Incorporating Intelligent Transportation Systems Deployment In Strategic Planning

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Incorporating ITS deployment in strategic planning requires a fundamental change in forecasting procedures (e.g. moving to activity-based travel demand modeling), the reality of the situation is that agencies with responsibilities for long range planning, given their perennial resource constraints, are unlikely to make drastic changes in their modeling procedures. Thus, it would appear there is a real need to explore the ramifications of deploying ITS with regard to planning procedures based on the existing four-step process.

The objective of the current research effort is twofold. First, the study makes an assessment for the sensitivity of the traditional four-step planning process to the likely impacts of ITS deployment. Second, the study explores how these anticipated impacts should be best incorporated in the planning process; a novel approach based on combining case-based reasoning (CBR), an emerging artificial intelligence (AI) paradigm, and dynamic traffic assignment (DTA) models is proposed for accomplishing this goal. In answering these two research questions, the focus of the study will be on two popular ITS technologies, freeway incident management systems (FIMS) and advanced travel information systems (ATIS). The context for the analysis will be a freeway corridor.

The results of this research illustrate quantitatively that the current methods used in the planning process are incapable of accounting for the impacts of ITS. The study team suggests two reasons standing behind this deficiency. The absence of temporal dimension in the 4-Step process makes it incapable of capturing the expected benefits from some ITS components. The second reason is the absence of the delay spatial dimension in the 4-step process. Hence, new approaches, such as the CBR prototype developed in this research, are needed for accounting for ITS deployment effects in the planning process.

To illustrate the feasibility of using CBR to quantify the benefits of ITS deployment, a prototype system for determining the likely benefits of employing VMS for traffic diversion was developed. The performance of the prototype was then evaluated by comparing its predictions to those obtained using a detailed DTA model. The evaluation results were quite encouraging. The prototype system yielded high quality solutions comparable to those obtained using the DTA model.

Intelligent Transportation System, ITS, Dynamic Traffic Assignment, DTA, Four-Step Process, Case Based Reasoning, CBR, Variable Message Signs, Artificial Intelligence

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Abstract

Incorporating ITS deployment in strategic planning requires a fundamental change in forecasting procedures (e.g. moving to activity-based travel demand modeling), the reality of the situation is that agencies with responsibilities for long range planning, given their perennial resource constraints, are unlikely to make drastic changes in their modeling procedures. Thus, it would appear there is a real need to explore the ramifications of deploying ITS with regard to planning procedures based on the existing four-step process.

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Keywords:

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Table of Contents

Abstract ....................................................................................................................................... i
Table of Contents ....................................................................................................................... ii
List of Figures ........................................................................................................................... iv
List of Tables ............................................................................................................................ iv
1 INTRODUCTION AND PROJECT OBJECTIVES.......................................................... 1
2 LITERATURE REVIEW ................................................................................................. 2
  2.1 Understanding the Sensitivity of the 4-step Planning Process to ITS Deployment .... 2
  2.2 DTA Models and CBR .............................................................................................. 3
    2.2.1 DTA Models ....................................................................................................... 3
    2.2.2 The CBR Paradigm ........................................................................................... 4
    2.2.3 Rationale Behind Proposed Approach .............................................................. 5
3 METHODOLOGY .............................................................................................................. 7
  3.1 Test Network Selection and Data Acquisition ........................................................... 7
  3.2 DTA Model Development .......................................................................................... 8
    3.2.1 The Simulation Component ............................................................................... 8
    3.2.2 The Routing Logic ............................................................................................ 9
    3.2.3 Modeling Incidents and Diversion ................................................................... 9
  3.3 Assessing the Sensitivity of the 4-Step Process to ITS Deployment ....................... 9
    3.3.1 ATIS .............................................................................................................. 10
    3.3.2 FIMS .............................................................................................................. 12
    3.3.3 Sensitivity Measure ......................................................................................... 16
  3.4 Developing the CBR Module .................................................................................... 19
    3.4.1 Developing the INTEGRATION Model for the Test Network ......................... 20
    3.4.2 Selecting the Prototypical Cases to be included in the Case-base ................. 21
    3.4.3 Developing the CBR system ......................................................................... 24
4 RESULTS AND DISCUSSION ......................................................................................... 28
  4.1 Sensitivity of the 4-step Planning Process ............................................................... 28
    4.1.1 ATIS ............................................................................................................... 28
    4.1.2 FIMS .............................................................................................................. 30
  4.2 Evaluating the Performance of the CBR System ...................................................... 32
5 SUMMARY AND CONCLUSIONS .................................................................................................................. 34
  5.1 Sensitivity of 4-Step Process to ITS Deployment .................................................................................. 34
  5.2 CBR for Quantifying ITS Benefits ....................................................................................................... 35
REFERENCES .................................................................................................................................................. 36
List of Figures

Figure 1 The CBR Cycle (Adapted from Watson 1995) .......................................................... 5
Figure 2 ATIS Test Network .................................................................................................... 7
Figure 3 FIMS Test Network ............................................................................................... 13
Figure 4 Anticipated Network Travel Time Results and Model Variables ...................... 17
Figure 5 CBR Modeled Network ....................................................................................... 19
Figure 6 Diversion Opportunities and Incident Location .................................................. 23
Figure 7 Network Travel Times Results for ATIS .............................................................. 29
Figure 8 Network Travel Times Results for FIMS ............................................................... 31

List of Tables

Table 1 Comparing the CBR and the INTEGRATION Model Results................................. 33
1 INTRODUCTION AND PROJECT OBJECTIVES

Various elements of intelligent transportation systems (ITS) are being implemented worldwide under the assumption that they will certainly produce benefits. However, although plans for deployment of ITS are often well thought out, their impacts are rarely explicitly considered or quantified in technical travel demand modeling procedures such as the somewhat ubiquitous "Four-Step Process." There are in fact many reasons behind such a lack of integration. Besides the fact that empirical observations of how ITS impact travel behavior are very scarce at the current moment, there is a fundamental difference between the philosophy of the traditional four-step planning process and the likely impacts of ITS deployment. The focus of the traditional four-step planning process has always been on average travel conditions; the impact of unusual occurrences such as incidents are typically not considered. On the other hand, ITS (incident management systems for example) are mainly aimed at these unusual occurrences (Hatcher et al., 1998).

While one could argue that incorporating ITS deployment in strategic planning requires a fundamental change in forecasting procedures (e.g. moving to activity-based travel demand modeling), the reality of the situation is that agencies with responsibilities for long range planning, given their perennial resource constraints, are unlikely to make drastic changes in their modeling procedures. Thus, it would appear there is a real need to explore the ramifications of deploying ITS with regard to planning procedures based on the existing four-step process.

The objective of the current research effort is twofold. First, the study will assess the sensitivity of the traditional four-step planning process to the likely impacts of ITS deployment. Second, the study will explore how these anticipated impacts should be best incorporated in the planning process; a novel approach based on combining case-based reasoning (CBR), an emerging artificial intelligence (AI) paradigm, and dynamic traffic assignment (DTA) models is proposed for accomplishing this goal. In answering these two research questions, the focus of the study will be on two popular ITS technologies, freeway incident management systems (FIMS) and advanced travel information systems (ATIS). The context for the analysis will be a freeway corridor.

In addition to this introductory section, the current report has another four main sections. Section two provides a quick review of the literature pertaining to the sensitivity of the four-step planning process to ITS deployment, to DTA models, and to the CBR paradigm. In section three, we describe the different tasks of the methodology we followed in order to achieve the objectives of the projects. The results are presented and discussed in section four. Finally, section five summarizes the main conclusions derived from the study.
2 LITERATURE REVIEW

This section is divided into two main subsections. In the first subsection (section 2.1), we review the literature regarding the sensitivity of the four-step planning process to ITS deployments. Section 2.2, on the other hand, discusses DTA models and the CBR paradigm.

2.1 Understanding the Sensitivity of the 4-step Planning Process to ITS Deployment

The traditional planning method for transportation systems consists of four steps: trip generation, trip distribution, mode choice and traffic assignment, and is usually referred to as the four step process. The 4-step process represents the transportation-planning problem in a logical and intuitive sequence. The simplicity of the 4-step process has made it popular and commonly used by transportation planners and analysts for both long and short term planning purposes. Despite the simplicity and intuitiveness of the 4-step, it suffers from inherent shortcomings and limitations. The sequential nature of the 4-step process omits the interaction and dependencies among the different steps in the process. In addition, the analysis of the 4-step process is usually done on an aggregate basis in most of the steps, which affects precision level of the analysis. The relevance of these shortcomings varies by the type of the sought analysis. For example, in developing a 10-year transportation improvement plan (TIP); the 4-step process is considered adequate. On the other hand, if the subject analysis is to study the impact of construction work on a specific link in a transportation network, the accuracy of the results obtained using the 4-step is not considered acceptable.

