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A COMBINED TRAVELER BEHAVIOR AND SYSTEM PERFORMANCE MODEL WITH ADVANCED TRAVELER INFORMATION SYSTEMS

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Abstract—The goal of this paper is to develop a framework for evaluating the effect of Advanced Traveler Information Systems. The framework uses a composite traffic assignment model which combines a probabilistic traveler behavior model of route diversion and a queuing model to evaluate Advanced Traveler Information Systems impacts under incident conditions. The composite assignment model considers three types of travelers: those who are unequipped with electronic devices, i.e. they do not have Advanced Traveler Information Systems or radio in their vehicles; those who receive delay information from radio only; and those who access Advanced Traveler Information Systems only. The unequipped travelers are able to observe incident-induced congestion, if the congestion reaches or exceeds their decision point. The composite model assigns travelers with Advanced Traveler Information Systems to the shortest travel time route. Travelers with radio information and those who can observe the congestion are assigned according to a behavioral model calibrated on revealed preference data. Travelers who are completely unaware of the incident-induced congestion are assigned to their usual route. The unique feature of the composite model is the integration of realistic traveler behavior with system performance while accounting for the effect of real-time travel information. To demonstrate the application of the composite model, we consider the evolution of queues on a two link network with an incident bottleneck. The findings indicate that the overall system performance, measured by average travel time, improves marginally with increased market penetration of Advanced Traveler Information Systems. However, the benefits of Advanced Traveler Information Systems under incident conditions are expected to be marginal when there is more 'information' available to travelers through their own observation or radio. Specifically, delay information received through radio and from observation of incident-induced congestion induces people to divert earlier causing the network to operate closer to system optimal than user equilibrium. This limits the potential benefits of Advanced Traveler Information Systems.

Keywords: advanced traveler information systems, traffic assignment.

1. INTRODUCTION

Advanced Traveler Information Systems (ATIS) may offer significant benefits in terms of improving the travel experience of individuals and enhancing system performance. They may be particularly useful in the context of incident-induced congestion. However, the true potential of these systems has yet to be evaluated. This study assesses the impacts of auto-related ATIS technologies in incident congestion conditions. Using a simple model, the benefits of travel information received from various sources are compared. A microscopic simulation model is developed for a simple two-link network where drivers can either use their usual route or divert to an alternate

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route due to incident-induced congestion on their usual route. Drivers can either be unaware of the incident congestion or receive information from three sources: observation of queues, radio traffic reports and ATIS. The probability of diversion for uninformed drivers is zero, the probability for incident information received from observation or radio is obtained from a statistically estimated revealed behavior model and the ATIS informed drivers are assumed to take their shortest path (commonly assumed user equilibrium assignment). The main purpose of this study is to demonstrate the benefits of travel information, given these assumptions. The study accounts for existing travel time benefits from available information sources (observation of queues and radio) while evaluating the potential benefits from ATIS.

Real-life ATIS data on driver behavior are not available. Therefore, it is not possible to calibrate revealed preference models for ATIS drivers. ATIS is intended to provide more accurate real-time information than other sources, reducing uncertainty in information about travel times. Therefore, we assume that if all drivers are equipped with ATIS, then user equilibrium will occur in incident conditions. Although this assumption may not reflect real-life ATIS behavior without real-life behavioral data on response to ATIS, it is reasonable to assume that ATIS equipped drivers are likely to use their shortest paths. The research issue is to find how will ATIS impact system performance, given that there are other travel information sources available to drivers. Also, what are the benefits of ATIS under different market penetration scenarios?

2. SCOPE

The impacts of ATIS technologies depend, to a large extent, on how travelers will respond to such systems. Therefore, it is important to understand what factors influence travel decisions. The existing behavioral choice models usually assume perfect information, that is, individuals have knowledge of all alternatives. Clearly, such an assumption is not defensible when the purpose is to evaluate the effect of information. Similarly, many network performance models do not explicitly account for the effect of information, and use unrealistic behavioral rules.

This research is based on our earlier work regarding traveler behavior and system performance impacts of congestion in the presence of information (Al-Deek, 1991; Khattak, 1991). In this paper we enhance our previous work and develop a richer and more comprehensive approach for evaluating ATIS technologies. Specifically, a comprehensive traffic assignment model responsive to various types of information sources is combined with a dynamic network performance queuing model.

While ATIS is likely to influence travel decisions (e.g. mode, route, schedule, trip chaining, parking) and activity participation decisions (e.g. work, recreation, shopping), this study focuses on route diversions. Further, while ATIS may impact network performance in many ways, we choose a two-route corridor with single origin and destination. The intention is to describe our efforts and demonstrate the application of our methodology. Development of a network model complete with realistic behavioral rules that can evaluate impacts of information is an ambitious undertaking that will require time. An ATIS-based network model may be developed and validated by using real-life data gathered during field operational tests in the United States.

3. LITERATURE

There have been worldwide efforts during the last decade to study various aspects of ATIS, including the evaluation of their impacts on travelers and on the transportation system. But there remains a lack of ‘connectivity’ between behavioral and system performance models, and no clearly defined mechanism exists for unifying them.

An exhaustive study of existing traffic models was conducted by Gardes and May (1990) and Gardes *et al.* (1991), followed by some applications to model traveler information systems (Gardes *et al.*, 1993). They concluded that only three models had both assignment and queuing capabilities: SATURN, CONTRAM, and INTEGRATION. Based on our review of these models, it was found that none of them incorporate significant traveler behavior. An extension to CONTRAM is reported by Smith and Ghali (1991), in which the model is extended to accommodate a second route policy with minimum local marginal cost. These models assume total compliance and travel time optimizing behavior of drivers. DYNASMART (Chang *et al.*, 1985; Jayakrishnan and

Mahmassani, 1992; Chen and Mahmassani, 1993) is a macroscopic simulation model and has the ability to track individual vehicles. The model also has path selection capabilities, and has route selection models based on bounded rational behavior.

The traveler decision process is an intrinsic element in modeling traffic conditions with traveler information systems. Consequently, several researchers have conducted simulation studies and/or proposed theoretical frameworks that incorporate behavioral characteristics into the traffic modeling process (Ben-Akiva *et al*., 1986, 1991; Al-Deek *et al*., 1990; Arnott *et al*., 1990, 1991; Kanafani and Al-Deek, 1991; Mahmassani *et al*., 1990; Mahmassani and Chen, 1991; Mahmassani and Jayakrishnan, 1991; Cascetta *et al*., 1991; Hamerslag and Van Berkum, 1991; Van Vuren and Watling, 1991; Papageorgiou and Messmer, 1991; Bonsall and Parry, 1991). The dynamic network modeling framework proposed by Ben-Akiva *et al*. (1991) presents a detailed description of the traveler decision process. Their research also explores deterministic user-equilibrium and system-optimal conditions. More specific simulation results are presented by Mahmassani *et al*. (1991)—based on a three-route network. These studies address the impact of real-time information on travelers, supplied at the origin or en route, and exhibit route switching and departure time decision capabilities. However, the studies do not explore the actual benefits of information under different incident and network characteristics.

