general parametric nonlinear programming problem by using a logit-type model for compliance behavior. For the traffic assignments under route guidance, we have used two mixed equilibrium traffic assignments: one for UERG and the other for SORG.

This paper has pointed out that unguided drivers' perception error is an important factor affecting the performance of the route guidance system; however, it is not easy to observe such perception errors under recurrent congestion. In fact, understanding current traffic condition is a key for the better route guidance system. One of findings from this study is that high market penetration may decrease relative user benefits, but it does not deteriorate the total system due to drivers' compliance behavior. In comparison of route guidance strategies, it seems that UERG performs better in general network and attractive to drivers though results in this paper cannot be viewed as general ones. It is mainly because they are drawn from limited examples and the results will be different under different compliance models. Therefore, further investigations with the different networks and compliance models are needed to draw generalized conclusions.

This research has also extended the approach to the dynamic CMS routing case. We compared four CMS routing methods, such as static routing, feedback routing, predictive average cost routing, and predictive marginal cost routing. In their comparison, information update interval is incorporated to see its effect on overall performance. **As** general results, the predictive average cost routing, expectedly, showed best performance and routing with shorter update interval performed better. This analysis also reveals that update interval in dynamic route guidance system is as important as route guidance strategy.

CHAPTER 6: CONCLUSION AND FURTHER RESEARCH

This research project has developed 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 has proposed several algorithmic approaches, such as static approach, dynamic feedback approach, and dynamic predictive approach. The dynamic approach includes both average cost routing and marginal cost routing.

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, but to the rather simple link travel time functions used. Therefore, in this research dynamic approaches are developed based on dynamic simulation tool, DYNASMART (Dynamic Network Assignment Simulation Model for Advance Road Telematics) that is also used for ATIS evaluation. Driver's behavior model was incorporated into the DYNASMART in order to reflect more drivers' heterogeneity and traffic condition variations.

Even though dynamic CMS routing can be found in the laboratory level, there are many obstacles in real world implementation. One of the reasons is low capability of network monitoring system in current loop detector systems. Therefore, a static CMS routing for event traffic management was implemented. As a real world implementation, a set of new CMS messages, tested and evaluated via 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 not high but enough to improve traffic condition, though exact compliance rate could be estimated via drivers' behavior survey. This field test showed that CMS routing can be used a useful tool for event traffic management. The second test was conducted to observe drivers' responses which directly affect performance of CMS routing.

In this research a parametric evaluation framework for ATIS was developed to evaluate ATIS without relying on assumed fixed rate of compliance. In the model, the drivers' compliance rates are determined endogenously. Various routing strategies both static and dynamic case were tested and evaluated. The model framework is expected to be a useful tool for long-term analysis of ATIS as well as guideline for future ATIS design with respect to routing strategy to apply and system reliability.

REFERENCES

Adler, Jeffrey L. (1993) An Interative Simulation Approach to Systematically Evaluate the Impacts of Real-Time Traffic Condition Information on Driver Behavioral Choice. Ph.D. Dissertation, University of California, Irvine.

Al-Deek, H., Khattak A., and Thananjeyan P. (1998) A combined traveler behavior and system performance model with advanced information systems. Transportation Research 32A, 479-493

Arnott, R., De Palma, A. and Lindsey, R. (1991) Does providing information to drivers reduce traffic congestion? Transportation Research 25A, 309-318.

Arezki, Y. and Van Vliet, D. (1990) A Full Analytical Implementation of the PARTAN/ Frank-Wolfe Algorithm for Equilibrium Assignment, Transportation Science, 24, 58-62.

Bertsekas, D. (1976) On the Goldstein-Levitin-Polyak Gradient Projection Method, IEEE Transactions on Automatic Control, 21(2), 174-183.

Bertsekas, D. and Gallagher, R. (1992) Data Networks, Prentice-Hall.

Bell M.G.H, Bonsall P.W., and O'Flaherty C.A. (1997) Driver Information System. Transport Planning and Traffic Engineering. Chapter 28, pp.517-531

Ben_Akiva, M., De Palma, A., and Lindsey, R. (1991) Dynamic network models and driver information systems. Transportation Research 25A, 251-266.

Bonsall P. and Parry T. (1990) A Computer Simulation Game to Determine Drivers' Reactions to Route Guidance Advice. Proceeding 18th PTRC Summer Annual Meeting, London

Catling I. and McQueen B. (1991) Road Transport Informatics in Europe-Major Programs and Demonstrations. IEEE Vehicular Technology Society, New York, pp.132-149

Chen, A. and Jayakrishnan, R. (1996) Path and Link Flow Based Assignment Algorithems: Finding and Storing Path-Flow Solutions and Computational Performance, submitted to Transportation Research.