Several researchers have investigated other approaches for improving the planning process addressing the deficiencies of the 4-step process. Some research focused on the shortcoming in performing the planning process in a sequential manner, (Evans, 1976) and suggested integrating trip distribution and traffic assignment in a single model that simultaneously solves both steps. On the other hand, the TRANSIM team at Los Alamos national laboratory has introduced a micro-simulation model for transportation planning as an alternative for the macroscopic based 4-step process. Other researchers (Koppelman 1988, Jones et al 1990, Ben-Akiva and Bowman 1995) have suggested activity-based transportation planning, a totally new paradigm for transportation planning still in research stages.

Although as mentioned above, there is a fundamental difference between the philosophy of the traditional planning process and what a number of ITS applications are intended to achieve, the 4-step process might still be sensitive to ITS deployment. Travel time has long been an important input factor in several of the steps in the classic four-step travel demand forecasting process. Researchers have also investigated the impact of travelers' perceived travel time on their travel decisions, and a wealth of research points to the importance of uncertainty in travelers' decisions. For example, Noland and Small (1995) model total commute time as comprising three elements:

- commute time with no congestion,
- extra time when congestion is certain, and
- extra time due to unexpected congestion.
Implementing a FIMS can reduce the second of these elements by expediting incident clearance. ATIS deployment potentially affects both the second and third elements, by reducing the variance of the user's expected travel time; estimating travel time variance is one way to represent this third element. More recently, work at the operational level examined the importance of travelers' perceptions of the reliability of ATIS delay predictions (Khattak et al., 1995). It is our thesis that travelers' perceptions of their ability to predict both travel time and its variance is a primary determinant of their departure time, mode and route decisions. The variance in travel time, and hence arrival time, is also important in the work trip where arrival say, 15 minutes late "is likely to be onerous" (Khattak et al., 1995) for some employees. To the extent that FIMS and ATIS have significant impact on drivers' perceptions of their ability to predict both travel times and variances in travel times, deployment of these systems is likely to have important consequences for the accuracy of long-range forecasts. The proposed research will examine these consequences.

Ben Akiva et al. (1994) give an extensive review of user response to ATISs (more recent work has been done by Khattak et al. (1995) and Polydoropoulou et al. (1995). In the current research, we build upon these findings, by determining the sensitivity of the four-step process to the deployment of ATIS and FIMS. Of course, it is possible that, in some cases, the effects of their introduction will be hidden in the error inherent in the process as it is now conducted. This result in itself will be a useful finding, indicating that the effects of these systems cannot be estimated in this context. In any case, the results will provide valuable information to practitioners, either by providing them with new analysis tools or by showing that existing tools are inadequate for evaluating the effects of such systems.

2.2 DTA Models and CBR

2.2.1 DTA Models

DTA has been the subject of increased research activity in the recent years, thanks to the rapid development of ITS technologies. Unlike static traffic assignment (which represents the last step in the conventional planning process), DTA models permit the supply and demand of the transportation network to vary over time. This allows for more accurate modeling of incident scenarios where the available capacity (i.e. network supply) changes over time, as well as modeling peak-hour conditions where the demand is time-variant. The price for this refined modeling capability, however, comes in the form of increased model complexity, data input and computational requirements.

As opposed to its static counterpart, the DTA problem is much more complex. This is because the time dimension of the problem needs to be considered. Current approaches to the solution and formulation of DTA models could be classified into two groups: (a) the analytical approach; and (b) the simulation-based approach. The analytical approach attempts to represent traffic flow using a set of equations that are then solved for the optimal solution (Merchant and Nemhauser, 1978; Carey, 1987; Friesz et al., 1989; Papageorgiou, 1990; Janson, 1991; Lafortune et al., 1993; Ran et al., 1993). The simulation-based approach, on the other hand, uses simulation to more accurately traffic dynamics. Examples of available models that use the simulation-based approach include INTEGRATION (Van
Aerde and Yagar, 1988; Yagar, 1993; Van Aerde, 1995), DYNASMART (Mahmassani et al., 1993) and DYNAMIT (Ben-Akiva et al., 1997a; Ben-Akiva et al., 1997b).

Owing to their ability to model time-varying travel conditions, DTA models would most probably allow planning agencies to more accurately quantify the impacts of ITS deployments than static traffic assignment. For example, to quantify the impacts of an incident management system, a typical incident frequency and duration would have to be assumed first, based on conditions in the region; the assumed conditions represent what is typically referred to as a representative day scenario (Hatcher et al., 1998). The DTA model could then be used to model travel conditions with the incident management system in place as well as to model the case without the system. The difference in travel conditions between the two cases would thus give a quantitative assessment of the FIMS impact.

2.2.2 The CBR Paradigm

While DTA models are more accurate in quantifying ITS deployments compared to models based on the 4-step planning process, the question still remains as to whether planning agencies would have the resources to use DTA models in their analyses. To help alleviate this problem, the study proposes to develop a CBR module for quantifying the likely impacts of ITS projects. A brief description of CBR is given below followed by a discussion of the rationale behind the proposed approach.

CBR is a reasoning paradigm and computational problem solving method that is attracting increased attention in the AI community (Aamodt and Plaza, 1994). At a very basic level, CBR is based on the observation that when people solve a new problem, they often base the solution on one that worked for a similar problem in the past. A complete CBR process can be represented as a cycle consisting of the following tasks (Figure 1):

1. **RETRIEVE** the most similar case(s);
2. **REUSE** the case(s) to solve the problem;
3. **REVISE** the proposed solution if necessary; and
4. **RETAIN** the parts of this experience to be used for future applications.
At the core of the CBR process is a case-base that stores previous instances of problems and their derived solutions. When faced with a new problem, a CBR system matches the new problem against cases in the case base, and RETRIEVES the most similar case(s). Since the retrieved case is likely to be somewhat different from the current case, a CBR system typically adapts the retrieved solution to closely suit the new problem during the REUSE step. The proposed solution is then implemented and tested for success; any REVISIONS are then made, if needed. Finally, the new case is RETAINED, allowing the system to learn and refine its knowledge with usage.

As can be seen from the above, CBR is quite different from other major AI approaches. Instead of depending on just general knowledge, CBR uses specific knowledge of previously experienced situations or cases. During the last few years, CBR has been successfully applied to a wide variety of application areas. These include (a) help-desk applications (Bergmann et al., 1999); (b) diagnostic systems (Allen et al., 1995; Malek and Relle, 1994); (c) design problems (Barletta and Hennessy, 1989; Goel and Chandrasekaran, 1989; Pearce et al., 1992); and (e) real-time control problems (Ram et al., 1992). CBR applications in civil and infrastructure engineering, however, are still in an early stage. It is hoped that the current research would encourage further applications of the paradigm to such problems.

2.2.3 Rationale Behind Proposed Approach

While DTA models should be expected to allow for more accurately quantifying ITS impacts, building DTA models is a rather complex task that requires a lot of effort, time, computational resources, and a certain level of technical skills. The approach that this study
is proposing attempts to alleviate this problem through the development of a CBR system for quantifying the likely impacts of ITS projects. The CBR system’s case base would store cases of the likely impacts of an ITS deployment under different travel demand and supply conditions. Once the case-base is developed, when a planning agency is attempting to quantify the impacts of a proposed deployment in its jurisdiction, the CBR module would search the case-base for the most similar stored case(s) in terms of travel conditions and demographics in the region. The likely impact of ITS deployment stored in the retrieved case will then be adapted to the current situation. By adopting this CBR approach, the planning agency will avoid the need to go through the process of coding and running a DTA model.

The case-base of the CBR system will be generated in the following fashion. First, the range of travel demand and supply conditions to be expected on a network will be identified. A DTA model will then be used to model each combination of travel demand and supply conditions twice; one time with the ITS component deployed, and a second time for the case of no deployment. The difference of travel conditions between these two scenarios will then be used as a measure of the likely impacts of ITS for the case modeled.
3 METHODOLOGY

The methodology we designed to accomplish the objectives of the project consisted of the following tasks:

- Selecting the study’s test network selection and acquiring the required data;
- Developing a DTA model for the test network
- Assessing the sensitivity of the 4-step planning process to ITS deployment
- Developing and testing a CBR module for quantifying benefits of ITS deployment

Each of these tasks is described in some detail below.

3.1 Test Network Selection and Data Acquisition

In selecting a test network for this study, it was important to select a sub-area where the benefits of deploying ITS will be vivid. The criteria upon which the test network was selected are a) a congested area where volume to capacity ratio is between 70% & 90%, b) an area where a reasonable alternative route exists and drivers have multiple access points to those alternatives. The area south of Hartford CT, and north of Meriden CT was identified as a test network, Figure 2. Interstate I-91 is the main link on that corridor and the primary alternative is Rt 15. From the map on Figure 1, it is clear that I-91 and CT-Rote 15 are parallel with multiple access points between the two corridors. The modeled network consists of 288 nodes, 709 links, and covers 554 lane miles. The traffic demand was obtained from the daily origin-destination trip tables from Connecticut Department of Transportation.