The important aspects of information are its content and whether the information is (a) historical, real-time, or predictive, (b) qualitative or quantitative, and (c) accurate, timely, relevant, and reliable (Schofer *et al*., 1993). On the issue of route diversion, researchers have found that travelers are more willing to divert in response to prescriptive and descriptive traffic information and increasing delays and/or congestion (Heathington, 1969; Dudek *et al*., 1971; Mannering, 1989; Mahmassani *et al*., 1990; Allen *et al*., 1991; Bonsall and Parry, 1991). In addition, longer trip length, lower number of traffic stops on alternate routes, and familiarity with the alternate route encourage diversion. Further, younger, male, and unmarried travelers are more likely to divert.

In summary, studies on diversion behavior provided useful insights, but indicated that the effect of ATIS and other information sources along with contextual factors on traveler behavior has not been adequately quantified. Moreover, evaluation of system performance with ATIS requires the ability to model travel conditions at bottlenecks. With ATIS, drivers will be able to obtain detailed information on travel conditions. Hence, traffic simulation models for ATIS should include queuing conditions and dynamic path assignment capabilities. It appears that no model sufficiently addresses the issue of combining system performance and traveler behavior in the presence of information. Also ATIS models do not account sufficiently for route choice decisions taken with existing information sources.

4. METHODOLOGY

4.1. Theoretical models for system performance

In the real world, traffic diversion during incidents can be complicated. Under normal conditions, the hypothesis is that the transportation system is in equilibrium; i.e. no driver can improve his/her travel time by switching routes (Wardrop, 1952). Traffic incidents cause system disequilibrium, and travelers may be able to reduce their travel time by diverting to alternate routes. Actual diversions will depend on many factors, including incident and network characteristics, as well as behavioral response. The addition of ATIS increases the complexity because the travelers' perception of ATIS and compliance to guidance instructions are also important factors in estimating the total system benefits. In the following sections we will describe in detail the elements of our assumptions and the composite assignment model used in this research framework.

4.1.1. Idealized corridor and assumptions. The network analyzed in this paper is a simplified corridor that consists of two routes connecting a single origin (point A) and a single destination (point B), as shown in Fig. 1. We have used a simplified corridor because we believe it is important to develop a comprehensive model that integrates traveler behavior and queuing at bottlenecks in a simple network before extending the model to simulate larger scale networks.

Route 1 is a freeway with capacity μ_1 and free-flow travel time T_1, and Route 2 is an alternate route with free flow travel time T_2 and capacity μ_2, where $\mu_2 \leqslant \mu_1$. The alternate route may

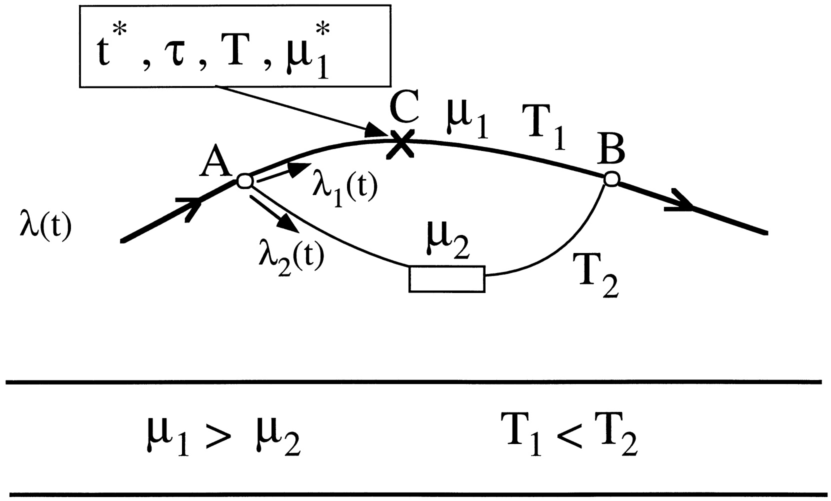

Fig. 1. Corridor and incident parameters.

represent a collection of city streets with lower speeds and surplus capacity, or it could be a freeway with longer travel distance than Route 1. Furthermore, $T_1 < T_2$, and it is assumed that travel times on Routes 1 and 2 are independent of flow except under queuing conditions. This assumption has been empirically validated by Hurdle and Solomon (1986). The incident occurs at point C and reduces the capacity of Route 1 from μ_1 to μ_1^*. The incident occurs at time t^* and lasts for a duration T. As illustrated in Fig. 1, point C is τ units of travel time away from point A along Route 1, and $0 < \tau < T_1$. If the arrival flow rate to point C, $\lambda_1(t)$, exceeds the capacity of the bottleneck, a queue forms upstream of the incident bottleneck on Route 1.

In this paper, we simulate incidents that occur during the off-peak period (when demand is less than normal capacity and traffic conditions are unsaturated). Normal capacity is defined as maximum flow under non-incident conditions. The cumulative queuing diagram for incidents is illustrated in Fig. 2. During the unsaturated conditions, arrival rate $\lambda_1(t)$ is assumed to be constant.