Conquest L. and et al (1993) "The Effect of Motorist Information on Commuter Behavior; Classification of Drivers into Commuter Groups", *Trunsportution Research. Part C, Vol. I C.*

Dafermos, Stella C. (1971) "The traffic assignment problem for multiclass-user transportation networks", Series title: Technical report / Cornell University, Dept. of Operations Research; no. 115.

Daganzo, Carlos F. (1981) "Stochastic network equilibrium with multiple vehicle types and asymmetric, indefinite link cost Jacobians", Series title: University of California, Berkeley. Institute of Transportation Studies Working paper ; UCB-ITS-WP-81-5.

Dijkstra, E.W. (1959) A Note on Two Problems in Connection with Graphs, Numerische Mathemtik, 1, 269-271.

Emmerink, R., Nijkamp, P., and Rietveld, P., and Axhausen, K. (1994) The economics of motorist information systems revisited. Transport Review 14, 363-388.

Frank, M. and Wolfe, P. (1956) An Algorithm for quadratic programming, Naval Research Logistics Quarterly, 3, 95-110.

Fukushima, M. (1984) A Modified Frank-Wolfe Algorithm for Solving the Traffic Assignment Problem, Transportation Research, 18B, 169-177.

Hall, R. (1993) Non-recurrent congestion: how big is the problem? Are traveler information systems the solution? Transportation Research 1C, 89-103.

Hall, Randolph W. (1996) Route Choice and Advanced Traveler Information Systems on a Capacitated and Dynamic Network. Transportation Research Part C, Vol. 4, No. 5, pp. 289-306

Harker, P. (1988) Multiple equilibrium behaviors on networks. Transportation Science 22, 39-46.

Hatcher and Mahmassani H. (1992) Daily Variability of Route and Trip Scheduling Decisions for the Evening Commute. Presented at the 71st. Annual Meeting of transportation Board, Washington D.C.

Haselkorn M., Spyridkis J., and Barfield W. (1991) Surveying Commuters to Obtain Functional Requirements for the Design of a Graphi-Based Traffic Information System. Society of Automotive Engineers, Warrendale, PA, pp. 1041-1044

Hearn, D., Lawphongpanich, S., and Ventura, J.A. (1985) Finiteness in Restricted Simplicial Decomposition, Operations Research Letters, 4(3), 125-130.

Hicks, J. (1992) Static network equilibrium models and analyses for the design of dynamic route guidance systems. Ph.D. Dissertation, University of Illinois at Chicago.

Holloway, C.A. (1974) An Extension of the Frank-Wolfe Method of Feasible Directions, Mathematical Programming, 6, 14-27.

Janson, B. (1995) Network Design Effects of Dynamic Traffic Assignment, Journal of Transportation Engineering, 121, 1-13.

Jayakrishnan, R., Tsai, W.K., and Chen, A. (1995) A Dynamic Traffic Assignment Model with Traffic Flow Relationships, Transportation Research, 3C, 51-72.

Jayakrishnan, R., Tsai, W.K., Prashker, J.N., and Rajadhyaksha, S. (1994) A Faster Path-Based Algorithm for Traffic Assignment, Transportation Research Record, 1443, 75-83.

Kanafani, A., and Al-Deek, H. (1991) A simple model for route guidance benefit. Transportation Research 25B, 191-202.

Khattak A., Koppelman F., and Schofer J. (1992) Stated Preference for Investigating Commuters' Diversion Propensity. Presented at the 71st. Annual Meeting of Transportation Research Board, Washington D.C.

King G.F. and Mast T.M. (1987) Excess travel: Causes, Extent, and Consequences. Transportation Research Record 1111, pp. 126-134

Koutsopoulos, H. and Lotan, T. (1990) Motorist information systems and recurrent traffic congestion: sensitivity analysis of expected results. Transportation Research Record 1281, 145-158.

Lam, William H. K. and Huand, Hai-Jun (1992) "Calibration of the combined trip distribution and assignment model for multiple user classes", *Transportation Research. Part B, Methodological. Vol. 26B, no. 4*

Liu Y. (1997) Day-to Day Dynamics of Commuter Behavior under Real-Time Traffic Information. Ph.D Dissertation, University of Texas, Austin

Larsson, T. and Patriksson, M. (1992) Simplicial decomposition with disaggregated Representation for the traffic assignment problem, Transportation Science, 26, 4-17.

LeBlanc, L.J., Morlok, E.K., and Pierskalla, W.P. (1975) An Efficient Approach to Solving the Road Network Equilibrium Traffic Assignment Problem, Transportation Research, 9, 309-318.

LeBlanc, L.J., Helgason, R.V., and Boyce, D.E. (1985) Improved Efficiency of the Frank-Wolfe Algorithm for Convex Network problems, Transportation Science, 19, 445-462.