![Figure 2 ATIS Test Network](image)
The data available has a normal OD table, meaning that it does not have data related to unusual occurrences like accidents/spillage or any major holiday events. Since we know that the OD table is fixed, the route choice and time choice of departure only can change and the destination choice is not changed. This is important in the analysis because, DTA models (or micro-simulation) can change the time choice of departure and hence give better results as compared to the four-step process (macro-simulation).

3.2 DTA Model Development

For DTA modeling, this study decided to use the INTEGRATION model developed by Van Aerde and Associates (Van Aerde, 1995). The INTEGRATION model is a simulation-based DTA model. The model was conceived in the mid 1980s as an integrated simulation and traffic assignment model that could be used for modeling integrated freeway and arterial networks. INTEGRATION thus combines two models: one for assignment, and another for simulation. A brief overview of how each of these two components work is given below.

3.2.1 The Simulation Component

INTEGRATION is a fully microscopic simulation model capable of modeling many dynamic traffic flow phenomena including shock waves, gap acceptance behavior and weaving sections. The model allows for modeling time-varying demand conditions, since the user is permitted to specify the traffic demand in the form of a time series sequence of O-D departure rates for each O-D pair in the network. Vehicles are then generated in a fashion consistent with the time-varying departure rates specified by the user for each time interval. In INTEGRATION, vehicles select their desired speeds based upon the headway between a vehicle and the one ahead. The computation is based upon link-specific car following relationships that are calibrated macroscopically to ensure consistency with the specified flow-speed-density relationships for each link.

As was previously mentioned, INTEGRATION allows for modeling both freeways, as well as arterial networks. With respect to freeways, the model is capable of modeling on-ramp, off-ramp, and weaving sections, and is capable of accurately modeling the queues that might form at these locations. For arterial networks, INTEGRATION can model signalized intersections, including modeling permissive left turn behavior and the impact of alternative signal coordination effects. The model can also automatically optimize cycle and phase splits at a user-specified frequency; this allows the model to simulate advanced traffic control systems. However, the user has to specify the phasing sequence and the signal offsets for signal co-ordination operation. The current version of the model does not optimize signal offsets as a part of its automatic signal re-timing routine; instead, the offsets are held constant, while each signal is optimized.
3.2.2 The Routing Logic

The model’s internal routing logic determines the next link a vehicle would take as it traverses the network toward its destination. There are several different ways within the model that could be used to determine a vehicle routing. Generally speaking, INTEGRATION allows the user to model 5 different types or classes of drivers that differ in their routing behavior. For each type, the user specifies the intervals at which routes will be computed for each of the different driver classes. By default, routes are computed on the basis of real-time link travel information available from the simulation results.

3.2.3 Modeling Incidents and Diversion

INTEGRATION is capable of modeling incidents, along with modeling the subsequent diversion that would occur in case drivers have access to real-time travel information. The model allows the user to specify the exact location of the incident along a link, its expected duration, and its severity in terms of the number of lanes blocked by the incident. While the model’s routing logic does not directly respond to the occurrence of an incident, it responds to the delay resulting from the incident. The implication of this is that diversion would not start until the delay is significant enough so as to make other alternate routes attractive.

Besides being able to model in-vehicle route guidance systems, INTEGRATION is also capable of modeling the impact of Variable Message Signs (VMS) on drivers behavior. To model VMS, the user has first to specify the nodes at which VMS exist. Next, the user has to specify at least two different classes of drivers in terms of driver behavior. One class (e.g. class 1) would represent drivers with no access to real-time information (i.e. drivers whose routes are not updated in an on-line fashion), and the other class (class 2) would represent drivers with access to real-time information (drivers whose routes are recomputed at very short intervals). When a vehicle of class 1 enters the upstream end of a link at the end of which a VMS exists, the model would transform the behavior of this class 1 vehicle to the behavior of a class 2 vehicle, and hence the transformed vehicle would be able to alter its route in response to real-time traffic conditions; this transformation is sustained for a period of 180 seconds after the vehicle has departed the link. By doing so, the impact of VMS is approximated. The user is also allowed to specify the percentage of vehicles that would respond to the VMS message (i.e. specify the percentage of class 1 vehicles that would undergo the transformation to class 2 vehicles).

3.3 Assessing the Sensitivity of the 4-Step Process to ITS Deployment

To assess the sensitivity of the 4-step process to ITS deployment, this considered two specific ITS applications: Advanced Traveler Information Systems (ATIS) and Freeway Incident Management Systems (FIMS). The following subsections describe the methodology followed for each case.
3.3.1 ATIS

The analysis consisted of two parallel phases. The first phase is emulation for ATIS using current tools and models that are used in the 4-step process. The goal of this phase is to obtain a prediction for benefits anticipated from deploying ATIS on a test network. The results of the first phase will depict the capabilities of the current tools used in the 4-step process in capturing ATIS impact. Optimally, the results from the first phase would be compared against actual benefits of ATIS to evaluate the sensitivity of the 4-step process to ATIS. While the actual ATIS benefits are difficult to quantify and measure, the second phase will be focusing on estimating “actual” benefits of ATIS using a DTA model (a micro-simulation model). Because of the disaggregate nature of microscopic simulation, its results are assumed to be the closest to reality if compared with results obtained from macroscopic simulation, which is commonly used in the traffic assignment step of the 4-step process. Then, results from both phases are used to obtain a normalized sensitivity index that will be used to quantify the sensitivity of the 4-step process to ATIS. This is explained in more detail below.

Emulation of ATIS In The 4-Step Process

The goal in this section is to develop a method that will emulate the likely impacts of deploying ATIS in the traffic assignment step. The current traffic assignment criteria are based on Wardrop’s user equilibrium criterion. Of course, stochastic user equilibrium is more accepted and also available as an option in most transportation planning packages. Traffic assignment models used in the 4-step process are usually static, i.e. they do not take into consideration changes in traffic demand and link travel times with respect to time. In addition the traffic assignment step assumes normal network condition, i.e. does not take into consideration delays due to traffic accidents or nonrecurring congestion associated with special events. On the other hand, ATIS is aimed at disseminating network travel time information to drivers, so that they can use this information to review their route choice decisions and to divert to other routes with less travel times. In other words, drivers will benefit from ATIS in the cases of traffic accidents and nonrecurring congestion associated with special events.

Therefore, in order to emulate ATIS, drivers’ population will be divided into two groups. The first group represents the portion of drivers \(X_{\text{ATIS}}\%) with full access to information delivered by ATIS. The second group of drivers is the rest of the population with no access \((1- X_{\text{ATIS}})\%). The percentage of drivers with access to travel time and network information \(X_{\text{ATIS}}\%) represents the ATIS market penetration, which is one of the analysis variables. Two different traffic assignment criteria will be used for each group. The second group of drivers with no access to information will be assigned first to the test network using deterministic assignment criterion like all or nothing. The first group will then be assigned to the test network using a user equilibrium criterion, which reflects the advantageous position of this category of drivers with respect to awareness of actual network travel times. The following are the steps for emulating ATIS in the traffic assignment step.
**Step 1:** Assign traffic to test network using user equilibrium criterion and obtain travel time on links,

**Step 2:** Identify a critical link where a hypothetical accident is assumed to occur. The accident characteristics considered are number of lanes blocked and duration before clearing.

**Step 3:** Update the characteristics of the critical link identified in Step 2 on the network. Also, use link travel times obtained from Step 1 as the free flow travel times for subsequent steps.

**Step 4:** Divide drivers population into two groups. The first Group $(X_{ATIS})\%$ are drivers with access to ATIS. The second group is $(1-X_{ATIS})\%$ with no access to ATIS.

**Step 5:** Assign drivers in the second group $(1-X_{ATIS})\%$ using network travel times resulted in Step 1 using all or nothing criterion, then,

**Step 6:** Assign drivers in the first group $(X_{ATIS})\%$ using network travel times and adjusted capacities resulting from Step 5 following a user equilibrium criterion.

Step 1 emulates normal conditions, where drivers will seek user equilibrium. During normal conditions, drivers primarily rely on their experience with travel times on the network in making route selection decisions. In the case of nonrecurring congestion resulting from accident (Step 2) and/or special events, the group of drivers with access to ATIS will still be able to optimize their routes in a user equilibrium fashion (Step 6). However, the set of drivers without access to ATIS information, will not change their route choices (Step 5), which is equivalent to assigning them using AON criteria on the network with user equilibrium travel times obtained in (Step 1).