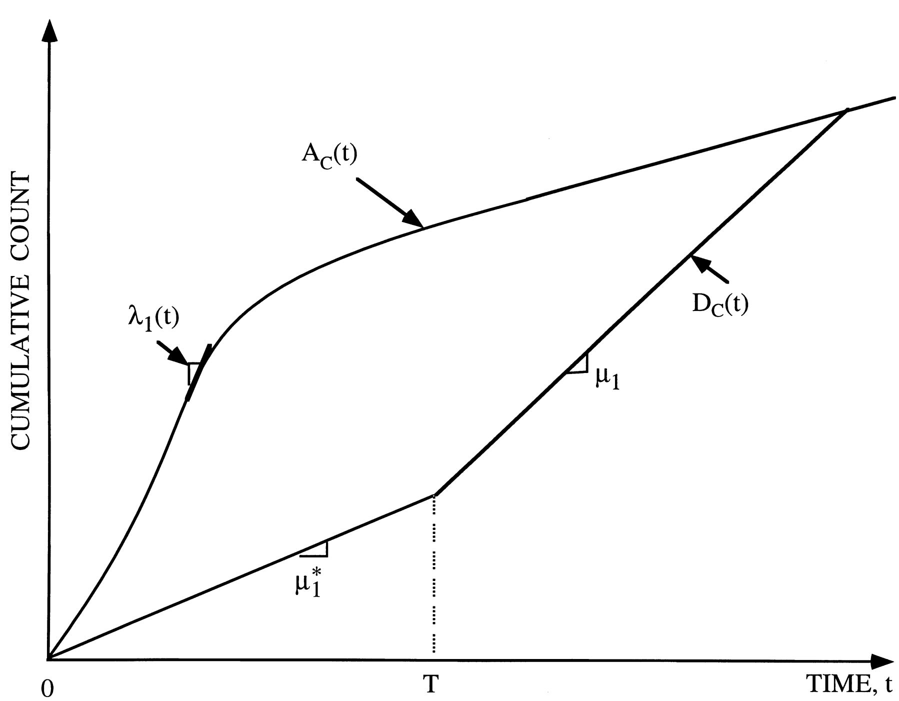

Fig. 2. Queuing diagram for incident conditions.

Dynamic travel time information is received as travelers approach point A. Once travelers pass point A, travel time information becomes irrelevant since they would already be committed to one of the two routes. In the absence of queues, Route 1 is usually preferred to Route 2. When the delay on Route 1 exceeds the difference in free-flow travel times between Routes 1 and 2, that is $T_2 - T_1$, travelers may be able to reduce their travel time by switching to Route 2. However, if the travelers are unaware of the expected travel times and delays, they may continue to travel on Route 1, perpetuating disequilibrium between the two routes.

The amount of queuing delay experienced by a traveler depends on his/her arrival time at junction A. The expected delay at an arrival time t can be determined from the daily cumulative arrival pattern at the location of incident and the capacity of the section during the incident. Thus, based on their usual arrival times at the location of the incident, travelers could be provided the expected delay information through electronic sources. A microscopic time slice approach for calculating expected delays is presented in the next section.

4.1.2. Determination of queuing delays and queue lengths on routes. In this section we derive the formulas for delays and queue lengths on Routes 1 and 2 with and without diversion as illustrated in Figs 3 and 4. Traffic arrives at the incident location according to curve $A_C(t)$ as shown in Fig. 3. The departure curve $D_C(t)$ shows the departure from the incident bottleneck. The departure flow rate is initially μ_1^*, the reduced capacity of the bottleneck, and then after the incident is cleared at time T, is the restored capacity, μ_1.

The delay to travelers arriving during the nth time interval on Route 1 in case of no traffic diversion to Route 2, is denoted as $d(t_n)$, and is given by:

$$d(t_n) = d(t_{n-1}) + (t_n - t_{n-1})((\lambda_n/\mu_1) - 1), \qquad \text{for } t_n, t_{n-1} > T' \tag{1a}$$

$$d(t_n) = d(t_{n-1}) + (t_n - t_{n-1})((\lambda_n/\mu_1^*) - 1), \qquad \text{for } t_n, t_{n-1} < T' \tag{1b}$$

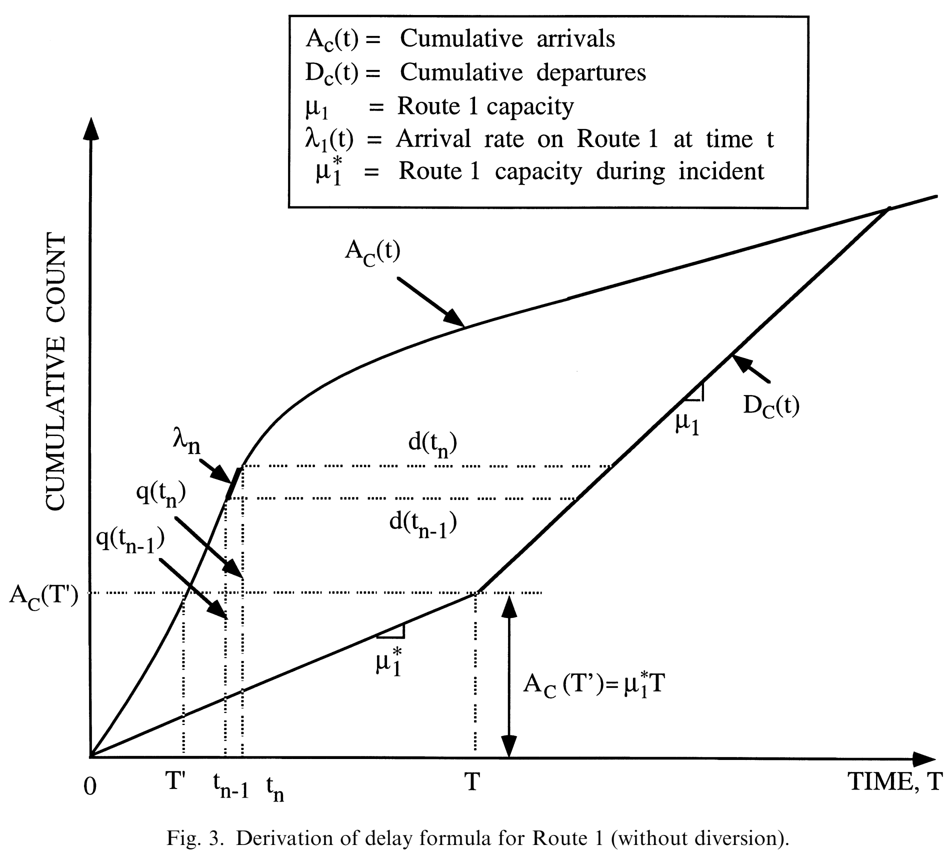

Fig. 3. Derivation of delay formula for Route 1 (without diversion).