Lotan T. and Koutsopoulos H. (1992) Fuzzy Control and Approximate Reasoning Models for Route Choice in the Presence of Information. Presented at the 71st Annual Meeting of Transportation Research Board, Washington D.C.

Mahmassani H. and Chen S. (1991) Comparative Assessment of Origin-Based and En-route Real-Time Information under Alternative User Behavior Rules. Transporattion Research Record 1306, pp. 69-81

Mahmassani, H. and Jayakrishnan, R. (1991) System performance and user response under real-time information in a congested traffic corridor. Transportation Research 25A, 293-307.

Mahmassani, H.S., Peeta, S., Hu, T., and Zilaskopoulos, A. (1993) "Algorithm for dynamic route guidance in congested networks with multiple user information availability groups", *International Symposium on Automotive Technology & Automation (26th : 1993 : Aachen, Germany). Dedicated Conference on Advanced Transport Telematics/Intelligent Vehicle Highway Systems.*

Mammar, S., A. Messmer, P. Jensen, M. Papageorgiou, H. Haj-Salem, and L. Jensen (1996) Automatic Control of Variable Message Signs in Aaloborg, Transportation Research, 3C, 131-150.

Messmer A., M. Papageotgiou and N. Mackenzie Automatic Control of VMS in the Interurban Scottish Highway Network, the 8th IFAC/IFIP/IFORS Symposium, Chania, Greece, 1997, 1060-1065

Ppageorgiou M. (1990) Dynamic Modeling, assignment, and route guidance in Traffic Networks, Transportation Research, 24B, 471-495.

Peeta, S. and Mahmassani H. (1995) Multiple user class real-time traffic assignment for online operations: a rolling horizon solution framework. Transportation Research 3C, 83-98.

Ran, B., Boyce, D. E., and LeBlanc, L. J. (1993) A new class of instantaneous dynamic traffic assignment models, Operations Research, 41, 192-202.

Sheffi, Y. (1985) Urban Transportation Networks. Englewood Cliffs, NJ, Prentice-Hall.

Smith, M. J. and Van Vuren, Tom. (1992) "Equilibrium traffic assignment with two vehicle types", *Mathematics in transport planning and control.* Oxford : Clarendon Press

Sun, C., Jayakrishnan, R., and Tsai, W.K. (1996) Computational Study of a Path-Based Algorithm and Its Variants for Static Traffic Assignment, forthcoming in Transportation Research Record.

Tomas, Roy. (1991) "*Traffic Assignment Techniques*", Avebury Technical.

Van Vuren, Tom, Van Vliet, Dirck, and Smith, Michael J. (1990) "Combined Equilibrium in a network with partial route guidance", *Traffic control methods. New* ***York,*** *NY* **:** *Engineering Foundation*

Van Vuren, Tom. (1990a) "The interaction between route guidance and signal control : development of a multiple user class model", Series title: Working paper (University of Leeds. Institute for Transport Studies) ; 318.

Van Vuren, Tom. (1990b) "The interaction between route guidance and signal control : model results", Series title: Working paper (University of Leeds. Institute for Transport Studies) ; 319.

Van Vuren, T., and Watling, D. (1991) A multiple user class assignment model for route guidance. Transportation Research Record 1306, 22-31.

Van Vuren, Tom and Van Vliet, Direk (1992) *"Route choice and signal control* **:** *the potential for integrated route guidance"*, Aldershot, Hants ; Brookfield, Vt., USA : vebury, c1992., Series title: Institute for transport Studies (Series) ; 5.

Wardrop J.G. (1952) Some Theoretical Aspects of Road Traffic Research. Proceeding of the Institute of Civil Engineer. Part II, pp. 325-378

Wardman M., Bonsal P., and Shires J. (1996) State Preference Analysis of Driver Route Choice Reaction to Variable Message Sign Information. Working Paper, I.T.S., University of Leeds.

Watling, David, and Van Vuren, Tom. (1991) "The modelling of dynamic route guidance systems", Series title: Working paper (University of Leeds. Institute for Transport Studies) ; 341.

Watling, David. and Van Vuren, Tom. (1993) "The modelling of dynamic route guidance systems", *Transportation research. Part C, Emerging technologies. Vol. IC, no.2*

Weintraub, A., Ortiz, C., and Gonzalez, J. (1985) Accelerating Convergence of the Frank-Wolfe Algorithm, Transportation Research, 19B, 113-122.

Whelan, Richard (1995) *"Smart Highways, Smart Cars"*, Artech House

Yang H., Kitamura R., Jovanis P., Vaughn K., and Abdel-Aty M. (1992) An Analysis of Route Choice Behavior under Advanced Travel Information Systems: A Neural Network Approach. Research Report, I.T.S., University of California, Davis.

Yang H. (1998) Multiple equilibrium behaviors and advanced traveler information systems with endogenous market penetration. Transportation Research 32B, 205-218.