**Estimating ATIS Benefits using DTA or Micro-simulation**

Measuring and quantifying the actual benefits for a specific ITS subsystem is extremely complex due to the multilevel and interdependencies of benefits. Hence, an “estimation” of benefits is usually carried out using traffic simulation means. Traffic simulation could be divided into three categories according to the level of modeling aggregation. These categories are macroscopic, mesoscopic, and microscopic. The first category, macroscopic simulation, models traffic flow as a stream flow assuming homogeneity in drivers’ behaviors, which is typically used in planning applications. The second category, the mesoscopic, models traffic flow in terms of platoons, which is less aggregate than the first category and usually used in simulating traffic signals over corridors. The third category, microscopic simulation, is disaggregate and the most detailed in terms of modeling individual vehicle behavior models. In this study, we decided to use microscopic simulation, because it is the closest modeling environment that replicates reality with least aggregation.

Similar to emulating ATIS in the 4-step process, drivers are divided into two groups. Traffic flow in the first group comprises of drivers with access to information from ATIS, while the second group of drivers are those with no access to real time network travel times. Drivers in the first group make their route selection decisions dynamically and before their departure time. The drivers in the second group use their previous knowledge of the network in determining their routes. In order to separate other variables affecting network travel times from the analysis, it was assumed that drivers in the second group are assigned using free flow link travel times.
Available microscopic simulation packages enable users to identify different classes of drivers with different access level to network travel time and route choice criteria. Travelers can be divided into two groups, the first group \((X_{ATIS} \%)\) was assumed to be aware of the current traffic conditions and the second group \((100 - X_{ATIS} \%)\) oblivious of the current traffic conditions. Then the net travel-time savings can be estimated for different market penetrations. First we simulate the base case where \(X_{ATIS} \% = 0\), then the simulation is carried on for other percentages of \(X_{ATIS} \%\) \((10\%, 20\%, \ldots, 100\%)\). The average travel time will be later used to estimate the benefits for each market penetration levels. Market penetration levels are the levels to which the information being broadcast is used by the travelers because we know for sure that not all people will get to lay their hands on the available information or not everyone aware might use the information.

The steps for estimating ATIS benefits are:

**Step 1:** Simulate traffic flow on the test network with no accident and allow all drivers to update their route choices at short time intervals, which is equivalent to user equilibrium assignment.

**Step 2:** Update the characteristics of the critical link identified in Step 2 of phase 1 on the network. Also, use link travel times obtained from Step 1 as the free flow travel times for subsequent steps.

**Step 3:** Divide driver population into two groups. The first Group \((X_{ATIS} \%)\) is drivers with access to ATIS. The second group \((1 - X_{ATIS} \%)\) is drivers with no access to ATIS.

**Step 4:** Simulate traffic flow on the network for both groups of drivers such that the second group \((1 - X_{ATIS} \%)\) will not update their route selection during the term of the simulation, which replicates all or nothing assignment, while the first group \((X_{ATIS} \%)\) will update their route choices at short time intervals.

### 3.3.2 FIMS

Similar to ATIS, sensitivity analysis of the 4-Step process to FIMS consists of two phases. The first phase is an emulation of FIMS in the 4-Step process using macroscopic simulation. The second phase is to estimate the actual benefits of FIMS using microsimulation (the INTEGRATION model). Then, a sensitivity index is defined to determine the level of sensitivity of the 4-Step process to the deployment of a FIMS.

For FIMS, a sub-network of the test network used in the ATIS part was selected. Figure 3 illustrates the relative location of the sub-network, location of accident, and the location for a variable message sign (VMS). The sub-network covers a part of I-91 with relatively high traffic demand where Rt. 15 could be an alternative and drivers could divert to. The accident defined was a single lane blockage for 20 minutes. The sub-network consists of 41 nodes, 108 links, and a total of 81.47 of lane miles. The traffic demand was obtained from the daily origin-destination trip tables from Connecticut Department of Transportation.
Emulation of FIMS In The 4-Step Process

The goal in this section is to develop a method that will emulate FIMS in the traffic assignment step. Incident management involves the coordinated, preplanned use of human and technical resources to restore highway to its normal situation. The most important component of the Incident Management System that the drivers respond to immediately is the Variable Message Signs (VMS) that provide travelers with incident information. Providing that VMS might change the drivers’ decision about their route choice to avoid
delay due to an incident downstream. However, drivers respond differently to messages posted on VMS, depending on availability of alternatives and the relative location of VMS to incident location. As a result, only a percentage of drivers diverge from their original routes and use alternatives to avoid delays due downstream incidents. Following are the steps for emulating FIMS in the 4-Step process.

**Step 0:** Identify a candidate link where an accident will be defined. A suitable link will be a link that satisfies the following two criteria. First, congested link but not over saturated, the second is that it should be in a location where other relevant alternatives could be used.

**Step 1:** Assign traffic using user equilibrium criteria to the base network \( N_0 \) (the original network and without any adjustments for the capacity due to accidents). The outcome of this step is total network travel time \( TT \) and traffic volume on the accident link is \( Vol_0 \).

**Step 2:** Divide drivers population into two groups. The first group \( X_{FIMS} \% \) represents the portion of drivers that will diverge due to VMS and the second group \( (1- X_{FIMS}) \% \) represents the rest of drivers that wont diverge.

**Step 3:** Adjust the capacity of the accident link according to the accident attributes as following:

\[
C_{adj} = C \times \left( n_{lanes} - acc_{lanes} \times \frac{t_{acc}}{60} \right) \tag{1}
\]

where,
- \( C \) - Original link capacity in (vph),
- \( C_{adj} \) - Adjusted link capacity in (vph),
- \( n_{lanes} \) - Total number of lanes on the accident link,
- \( acc_{lanes} \) - Number of lanes blocked due to the accident,
- \( t_{acc} \) - Accident time duration in minutes (assumed to be <=60 minutes)

**Step 4:** Then, estimate total travel time due to the accident by adjusting \( TT \) as follows:

The original travel time on the accident link could be estimated as a function of the volume to capacity ratio \((V/C)\) as follows,

\[
t_0 = t_f \left(1 - \alpha (V / C)^\beta \right) \tag{2}
\]

Where, \( t_0 \) is the original link travel time without accident, \( t_f \) is the link free flow travel time, \( V \) is the link volume, \( C \) is the original link capacity (unadjusted due the accident), and \( \alpha , \beta \) model parameters (“typical” values for \( \alpha \) and \( \beta \) are 0.25 and 4 respectively).

Then, due to traffic accidents, there will be a loss in capacity. Hence, Eq.(2) becomes,

\[
t_a = t_f \left(1 - \alpha (V / C_{adj})^{\beta} \right) \tag{3}
\]

Then, the increase in travel time on the accident link will be:

\[
\Delta t_a = t_a - t_0 \tag{4}
\]

Substituting for \( t_0 \) and \( t_f \) in Eq.(4),
\[ \Delta t_a = t_f \frac{a V^\beta (C^{\beta} - C_{adj}^{\beta})}{(C C_{adj})^{\beta}} \]  

(5)

Hence, the total network travel time \( TT \) adjusted for the accident will be:

\[ TT_0 = TT + \Delta t_a * V \]  

(6)

Where,

\( TT_0 \) - Total network travel time adjusted for the accident, and with 0% FIMS

**Step 5:** Estimate total network travel time for \( X_{FIMS} \% \) divergence. Eq.(5) could be generalized for the case where some drivers \( X_{FIMS} \% \) traveling on the accident link will diverge in response for a FIMS, then, Eq. (5) becomes,

\[ \Delta t_{a,x} = t_f \frac{a V^\beta (1 - X_{FIMS})^\beta (C^{\beta} - C_{adj}^{\beta})}{(C C_{adj})^{\beta}} \]  

(7)

The calculation of total network travel time for the case with \( X_{FIMS} \% \) will not be as simple as in Eq. (6). Due to the fact that drivers will diverge to other routes and will incur longer travel times, a new parameter \( \phi \) is introduced to account for that fact. Then, total network travel time for the case with \( X_{FIMS} \% \) will be:

\[ TT_x = TT_0 + \Delta t_{a,x} V (1 + \phi X_{FIMS}) + t_0 V (1 + \phi X_{FIMS}) \]  

(8)

Where,

\[ \phi = \left(1 - \frac{TT_0}{TT}\right) \]