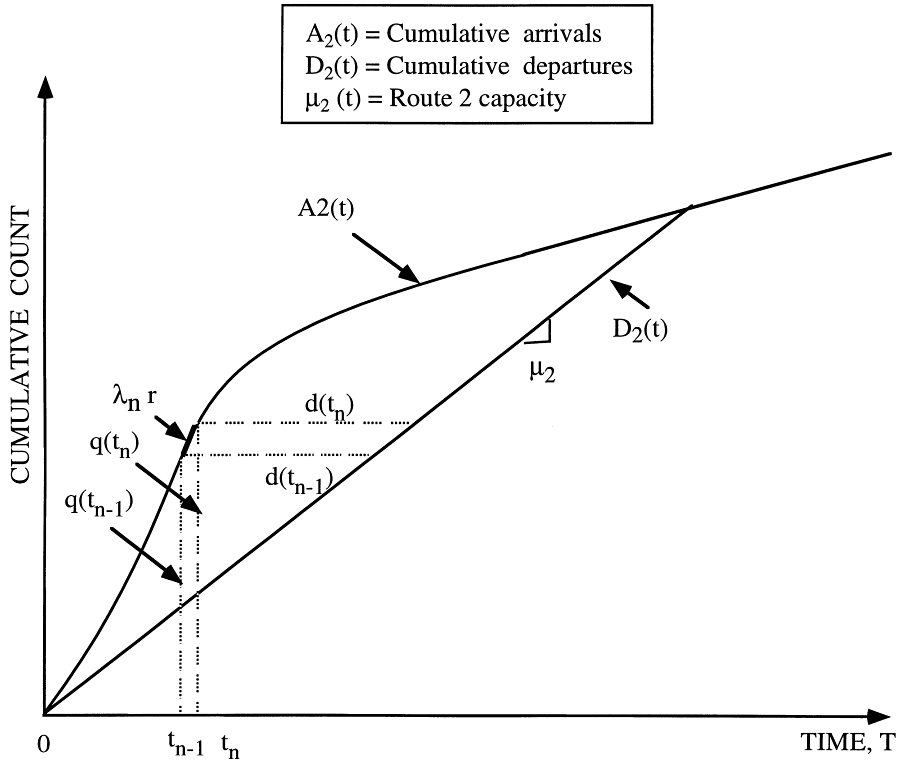

Fig. 4. Derivation of delay formula for Route 2.

where

$d(t_n)$ = expected delay of travelers arriving during time interval t_n without diversion
$d(t_{n-1})$ = expected delay of travelers arriving during time interval t_{n-1} without diversion
λ_n = arrival rate during time interval (t_{n-1}, t_n). Here, λ_n, equals the reciprocal of the inter arrival time or $1/(t_n - t_{n-1})$
μ_1 = normal capacity of Route 1 without incidents
μ_1^* = incident reduced capacity of Route 1
T' = $A_C^{-1}(\mu_1^* T)$
(= $\mu_1^* T/\lambda$, for the off-peak scenario with uniform arrival rate λ).

The queue length can be calculated as follows:

$$q(t_n) = q(t_{n-1}) + (t_n - t_{n-1})(\lambda_n - \mu_1), \qquad \text{for } t_n, t_{n-1} > T' \tag{1c}$$

$$q(t_n) = q(t_{n-1}) + (t_n - t_{n-1})(\lambda_n - \mu_1^*), \qquad \text{for } t_n, t_{n-1} < T' \tag{1d}$$

where

$q(t_n)$ = expected queue length for travelers arriving during time interval t_n without diversion
$q(t_{n-1})$ = expected queue length for travelers arriving during time interval t_{n-1} without diversion

When there is diversion to Route 2, the arrival curves to Routes 1 and 2 are affected and the above formulas must be modified. The modified delay and queue length formulas for Route 1 are:

$$d_1(t_n) = d_1(t_{n-1}) + (t_n - t_{n-1})[(\lambda_n(1-r)/\mu_1) - 1], \qquad \text{for } t_n, t_{n-1} > T' \tag{2a}$$

$$d_1(t_n) = d_1(t_{n-1}) + (t_n - t_{n-1})[(\lambda_n(1-r)/\mu_1^*) - 1], \qquad \text{for } t_n, t_{n-1} < T' \tag{2b}$$

$$q_1(t_n) = q_1(t_n - 1) + (t_n - t_{n-1})(\lambda_n(1-r) - \mu 1), \qquad \text{for } t_n, t_{n-1} > T' \tag{2c}$$

$$q_1(t_n) = q_1(t_{n-1}) + (t_n - t_{n-1})(\lambda_n(1-r) - \mu_1^*), \qquad \text{for } t_n, t_{n-1} < T' \tag{2d}$$

where,

$d_1(t_n)$ = expected delay of travelers arriving during time interval t_n on Route 1 with diversion
$q_1(t_n)$ = expected queue length for travelers arriving during time interval t_n on Route 1 with diversion
r = the proportion of travelers diverting to Route 2 between time t_{n-1}, and t_n.

The formulas for Route 2 are derived in a similar way as shown in Fig. 4:

$$d_2(t_n) = d_2(t_{n-1}) + (t_n - t_{n-1})[(\lambda_n r/\mu_2) - 1] \tag{3a}$$

$$q_2(t_n) = q_2(t_{n-1}) + (t_n - t_{n-1})(\lambda_n r - \mu_2) \tag{3b}$$

where,

$d_2(t_n)$ = expected delay of travelers arriving during time interval t_n on Route 2 with diversion
$q_2(t_n)$ = expected queue length for travelers arriving during time interval t_n on Route 2 with diversion
μ_2 = normal capacity of Route 2.

We have used a microscopic approach in our simulation [as outlined in eqns (1)–(3)] because it can represent individual behavior microscopically by choosing the time interval to be sufficiently small to reflect individual arrivals. The queuing equations, described in eqns (1)–(3), are independent of the shape of the arrival and departure curves. Daily arrival patterns also can be simulated by approximating them linearly for small time intervals.

4.2. *Microscopic traffic assignment and simulation*

In this section, we discuss the traffic assignment model used in conjunction with simulation of traffic delays at bottlenecks. Table 1 summarizes the composite assignment model developed in the study. There are three types of travelers: those who are unequipped with electronic devices, i.e. they do not have ATIS or access to radio traffic reports in their vehicles; those who access radio only; and those who access ATIS only. For simplicity, we refer to travelers unequipped with electronic devices as 'unequipped.' One possibility for unequipped travelers is that they have no knowledge of incident delay (no radio or ATIS and they cannot observe the end of the queue) and therefore will not divert. Thus, travelers with no knowledge of incident always choose Route 1 even when Route 2 travel time is shorter ($r = 0$). Another possibility is that during the time when the incident queue backs up to the decision point (A in Fig. 1) and/or upstream of the decision point, all unequipped travelers arriving observe the queue and they are assigned according to a

Table 1. Summary of study design

Traveler type	Composite assignment model
Traveler unequipped with electronic information devices:	
1(a) No knowledge of incident induced delay (no electronic device or observation of queue)	1(a) Traveler always takes the usual route (Route 1)
(b) Observation of delay only (if incident queue reaches the decision point, then the traveler can observe the congestion and estimate delays)	(b) Traveler is assigned according to the behavioral (logit) model by calculating the probability of route diversion
2 Traveler equipped with radio only (receives quantitative incident delay information)	2 Traveler is assigned according to the behavioral (logit) model by calculating the probability of route diversion
3 Traveler equipped with ATIS device only (receives accurate quantitative incident delay information)	3 Traveler is assigned according to the full compliance model (ATIS equipped travelers take the minimum travel time route)

behavioral model, i.e. some of them might divert to the alternate route. Those who access delay information through the radio are assigned according to a behavioral model. Finally, those with ATIS access accurate travel time information on both routes and are assigned to the shortest travel time route. Thus, whenever an ATIS equipped traveler arrives at junction A and is informed that travel time (including delay) on Route 1 is larger than travel time on Route 2, he or she uses Route 2 ($r = 1$ because the time interval was set to reflect individual arrivals). In the absence of real-life ATIS, this assumption is made to examine the potential benefits. However, alternative behavioral assumptions, e.g. that the probability of diversion will increase further with ATIS compared to radio, may lead to different potential benefits and possibly different conclusions.

To capture realistic response of travelers informed through radio and observation, a behavioral model based on a survey of travelers in Chicago is used (Khattak, 1991). Automobile travelers who made repeated trips during which quantitative real-time traffic information broadcast through radio was available to them were asked via a mail-back survey if they knew about a delay, and if so, what was the context and did they divert to an alternate route. A binary logit model of route choice was estimated using the responses of those who knew about the traffic delays either by observing them or through the radio ($N = 372$). The dependent variable was the decision to divert to an alternate route or stay on the usual commute route. Table 2 presents a simple version of the model.

In response to the unexpected delay, 45% of the respondents diverted to their best alternate route. Their decision to divert is influenced by three independent variables included in the model. The constant term is negative and statistically significant (5% level), indicating that travelers prefer to stay on their usual route in unexpected delay situations, all else being equal. This is possibly due to their inertial tendencies. The information parameter is positive and statistically significant (10% level), implying that travelers are more likely to take their alternate routes if they receive the delay information through radio traffic reports as opposed to observing traffic congestion. This could be because drivers perceive radio traffic information as accurate, and/or they receive the information well in advance of the incident-induced congestion giving them more route diversion options (as opposed to when they observe the congestion). Note that the radio traffic information given in Chicago at the time of the survey included point-to-point travel times and delays, i.e. travelers could receive quantitative and real-time traffic information from radios. The travel time coefficient represents the reported difference in travel time on usual and alternate routes and it is positive and statistically significant (5% level). Longer travel times on the usual route and shorter travel times on the alternate routes increase the probability of route diversion, as expected. To simplify analysis and focus on information and travel time effects, driver attributes were not included in the model. To assign individuals between their usual and alternate routes, the probability of staying on usual route as opposed to diverting is calculated according to the formula:

$$P_n(i) = 1/(1 + \exp(\beta'(\mathbf{X_j n} - \mathbf{X_{in}}))) \tag{4}$$

where:

$P_n(i)$ = Probability of person n choosing the usual route, i
β' = Vector of parameters
$\mathbf{X}$ = Attributes of alternatives i (usual route) and j (alternate route).

Table 2. Traveler behavior input for revealed behavior model

Variables	β	(t-Statistics)
Constant	−0.717	(−4.27)
Information source (= 1 if delay information received from radio traffic reports, = 0 if observation of delay)	0.407	(1.88)
Travel time difference in minutes (average travel time on usual route + length of delay − travel time on alternate route)	0.022	(3.48)
Summary statistics		
Initial log-likelihood	−257.85	
Log-likelihood at convergence	−246.71	
Number of observations	372	

Also the probability of diversion, $P_n(j) = 1 - P_n(i)$

Suppose that $P_n(j) = y$, then a random number, z, is generated between 0 and 1.

If $(z \leqslant y)$, then $r = 1$, otherwise $r = 0$.

The binary logit model is sufficient for a two route network, however, for larger networks, where routes overlap, nested logit and probit models are more appropriate.

4.3. *Flow characterization*

If real-time delay information is not available (i.e. people cannot observe the incident or use electronic sources), then according to the composite model, nobody will divert and total network travel times are expected to be at a maximum. If, however, during the incident travelers can observe the queue, then according to the composite model, some will divert. This will reduce travel times compared with the no knowledge scenario. Now with the introduction of radio information, travelers' diversion propensity increases, therefore average travel times are expected to decrease. The introduction of ATIS where equipped travelers take the minimum time route is complicated. Compared with the no information scenario, increasing ATIS market penetration will improve travel times because of its tendency toward attaining user equilibrium. However, if people can observe and/or have access to radio information, then the behavioral assumptions for ATIS (take minimum time route) may worsen network travel times. Specifically, with observation and/or radio the network can be operating close to the system optimal—the introduction of ATIS, by tending toward user equilibrium, will cause a decrement in travel times. Put another way, after learning about the delay through observation or radio, people may divert *early* in the incident process (e.g. to avoid even small amounts of queuing delay), and therefore reduce the delay costs incurred by others arriving later. However, with ATIS, route diversions can only occur when travel time on the usual route exceeds the travel time on the alternate route—excluding the possibility of early diversions. Thus, it is possible that with increasing ATIS market penetration the travel times will worsen when the network moves away from system optimal and closer to user equilibrium.

5. RESULTS

The corridor and incident parameters used in simulations are as follows:

(a) Routes 1 and 2 free flow travel times are fixed at 40 and 50 min, respectively.
(b) Normal capacities of Routes 1 and 2 are fixed at 133 vehicles min^{-1} and 66.5 vehicles min^{-1} respectively.
(c) Incident duration is fixed at 45 min.
(d) Incident reduced capacity is fixed at 66.5 vehicles min^{-1}.
(e) Flow rate is fixed at 117 vehicles min^{-1}.
(f) There are two incident locations, one at 5 miles upstream of destination point (B) when the queue is never visible and the other at 2 miles downstream of decision point (A) when the queue is observable for some time.
(g) Percent unequipped, percent equipped with radio, and percent equipped with ATIS vary systematically as shown in Table 3 generating a total of 132 incident scenarios simulated.

Thus the only parameters that change in our simulations are incident location and percent equipped with radio and ATIS. We assume that the free flow travel speed is 60 mph, therefore the free flow travel time from A to the first incident location is 35 min (Set 1 scenarios, $\tau = 35$) and the free flow travel time to the second location is 2 min (Set 2 scenarios, $\tau = 2$). Travelers are unable to observe the queue in the first set of scenarios but some of them can observe it in the second set (when the queue extends beyond point A).