\( TT_0 \) - Total network travel time before

\( TT_x \) - Total Netowrk travel time with x% FIMS

**Estimating FIMS Benefits**

Since microscopic simulation is the closest modeling environment that replicates reality with least aggregation it will be used to estimate the near “actual” benefits anticipated from FIMS deployment. Similar to emulating FIMS in the 4-step process, drivers are divided into two groups. The first group comprises of drivers \( X_{FIMS} \% \), those that will respond to FIMS message and diverge to other routes, while the second group of drivers are those that will not respond. In simulation, the first group of drivers is defined in a class of drivers that update their routes based on in-route information conveyed via VMS located at specific nodes on the network, i.e. their knowledge of the accident will be accrued just in the upstream link of the accident. The second group of drivers is defined in a different class of drivers that make their route choices only at departure based on normal network conditions and will not revise their routes while traveling.
Some of the commercially available microscopic simulation packages enable users to define classes of drivers with different access and response behaviors to network travel time information. Furthermore, some packages enable global and local levels of network travel time information. In the ATIS section, the group of drivers \((X_{ATIS})\%\) with access to network travel times were granted global access. For FIMS and to measure the sensitivity of using VMS, all drivers in upstream links to the accident links will be given access to local information about travel times on the link with the accident. On the other hand, not all drivers will respond to the accident information. Hence, drivers are divided into two groups based on those that will respond \((X_{FIMS})\%\) and those that will not \((1-X_{FIMS})\%.\) Note that not all drivers that respond do have other alternatives and they might end up continuing without diverging. The following is a summary for the steps to estimate the actual benefits of FIMS. In addition, for consistency purposes, \((X_{FIMS})\%\) will be referred to as market penetration (similar to the ATIS part).

**Step 0:** Identify a candidate link where an accident will be defined.

**Step 1:** Divide drivers population into two groups. The first group of drivers \((X_{FIMS})\%\) which represents the portion of drivers that will respond to VMS information, and the second group \((1-X_{FIMS})\%\) represents the rest of drivers that won’t diverge.

**Step 2:** Adjust network dynamic characteristics for the accident, in terms of time of occurrence, number of lanes blocked, and duration of blockage. Then, simulate traffic flow for \(X_{FIMS} = 0\) and \((1 - X_{FIMS}) = 100\). This simulation case will represent the incurred delays due to the accident in absence of FIMS. The total network travel time in this case will be \(TT_0\).

**Step 3:** Repeat Step 3 for \(X_{FIMS} = (10\% - 60\%)\). Simulate traffic flow and obtain total network travel time \(TT_s\).

### 3.3.3 Sensitivity Measure

Based on the results obtained from emulating an ITS component and estimating actual benefits as described earlier, a sensitivity measure is calculated by comparing the ratio of average benefits estimated under different response levels. The formulation for obtaining the final sensitivity due to the presence of this specific ITS component is provided below.

**Variables:**

\(TT_{macro}^x\) - Total network travel time using macroscopic simulation and for market penetration \((x\%)\)

\(TT_{micro}^x\) - Total network travel time using microscopic simulation and for market penetration \((x\%)\)

\(R_{macro}^x\) - ITS Component benefit ratio at \((x\%)\) market penetration obtained from macroscopic simulation

\(R_{micro}^x\) - ITS Component benefit ratio at \((x\%)\) market penetration obtained from microscopic simulation
Figure 4 Anticipated Network Travel Time Results and Model Variables

**Formulation**

For both phases of the analysis, the ITS component emulation obtained from macroscopic analysis and the benefits estimation obtained from microscopic simulation, we estimate a network travel time benefits ratio \( |R| \) for each market penetration level. Figure 4 depicts the anticipated network travel time results for different market penetrations for both the microscopic and macroscopic simulation. The hatched portion in the figure demonstrates the potential area of savings in travel time. The benefits ratio is defined as the ration between the savings in total network travel time at market penetration (\( x\% \)) to network travel time in the base case with (0%) ATIS market penetration, then,

\[
|R_{\text{micro}}|_x = 1 - \frac{TT^\text{micro}_x}{TT^\text{micro}_0}
\]

(9)

\[
|R_{\text{macro}}|_x = 1 - \frac{TT^\text{macro}_x}{TT^\text{macro}_0}
\]

(10)

Market penetration will vary from one location to another and over the time period of system deployment. Furthermore, the range of market penetration varies by the ITS subsystem. Hence, it is justifiable to consider an average benefits ratio instead of comparing benefits.
ratios at specific market penetration level. An average benefits ratio for both macro $X_{macro}$ and micro $X_{micro}$ simulation results are developed as following:

$$X_{micro} = \int_{x_{max}}^{x_{max}} R_{micro} \, dx$$

$$X_{macro} = \int_{x_{min}}^{x_{max}} R_{macro} \, dx$$

The average benefits ratios $X_{macro}$ & $X_{micro}$ are $> 0$ and $< 1$, assuming that ITS subsystems will always decrease network travel times. Hence, the sensitivity index is defined as the ratio between $X_{macro}$ and $X_{micro}$,

$$S_X = \left( \frac{X_{macro}}{X_{micro}} \right) 100$$

The sensitivity index $S_X$ is bounded between 0% and 100%, assuming that $X_{macro} \leq X_{micro}$. If the average benefits ratio $X_{macro}$ estimated for ATIS using the traditional methods in the 4 Step process was equal or nearly equal to the corresponding value obtained using microscopic simulation $X_{micro}$, then the value of $S_{ATIS}$ will be near 100%. Hence the conclusion will be, for this case, that the current models and methods used in the 4-Step process are sensitive enough to capture the impacts of deploying ATIS. On the other hand, if the average benefits ratio $X_{macro}$ was significantly lower than the corresponding value obtained using microscopic simulation $X_{micro}$, then the value of the sensitivity index $S_X$ will be very low, and the conclusion in this case would be that the 4-Step is not sensitive enough to capture the benefits of this specific ITS subsystem and incapable of integrating it in the planning process.
3.4 Developing the CBR Module

In developing the prototype CBR system for quantifying the benefits of the benefits of ITS deployment, we considered the same subnetwork shown in Figure 3 above. In addition, we considered a specific ITS application, that is diverting traffic away from incident locations using variable message signs (VMS). The diversion scenario considered in this study involved the use of VMS to divert southbound I-91 traffic onto Route 99, in case of incidents occurring on I-91 (see Figure 5).

![Figure 5 CBR Modeled Network](image)

Developing the prototype CBR system involved the following three steps: (1) Developing the INTEGRATION model for the test network; (2) selecting the cases to be included in the
case-base; and (3) developing the CBR module. Each of these steps will be discussed in some detail below.

3.4.1 Developing the INTEGRATION Model for the Test Network

The selected highway network (Figure 5) was extracted from Connecticut Department of Transportation (ConnDOT) statewide planning model. While the planning model data provided a good start point for developing the INTEGRATION model, INTEGRATION called for a higher level of modeling accuracy. Several modifications thus needed to be made to the planning model network and data for use within INTEGRATION. These modifications are briefly discussed below.

Scaling Travel Demand

Typically, transportation planning models are concerned with modeling average travel conditions, and hence the volumes modeled are often daily volumes. This was the case with the planning model that our study obtained from the Connecticut DOT; the Origin-Destination (O-D) matrix and the assigned volumes of the model were 24-hour volumes. INTEGRATION, on the other hand, has the ability to model time-varying conditions, and hence is capable of more accurately modeling peak hour conditions. In our analysis, we have decided to focus on the evening peak hour. Consequently, we scaled the planning model daily volumes to hourly volumes based upon short-term traffic counts observed on similar facilities. To simulate the peak evening hour, the simulation was run for a total 4500 seconds (one hour and 15 minutes). Travel demand, however, was only introduced during the first hour. The additional demand-free 15 minutes is just intended to ensure all vehicles reach their destination at the end of the simulation for the purposes of collecting trip statistics.

Modeling the I-91 Interchanges and On- and Off-ramps

This modification involved modeling the I-91 on- and off-ramps, and the I-91 interchanges. To do this, new nodes were added, and new links were created representing the on- and off-ramps. The traffic flow parameters defining the appropriate flow-speed-density relationship for the ramp links were then assigned.

Modeling Signalized Intersections along Route 99

In this task, the signalized intersections along Route 99 were modeled. The first step toward that was to add some nodes and links to the planning model network in order to model lane channelization at the intersections. Next, the phasing sequence, the timing plan, and the signal offset were specified for each signal (as mentioned above, although INTEGRATION can automatically optimize signal timings, the user is still required to specify these parameters for the initial period). In order to come up with an optimal timing plan for signals along Route 99, the corridor was modeled in TRANSYT-7F. TRANSYT-7F is one of the most widely tools used for developing optimal signal timing plans for arterials and networks (Transportation Research Center, 1998). The results obtained from the TRANSYT-7F model were then used to define the initial timing plan for the INTEGRATION model.
Modeling the Operation of the VMS-Based Diversion System

As mentioned above, the diversion scenario considered involved the use of VMS to divert southbound I-91 traffic onto Route 99, in case of incidents occurring on I-91. To model the operations of such a system in the INTEGRATION model, the existence of VMS at nodes 101, 117, and 116 was specified (see Figure 5). Two classes of drivers were specified. Class 1 represented drivers whose routes were not to be updated, based on real-time travel information, during the course of the simulation. Class 2 drivers, on the other hand, recomputed their paths every 10 seconds. While all the travel demand was assumed to belong to class 1, twenty percent of those drivers were assumed to alter their behavior as a result of the messages posted on the VMS. That is to say, 20 percent of class 1 drivers were assumed to have their behavior transformed to class 2 drivers upon entering a link with a VMS at its downstream node. In addition, in order to accommodate the extra traffic on Route 99 diverted from I-91, INTEGRATION was requested to re-compute the timing plans for the signals along Route 99 every 5 minutes. This allows for modeling the operations of an adaptive traffic signal control system that adjusts timings in real-time in response to observed volumes.

3.4.2 Selecting the Prototypical Cases to be included in the Case-base

There are several factors that are likely to affect the effectiveness of a VMS-based diversion system. These factors include:

1) The traffic volume on the main route, as well as on the alternate route;
2) The network configuration and the attractiveness of alternate routes;
3) The percentage of traffic diverting in response to the FIMS messages;
4) The duration, location, and severity of the incident; and
5) The number of diversion opportunities relative to the location of the incident.

In building the case-base for the prototype CBR system, cases had to be included to provide for adequate coverage of the solution space. In other words, these cases had to represent several instances or levels of the different factors affecting the benefits of VMS diversion so that the system would be able to locate a similar case when faced with a new problem. This section will first briefly discuss those factors, and will then describe the framework used to select the cases to be included in the case-base.

Factors Affecting the Effectiveness of VMS Diversion

Traffic Volume. The benefits to be expected from traffic diversion are a function of the traffic volume, and more specifically the volume-to-capacity ratio on the main and alternate routes. The heavier the volume on the main route, the more significant the benefits of diversion are likely to be, in case an incident occurs on the main route. On the other hand, the more excess capacity an alternate route has the more the benefits of diversion, since in this case, the alternate route would be able to accommodate the additional diverted volume without excessive delays.
Network Configuration and Attractiveness of Alternate Routes. The network configuration and the availability of feasible, alternate routes should be expected to affect the benefits of traffic diversion. The more the alternate routes the network affords and the more attractive these routes are, the more the benefits are likely to be. An alternate route is considered attractive if the difference between its free-flow travel time and the free-flow travel time on the main is not very significant. An alternate route much longer than the main route will likely discourage most drivers to divert.

Percentage of Drivers Diverting in Response to VMS. The percentage of drivers diverting in response to the messages posted on the VMS is definitely likely to affect the benefits to be expected from traffic diversion. For a given demand and supply scenario (i.e. a given network, volume level and a given incident scenario), there will always be a “theoretical” optimal diversion percentage that would minimize the network-wide travel time. However, from a practical standpoint, it might be impossible to achieve this “optimal” diversion percentage, since there is no guarantee that drivers would follow the recommendations of the incident management system. In reality, however, studies show that the percentage of drivers that would change their route in response to the information provided by VMS ranges from 5 to 20% (Glassco et al., 1996).

Duration, Severity and Location of an Incident. The characteristics of an incident, such as its duration, severity and location, play an important role in determining the benefits of route guidance and diversion. For traffic management purposes, the severity of the incident is typically measured in terms of the number of lanes blocked by the incident, or in terms of the percentage of the roadway capacity lost as a result of the incident. In general, the longer the duration of an incident and the more severe it is, the more obvious the benefits of diversion would be. The location of the incident along a freeway link is also likely to affect the feasibility and benefits of diversion. For example, if the incident is located close to an exit, queues would build up quickly behind the incident and block the exit thus restricting access to an alternative route.

Diversion Opportunities relative to the Incident Location. The location of an incident relative to the diversion opportunities afforded by a network also affects the benefits to be expected from diversion. To illustrate this point, consider Figure 6 below. As can be seen, if the incident is at location 1, there are two alternate routes that drivers could use (although alternate route 1 is obviously more attractive than alternate route 2). On the other hand, if the incident is at location 2, only one alternative is available.
With the factors affecting the benefits of traffic diversion identified, the next task was to select a set of prototypical cases that would help cover the solution space of the problem. This set of cases would then be analyzed using the developed integration model, and the results would be used to build the case-base of the CBR system.

Because the primary focus of the current phase of the study was on investigating the feasibility of using CBR for assessing the benefits of ITS deployment such as VMS-based diversion systems, the study decided to initially focus on developing and evaluating a CBR system for predicting the likely benefits under various demand and supply scenarios, but considering only one specific network configuration (i.e. The test network). The hypothesis was that if CBR would succeed under this rather controlled testing scenario, it would have the potential for addressing the more general problem of predicting the impacts of deploying a VMS-based diversion system for a network other than the one used in building the case-base. We plan to address this issue in our future research.

While the scenario considered in this study is rather restrictive, the developed tool could still be quite useful for many purposes. For example, the tool could be used to assess the impacts of various assumptions regarding incident frequency and severity on the anticipated benefits of a proposed VMS system for traffic diversion. Moreover, the tool could be used in a real-time fashion, once the system is indeed deployed, to determine whether diversion is warranted for a given incident scenario.
Given the focus of this initial phase of the project, we considered cases corresponding to the following levels of the factors affecting FIMS effectiveness, as discussed below.

**Traffic Volume.** Three different levels were considered corresponding to the evening peak period volumes, 90% and 80% of the peak volume levels.

**Incident Duration.** Three levels of this variable were considered corresponding to incidents of 10-minute, 20-minute and 30-minute duration.

**Incident Severity.** The different levels considered for the incident severity depended upon the number of lanes on the freeway link under consideration. For 3-lane links, three levels were considered corresponding to a blockage of 1, 2 or 3 lanes. In a similar manner, four levels were considered for 4-lane links.

**Incident Location relative to Diversion Opportunities.** As previously mentioned, the scenario being modeled in this study involves diverting the I-91 southbound traffic onto Route 99 in case an incident occurs on I-91. In order to cover the incident location factor, therefore, three values for the incident location factor needed to be considered, corresponding to incidents occurring on links (101 – 117), (117 – 116), and (116 – 122) – see Figure 5. As can be seen, the specific link on which the incident occurs affects the number of feasible diversion opportunities available. For example, with an incident occurring on link (101 – 117), drivers can only use the node 101 exit to divert. On the other hand, if the incident were to occur on link (116 – 122), drivers could use the node 101, the node 117, or the node 116 exits.

**Incident Location within a Link.** Not only does the specific link on which an incident occurs affects the effectiveness of diversion, but also the specific location of the incident within that link is likely to affect the benefits to be gained from diversion, as previously discussed. To cover this factor in the case base, three levels for the specific location of an incident within a link were considered, corresponding to the cases where an incident is located within the upstream one third of the link, within the middle one third, and within the downstream one third.

The total number of cases required to cover the combinations of the different levels for the factors listed above was 270 cases. This number is computed as follows: 3 traffic levels x 3 incident duration x (3 – 4) incident severity levels depending upon the link considered x 3 links x 3 locations within the link = 270 cases. The percentage of drivers responding to VMS was assumed to be equal to 20 percent.

### 3.4.3 Developing the CBR system

The development of the CBR system involved the following five steps:

- The generation or collection of cases to be included in the case-base;
- The definition of an appropriate case structure;
- The development of a similarity metric for retrieving cases from the case-base;
• The choice of a retrieval algorithm; and
• The design of an adaptation procedure for adapting retrieved cases to more appropriately address the current problem.

Each of these steps is briefly described below.

**Generation of Cases**

With the cases to be included in the case-base selected as previously described, the next step was to use the developed INTEGRATION model to analyze these cases, and to determine the benefits of traffic diversion for the different supply and demand conditions considered. For each of the selected 270 cases, two scenarios needed to be modeled. The first scenario was for the case where VMS were not available to alter driver behavior, and the second was for the case where VMS were available. The difference in total network travel time between these two cases, expressed as a percentage of the total network travel time for the case when VMS are not used, was then computed as follows:

\[
\% \text{Time savings} = \frac{\text{Total travel time with no VMS} - \text{Total travel time with VMS}}{\text{Total travel time with no VMS}} \times 100 \quad (\text{Eq. 14})
\]

This parameter (i.e. percent time savings) constituted the measure that the study used for assessing the expected benefits of VMS diversion under the set of supply and demand conditions under consideration.