The parameters were carefully chosen to reflect real-life corridors and incidents. For example, Route 1 and Route 2 free flow travel times reflect the average travel times for usual and alternate route reported in the Chicago survey data (Khattak, 1991). The road capacities are for a typical four-lane freeway and a major two-lane arterial. The incident is a major one (but not untypical) which blocks two lanes of the four-lane freeway for 45 min. The flow rate is lower than freeway capacity reflecting non congested traffic conditions. We have assumed the normal roadway

Table 3. Incident scenarios simulated

No knowledge + observation only*	ATIS	Radio
100	0	0
90	0	10
90	10	0
80	20	0
80	10	10
80	0	20
70	30	0
70	20	10
70	10	20
70	0	30
0	100	0
0	90	10
0	80	20
0	70	30
0	60	40
0	50	50
0	40	60
0	30	70
0	20	80
0	10	90
0	0	100

*The split percentage between 'no knowledge' and 'observation only' travelers is not known *a priori*. Instead it depends on whether or not the queue backs up to point A. That is, travelers arriving are assigned to Route 1 if the queue does not reach A. Otherwise, travelers observe the queue and are assigned according to the behavioral model.
We have a total of 66 scenarios for each incident location (two locations are considered), resulting in a total of 132 incident scenarios simulated in this study.

capacity to be 2000 vehicles $h^{-1}\,ln^{-1}$ and the headway in queue to be 40 ft veh^{-1}. The information regarding delay is updated for each time interval (every individual arrival).

The queues in various scenarios would end at different times. However, to compare scenarios, a common base is needed. Therefore, the simulation duration was fixed at a 'base' when no driver diverts. That is, when the queue on Route 1 lasts longest.

Figures 5 and 6 show the three-dimensional representation of average travel times (free flow travel time plus delay) with varying percentages of radio and ATIS (observation/no observation is the complement). Three imaginary lines can be drawn on this figure: Iso-ATIS lines, Iso-radio lines, and Iso-observation lines. An Iso-ATIS line connects average travel time points which result from incident scenarios with the same percentage of ATIS equipped travelers (same level of market penetration). Similar definitions hold for the two other types of lines. First we discuss Set 1 scenarios where nobody can observe the queue ($\tau = 35$ min) as shown in Fig. 5.

The overall trend is toward reduced travel times with increased radio and ATIS penetration, as expected. Also, there is an increase in travel times with increasing unequipped travelers. There is a decreasing trend in travel times with increasing ATIS penetration, as expected. There is a marginal decrease in travel time beyond 20–30% ATIS, and therefore increasing market penetration beyond this limit may not be beneficial. The effect of having all individuals equipped with ATIS (average travel time = 45.34 min veh^{-1}) as opposed to having all travelers unequipped (average travel time = 49.71 min veh^{-1}) shows the benefits from ATIS. However, with all travelers accessing radio, the travel times are even lower (average travel time = 44.07 min veh^{-1}) than with all ATIS equipped. This is because radio causes people to divert *earlier* causing the network to operate closer to system optimal than user equilibrium. Overall, there are travel time benefits that will accrue from the introduction of ATIS under this scenario.

If the incident location is such that during the incident process some individuals can observe the queue (Set 2 scenarios, $\tau = 2$ min), then interesting similarities and differences can be observed. The trend that travel times decrease with increasing radio remains unchanged. However, a decrease in travel times with increased ATIS is observed with an optimal ATIS market penetration. Also, the increase in travel times with increasing unequipped travelers is consistent with Set 1 scenarios.

The effect of having all individuals equipped with ATIS (travel time = 43.74 min veh^{-1}) as opposed to having all travelers unequipped (travel time = 43.76 min veh^{-1}) is different from the

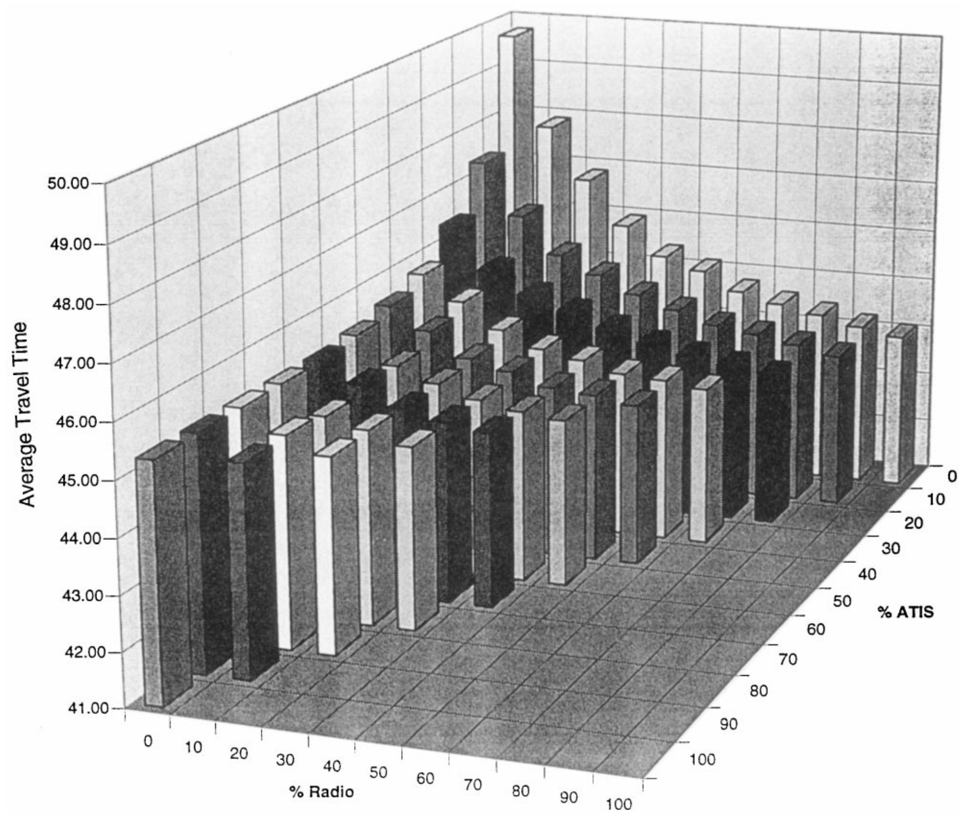

Fig. 5. Average travel time for Set 1 scenarios ($\tau = 35$ min).