**Defining the Case Structure**

The idea of a case is to record an episode where a problem situation was totally or partially solved (Kolodner, 1993). In its simplest form, a case is represented as an ordered pair: (problem, solution), where the problem component describes the state of the world when the case occurred, and the solution component gives the derived solution to that problem (Watson, 1995; Ritcher, 1998). For the application considered in this study, the problem we were trying to answer was determining the expected benefits of deploying a FIMS under various demand and supply conditions. The problem component of the cases thus had to describe the specific demand and supply scenario, and the solution component had to capture the benefit to be expected from VMS traffic diversion for the demand and supply scenario described in the problem component.

Describing the problem component of the cases thus required variables for describing the volume or congestion level on the main and alternate route, the characteristics of the incident, and the network configuration. The following variables were thus used to describe the problem component.

- The volume-to-capacity (v/c) ratio for the main as well as for the alternate route;
- The duration of the incident in minutes
- The severity of the incident in terms of the number of lanes blocked by the incident
• The link number where the incident occurred, and the associated number of feasible alternate routes; and
• The exact location of the incident on the link measured from the upstream node (in kilometers).

For the solution component of the cases, the percent timesavings in network travel time computed according to equation (14) above were utilized.

It should be noted that, because as previously mentioned, the focus of the current phase of the study was on evaluating the feasibility of CBR for one specific network, there was no need to capture the configuration of the network in detail in the case structure. However, for the second phase of this study that will attempt to apply CBR across networks, such variables will be needed.

**Similarity Metric and Retrieval Algorithm**

In the retrieval process, a CBR system uses the features of the cases (typically the features making up the problem component of the cases) to retrieve the most similar case(s) to the current problem or situation. There are several methods for case retrieval. Among the most important of which are (Watson, 1995):

(a) **Nearest Neighbor** - This approach assesses the similarity between the new and the stored cases based on matching a weighted sum of features. Given a query \( q \) and a case library \( L \), the nearest neighbor (NN) algorithm retrieves the most similar (i.e. least distant) case, \( x \), in \( L \). Currently, the NN algorithm is the most widely used approach for retrieval in CBR systems.

(b) **Induction Algorithms** - Induction algorithms, such as Quinlan’s ID3 algorithm (Quinlan, 1986), can be employed to determine which features can be used to best discriminate cases. These features can then be used to organize cases in the memory. The induction approach is most appropriate when a single feature is required as a solution.

(c) **Fuzzy Retrieval** – The idea here is to use fuzzy logic to handle variables within a case that are continuous, imprecise or ambiguous. Fuzzy logic helps impart to CBR the perceptiveness and case-discriminating ability of a domain expert, and hence can improve the effectiveness of case retrieval (Cheetham and Graf, 1997).

In the current study, we used a \( k \)-NN algorithm for case retrieval. The algorithm assessed the similarity between cases based on matching a weighed sum of the features making up the problem component of the cases (i.e. the v/c ratios, the incident severity and duration, the link number on which the incident occurred, and the incident location along the link). The distance between a query, \( q \), and a case, \( x \), was defined as:

\[
distance (x, q) = \sqrt{\sum_{f=1}^{n} w_f \times \text{difference}(x_f, q_f)^2}
\]

(Equation 15)

where,
- \( w_f \) is the parameterized weight value assigned to feature \( f \); (all \( w_f \) were assumed to be equal to 1); and
- the difference \( (x_f, q_f) \) is equal to
\[ \begin{align*}
|x_f - q_f| & \quad \text{if feature } f \text{ is numeric;} \\
0 & \quad \text{if feature } f \text{ is symbolic and } x_f = q_f; \\
1 & \quad \text{Otherwise}
\end{align*} \]

The link number and the incident severity were treated as if they were symbolic features, since they assumed only discrete values (e.g. the incident had to be on link (101 – 117), or link (117 – 116), or link (116 – 122)). The other features were normalized, by subtracting their mean and dividing by their standard deviation, to ensure they have the same range, and hence the expected impact.

**Adaptation**

A relatively simple approach to adaptation was adopted in this study. Essentially, the four closest neighbors (i.e. Cases) to the new problem were retrieved, and the solution to the new problem (i.e. The percent time savings to be expected) was computed as the weighted average of the solutions of the four closest retrieved cases. Weighing was done in a fashion proportional to the similarity metric (i.e. Distance) between the new problem and each of the retrieved cases.
4 RESULTS AND DISCUSSION

This section summarizes the results pertaining to assessing the sensitivity of the 4-step planning process, as well as the results of testing and evaluating the prototype CBR module.

4.1 Sensitivity of the 4-step Planning Process

4.1.1 ATIS

Macro Simulation Results

ATIS was emulated in the 4-Step process as mentioned in the methodology section. A commercial transportation software TP+ was used in performing the traffic assignment similar as in the 4-Step process. The results from emulating ATIS for different market penetrations in the 4-Step process using macroscopic simulation are shown in Figure 7a. The results shows an increase in network travel time as a result of the hypothetical accident at ATIS market penetration of 0%. The total network travel time decreased as the ATIS market penetration increased. However, at 50% market penetration, a maximum drop in travel times was observed, above 50%, network travel times started increasing. At 100% market penetration the results was similar to those at 0%. Also, it is important to notice that the maximum drop in travel time at 50% market penetration was only ~0.5%.

Micro Simulation Results

The same test network was simulated using INTEGRATION. The drivers were divided into two groups, one with no access to information and the second with full access to network travel times and congestion information. The results for different market penetrations are shown on Figure 7b. Total network travel times showed significant decrease as the market penetration increased. The maximum decrease in network travel time was observed at 80% and was ~22.5%. However, network travel times slightly increased at 100% market penetration.
Based on the results using both micro simulation and macro simulation the sensitivity index was calculated. The average benefits ratios for ATIS using macro simulation \( X_{\text{macro}} \) and from the microsimulation \( X_{\text{micro}} \) were calculated.

Figure 7 Network Travel Times Results for ATIS
Then, the ATIS sensitivity index $S_{ATS}$ is calculated as follows:

$$S_{ATS} = \left( \frac{X_{macro}}{X_{micro}} \right) \ast 100$$

$$S_{ATS} = \left( \frac{0.3}{15.2} \right) \ast 100 = 1.97\% \approx 2\%$$

The value of $S_{ATS}$ was ~2%. Based on the definition of the sensitivity index given in the methodology section, the macroscopic tools used in the traffic assignment step in the 4-step context can only capture 2% of the expected ATIS impact over the test network. Therefore, emulating ATIS in the 4-Step process would not reflect the ultimate impact and benefits from such systems. Furthermore, the 4-Step process evidently underestimates the impact of ATIS on total network travel times, hence, it would be difficult to justify the deployment of such systems based on the tools used in the 4-step process.

### 4.1.2 FIMS

#### Macro Simulation Results

FIMS was emulated in the 4-Step process as mentioned in the methodology section. A commercial transportation software TP+ was used to assign traffic to the network and estimate the normal case without capacity adjustments due to the accident. Then, the rest of the steps were performed using an MS-Excel™ spreadsheet. The results from emulating FIMS for different market penetrations in the 4-Step process using macroscopic simulation are shown in Figure 8a. The range considered for the number of people diverging was limited to be between 10% and 50%. This range should be flexible and varies according to the severity of the accident simulated. In other words, for the test accident, only one lane is blocked for 20 minutes over a highway that is 4 lanes, hence, it is counter intuitive to claim that more than 50% of drivers will diverge. On the other hand, if the number of lanes blocked was 2 or 3, i.e. ~50-75% blockage, possibly more than 50% will diverge. The results in Figure 8 shows a drop in total network travel times as the percentage of drivers diverging increases. The rate of the drop decreases to almost a no effect at 50% market penetration ratio. The maximum decrease in total network travel time was ~5% observed at 50% market penetration.

#### Micro Simulation Results

The same test network was simulated using a traffic micro simulation package (Integration™). The drivers were divided into two groups, one that will respond to the VMS information and the second will not. The results for different market penetrations are shown on Figure 8b. Total network travel times showed significant decrease as the market penetration increased. The maximum decrease in network travel time was ~15% and was observed at 20% market penetration. For market penetrations greater than 20%, network
travel time pattern reversed and started ascending. At 50% market penetration, total network travel time was nearly equal the base case with 0% market penetration. This reverse effect is explainable since the accident blocked only ¼th of the capacity of the link for 20 minutes.