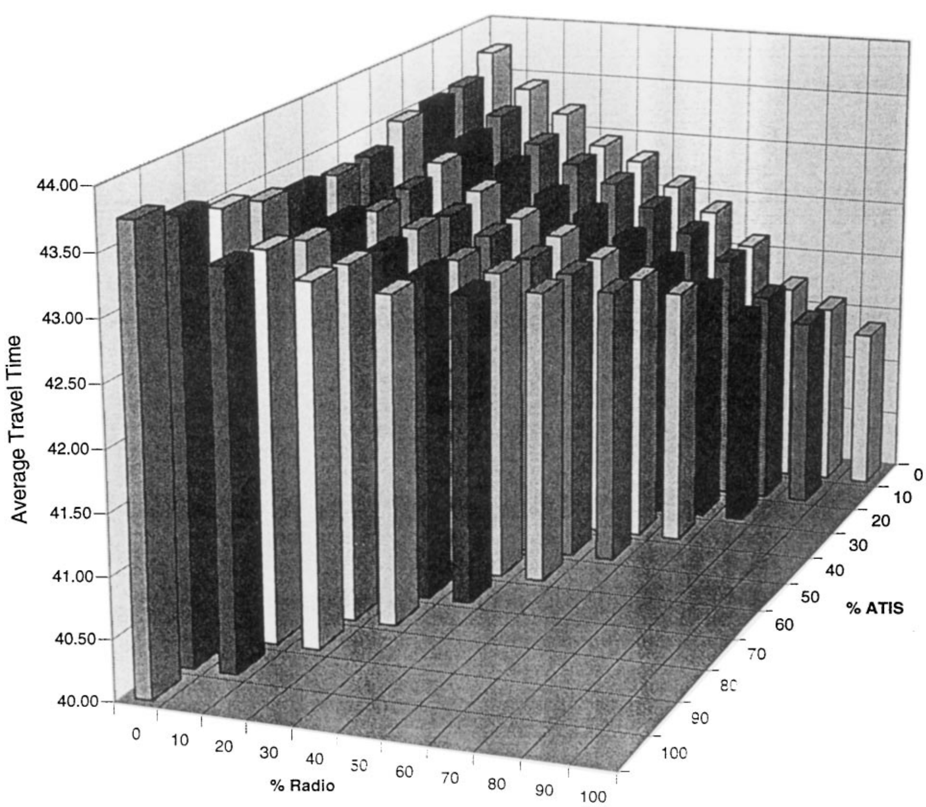

Fig. 6. Average travel time for Set 2 scenarios ($\tau = 2$ min).

previous scenario. By observing congestion and diverting early in incident occurrence process, the network conditions are closer to system optimal than user equilibrium. However, ATIS will lead to user equilibrium conditions and 100% ATIS gives higher travel times because diversion starts later and occurs only for a short time. When radio is also present along with observation, the tendency toward system optimal increases; observe that when all persons are equipped with radio, the travel times are lower (travel time is 41.38 min veh^{-1}) than with all travelers equipped with ATIS or when they can observe congestion.

Analysis of travel times on both routes resulted in the following observations (see Figs 7–9).

With 100% ATIS, equilibrium (in travel times) is reached (see Fig. 7). Diversion starts and ends based on equilibrium of travel times. With 100% observation, equilibrium (in travel time) is not reached (see Fig. 8). Diversion starts when queue is observed, and stops when queue is not visible. Compared with the 100% ATIS, diversion starts later, but the duration of diversion is longer,

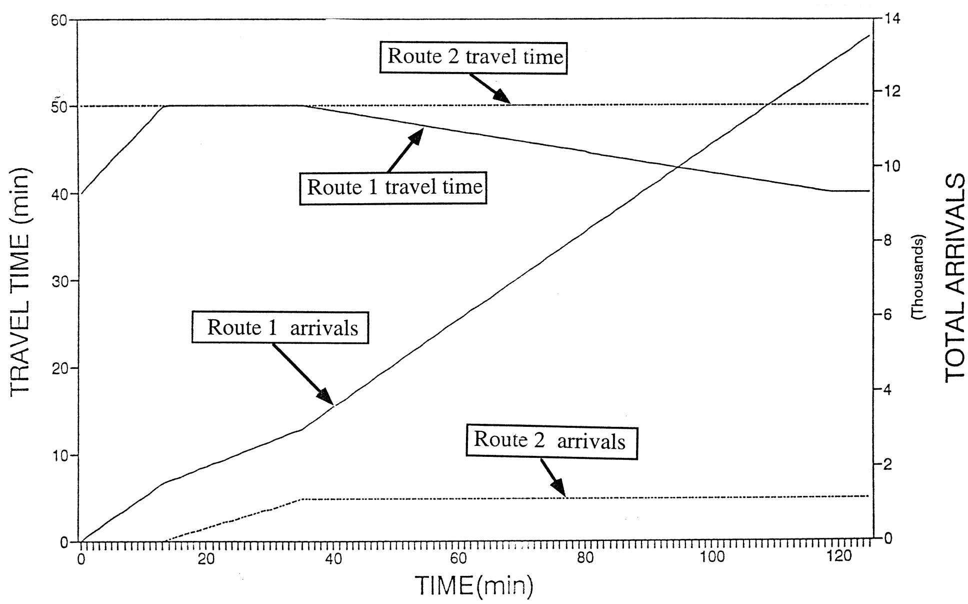

Fig. 7. Total travel time and total arrivals (ATIS = 100%).

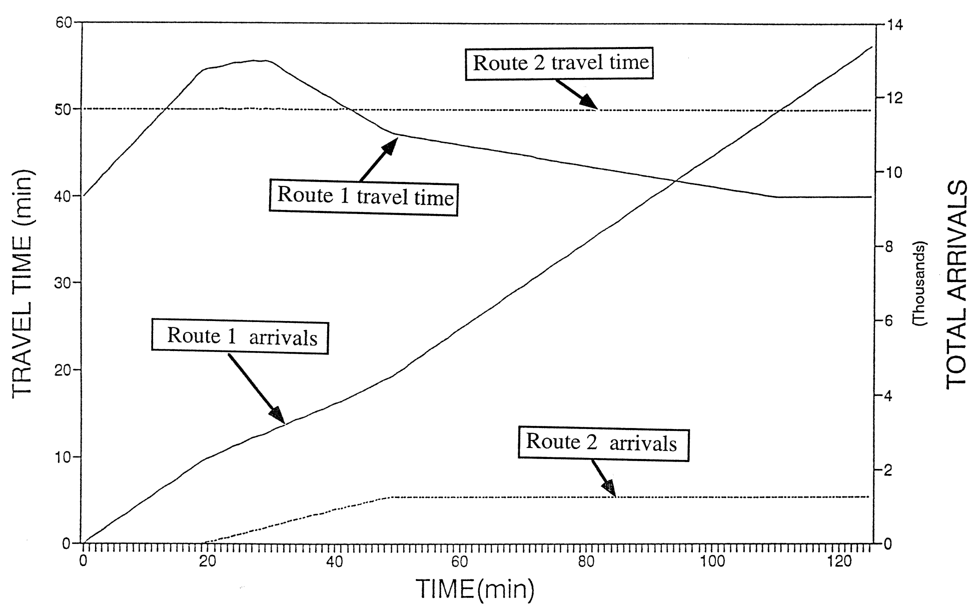

Fig. 8. Total travel time and total arrivals (observation = 100%).