Figure 8Network Travel Times Results for FIMS
**Sensitivity Index For ATIS**

Based on the results using both micro simulation and macro simulation the sensitivity index was calculated. The average benefits ratios for FIMS using macro simulation $X_{\text{macro}}$ and from the microsimulation $X_{\text{micro}}$ were calculated.

\[ X_{\text{micro}} = 10.5\% \]
\[ X_{\text{macro}} = 4.2\% \]

Then, the ATIS sensitivity index $S_{\text{ATS}}$ is calculated as follows:

\[
S_{FIMS} = \left( \frac{X_{\text{macro}}}{X_{\text{micro}}} \right) \times 100
\]

\[
S_{FIMS} = \left( \frac{4.2}{10.5} \right) \times 100 = 39.5\%
\]

The value of $S_{FIMS}$ was 39.5%. Based on the definition of the sensitivity index given in the methodology section, the macroscopic approach used in the traffic assignment step in the 4-step context can only capture 39.5% of the expected FIMS impact over the test network. Therefore, emulating FIMS in the 4-Step process would not reflect the ultimate impact and benefits from such systems. Furthermore, the 4-Step process evidently underestimates the impact of FIMS on total network travel times, hence, it would be difficult to justify the deployment of such systems based on the tools used in the 4-step process.

**4.2 Evaluating the Performance of the CBR System**

To evaluate the performance of the developed CBR system, 25 new cases were randomly generated, corresponding to randomly generated demand and supply conditions (i.e. different levels of traffic volumes, incident severity and duration, and incident location) on the test network. For each of these cases, the benefits to be expected from diversion, in terms of the percent time savings as defined in equation 14, was determined in two fashions. The first fashion involved directly using the developed CBR system to predict the expected benefit. In the second case, the scenario under consideration was modeled with the INTEGRATION model twice, once without VMS and once with VMS, and the difference in travel time was computed. The results obtained using the CBR system were then compared to those obtained from the more complicated approach that involved running the INTEGRATION model twice. Table 1 shows the results of the comparison.
### Table 1 Comparing the CBR and the INTEGRATION Model Results

<table>
<thead>
<tr>
<th>Case Number</th>
<th>% Time Savings (CBR)</th>
<th>% Time Saving (INTEGRATION)</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.16%</td>
<td>0.52%</td>
<td>0.64%</td>
</tr>
<tr>
<td>2</td>
<td>0.91%</td>
<td>0.17%</td>
<td>0.74%</td>
</tr>
<tr>
<td>3</td>
<td>-0.20%</td>
<td>-0.21%</td>
<td>0.01%</td>
</tr>
<tr>
<td>4</td>
<td>-0.51%</td>
<td>0.96%</td>
<td>-1.47%</td>
</tr>
<tr>
<td>5</td>
<td>0.86%</td>
<td>0.13%</td>
<td>0.73%</td>
</tr>
<tr>
<td>6</td>
<td>-0.09%</td>
<td>0.14%</td>
<td>-0.24%</td>
</tr>
<tr>
<td>7</td>
<td>6.29%</td>
<td>7.81%</td>
<td>-1.52%</td>
</tr>
<tr>
<td>8</td>
<td>1.50%</td>
<td>0.40%</td>
<td>1.10%</td>
</tr>
<tr>
<td>9</td>
<td>-0.16%</td>
<td>-0.19%</td>
<td>-0.03%</td>
</tr>
<tr>
<td>10</td>
<td>0.28%</td>
<td>0.03%</td>
<td>0.25%</td>
</tr>
<tr>
<td>11</td>
<td>-0.19%</td>
<td>-0.18%</td>
<td>-0.01%</td>
</tr>
<tr>
<td>12</td>
<td>-0.06%</td>
<td>0.06%</td>
<td>-0.12%</td>
</tr>
<tr>
<td>13</td>
<td>0.62%</td>
<td>-0.24%</td>
<td>0.86%</td>
</tr>
<tr>
<td>14</td>
<td>0.00%</td>
<td>0.10%</td>
<td>-0.10%</td>
</tr>
<tr>
<td>15</td>
<td>-0.14%</td>
<td>-0.33%</td>
<td>0.19%</td>
</tr>
<tr>
<td>16</td>
<td>4.29%</td>
<td>2.96%</td>
<td>1.33%</td>
</tr>
<tr>
<td>17</td>
<td>0.07%</td>
<td>0.11%</td>
<td>-0.04%</td>
</tr>
<tr>
<td>18</td>
<td>3.41%</td>
<td>1.78%</td>
<td>1.63%</td>
</tr>
<tr>
<td>19</td>
<td>7.30%</td>
<td>8.23%</td>
<td>-0.93%</td>
</tr>
<tr>
<td>20</td>
<td>8.05%</td>
<td>8.96%</td>
<td>-0.91%</td>
</tr>
<tr>
<td>21</td>
<td>3.78%</td>
<td>4.76%</td>
<td>-0.98%</td>
</tr>
<tr>
<td>22</td>
<td>4.44%</td>
<td>4.08%</td>
<td>0.36%</td>
</tr>
<tr>
<td>23</td>
<td>0.17%</td>
<td>-0.13%</td>
<td>0.30%</td>
</tr>
<tr>
<td>24</td>
<td>4.19%</td>
<td>4.75%</td>
<td>-0.56%</td>
</tr>
<tr>
<td>25</td>
<td>1.59%</td>
<td>1.50%</td>
<td>0.09%</td>
</tr>
</tbody>
</table>

As can be seen, the performance of the CBR tool appears to be quite satisfactory. For 20 out of the 25 cases evaluated (i.e. 80%), the CBR solution was off by less than 1.0 percent compared to the INTEGRATION model solution. The maximum difference between the CBR and the INTEGRATION solution was 1.63%. A secondary remark is worthy of mention here. While not the prime focus of the study, Table 1 reveals an interesting observation. As can be noted from Table 1, traffic diversion is not always a good strategy. For some cases, the percent timesavings parameter is negative indicating that the total network travel time with diversion is actually greater than the travel time without diversion. This typically occurs when the incident duration is rather short (i.e. 10-minute duration). In such cases, diversion actually results in an increase in the total network travel time.
5 SUMMARY AND CONCLUSIONS

The current study had two major objectives: (1) to assess the sensitivity of the 4-step planning process to ITS deployment; and (2) to assess the feasibility of using CBR to develop a tool for quantifying the benefits of ITS deployment. In the following paragraphs, we summarize our main conclusions regarding these two objectives.

5.1 Sensitivity of 4-Step Process to ITS Deployment

To assess the sensitivity of the 4-step process, methodologies for emulating the deployment of two ITS subsystems (ATIS and FIMS) in the traditional 4-step planning process were developed and presented, and a general sensitivity index for ITS deployment was defined. Test networks were identified and used to emulate ITS deployment using traditional means currently used in the 4-Step process. Microscopic simulation was used to get a near actual estimate for benefits of both ITS subsystems deployment on the test networks. Based on the results using macro and micro simulation, the sensitivity index was evaluated in both cases. The results showed quantitatively that the current methods deployed by the 4-Step process are insensitive to the benefits of both ITS subsystems. The sensitivity index for the test network was ~2%, i.e. only 2% of the actual benefits were detected by the microsimulation. Of course, the value of the sensitivity index would be different for different networks depending on network topology and congestion level. For example, if there were no alternative routes in the test network, and drivers were not able to diverge even though they know of the accident on the network. The sensitivity index in that case would have been significantly higher than 2%. Furthermore, if the traffic demand was very low, a traffic accident on the test network won’t increase travel time significantly and also, the sensitivity index would have been high.

Hence, the traditional methods adopted by the 4-step planning process are insensitive to Advanced Traveler Information System. The question now is why? What is causing this deficiency in microsimulation? We suggested two reasons standing behind this deficiency. While ATIS disseminates network travel times to driver dynamically, the traffic assignment step in the 4-Step process lacks the temporal dimension. The absence of temporal dimension in the 4-Step process makes it incapable of capturing the expected benefits from ATIS. The second reason is the absence of the spatial dimension in the 4-step process. The traditional models used in performing the traffic assignment step do not take into consideration the spatial aspects of queues and queue spillbacks. Link travel time is calculated based on the volume to capacity ratio and delay is limited to its length. For example, in the case of a traffic accident as illustrated in the FIMS test case, traffic demand exceeds link capacity and a queue upstream is developed. On the other hand, microscopic simulation is capable of capturing the spatial aspects of traffic congestion and queue spillbacks.

The results of this research illustrates quantitatively that the current methods used in the planning process are incapable of accounting for the impacts of ITS. These results suggest that new approaches, such as the CBR prototype developed in this research, are needed for accounting for ITS deployment effects in the planning process.
5.2 CBR for Quantifying ITS Benefits

To illustrate the feasibility of using CBR to quantify the benefits of ITS deployment, a prototype system for determining the likely benefits of employing VMS for traffic diversion was developed. The performance of the prototype was then evaluated by comparing its predictions to those obtained using a detailed DTA model. The evaluation results were quite encouraging. The prototype system yield high quality solutions comparable to those obtained using the DTA model. There are several future research directions that we plan to pursue to complement the current work. As was previously mentioned, our next major step is to test the applicability of the CBR approach across networks. We also plan to work on refining the CBR module and on experimenting with more elaborate approaches to case retrieval and adaptation.
REFERENCES