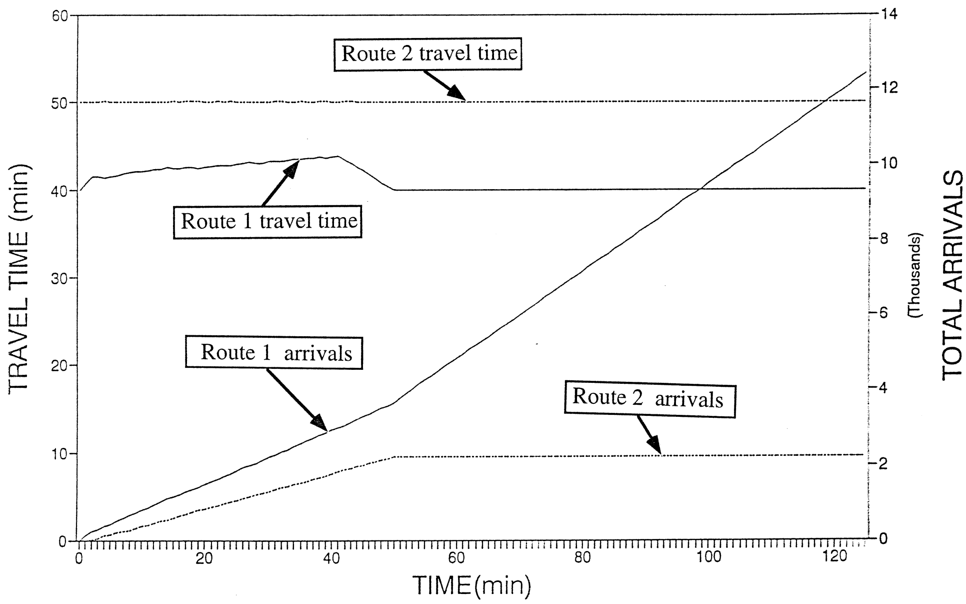

Fig. 9. Total travel time and total arrivals (radio = 100%).

resulting in almost equal system performance. With 100% radio, equilibrium (in travel times) is not reached (see Fig. 9). Diversion starts as soon as drivers hear about the incident. Diversion ends when queue ends because there is a non zero probability of diversion as long as the queue exists. Since diversion starts immediately, the system performance is closer to the system optimal than the other two cases, i.e. 100% ATIS and 100% observation. Table 4 summarizes the input parameters, the process needed to produce output, the output and results of the study.

Overall, the benefits of ATIS (under travel time minimization assumption) are limited when there is more 'information' available to travelers through their own observation or radio. However, it is possible that with alternative ATIS behavioral assumptions, e.g. that the probability of route diversion is x% more than that with radio, we could observe different results, e.g. greater ATIS benefits. We also caution that these results hold for downtown Chicago commuters who have access to real-time quantitative radio traffic reports and have good route diversion opportunities (average number of alternate routes known to respondents was about 3).

Table 4. Summary of study input and output parameters and results

Inputs	Process	Output	Results
(a) Route 1 travel time	(a) Simulation eqns (1–3)	Average travel time for the network and for each type of traveler:	(a) Radio may cause near optimal system performance under incident conditions
(b) Route 2 travel time	(b) Study design and assignment assumptions (Table 1) and eqn (4)	(a) observation or no observation of queues by traveler	(b) User equilibrium with ATIS may cause increased total system travel time
(c) Route 1 capacity	Incident scenarios simulated (Table 3)	(b) radio information access by traveler	(c) User equilibrium with ATIS may have incremental/modest benefits
(d) Route 2 capacity		(c) ATIS access by traveler	
(e) Route 1 incident reduced capacity			
(f) Incident location on Route 1			
(g) Incident duration			
(h) Total flow on both routes			
(i) Percent equipped with information			

6. CONCLUSIONS

To evaluate the benefits of traffic information, the results of a composite traffic assignment model are reported. The benefits are measured in terms of travel times and delay due to information dissemination on traffic incidents. The composite model is comprehensive in that it accounts for existing traffic information sources (radio), personal observation of congestion and ATIS. Travelers equipped with ATIS take the minimum time route. Completely uninformed travelers are assigned to their usual route. Travelers are assigned probabilistically to routes with those receiving radio traffic information being more likely to divert under incident conditions than those who observe traffic congestion. The probabilities of diversion are based on travelers' responses to a behavioral survey conducted in the Chicago area. The inclusion of revealed behavior represents diversion benefits due to the existing traffic reporting system (and/or benefits due to travelers' diversion after observation of incident queues). The presence of ATIS equipped travelers reflect the benefits that could accrue when ATIS is implemented.

The net effect of increasing ATIS market penetration on reduction of average delay depends on the diversion behavior of both equipped and unequipped travelers. Average delay may decrease with ATIS penetration in some scenarios (as was demonstrated in this paper) and it may not decrease in others. However, the decrease in delays also depends on radio market penetration and whether travelers can observe the incident.

Following the results of the survey, the probabilistic revealed behavior model gives a significant probability of diversion for congestion information received through radio and observation. This causes more traffic (radio informed and observation informed) to divert to the alternate route early in the incident occurrence process. Travelers who divert early benefit others who arrive later.

Results of the composite assignment model show that the overall trend is toward reduced average travel times in the corridor with increased radio and ATIS penetration. However, the benefits of ATIS under incident conditions are expected to be marginal when there is more 'information' available to travelers through their own observation or radio (at least in the analyzed two-route corridor). This is because radio causes people to divert earlier resulting in network conditions closer to system optimal than user equilibrium. It is possible that there are cases where active ATIS guidance to minimum time routes can produce significant system benefits (e.g. incident cases with high demand rates, long incident durations and sufficient alternate route capacity). Finally, there is a need to investigate and validate ATIS benefits from diversion in larger-scale networks using realistic behavioral assumptions for ATIS equipped drivers.

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