FINAL TECHNICAL REPORT

A Comparison of Mobility Impacts on Urban Commuting Between Broadcast Advisories and Advanced Traveler Information Services

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ABSTRACT

This report explores the effectiveness of relying on commercial radio as a source of traveler information, and presents an approach to quantify mobility benefits from radio traffic advisories. The study, conducted for the Washington, DC metropolitan area, used an analytical technique called the Heuristic On-line Web-Linked Arrival Time Estimator (HOWLATE) to examine if radio advisories can have similar mobility benefits as a notification-based traveler information service offering personalized estimates of travel times. Traffic reports were recorded from a local radio station and manually coded to translate them to a suitable format for analysis. Results from our analysis of 37 weekdays consisting of 4410 advisories indicate that overall radio traffic advisories were less effective in improving traveler on-time reliability than a service offering route-specific travel time reports. In our experiment, the simulated commuter receiving regular, quantitative estimates of travel times on relevant roadways typically made more effective route and trip timing decisions than the simulated commuter who received comparatively incomplete, irregular and vague advisories on prevailing congestion conditions from broadcast traffic reports. In fact, the simulated commuter listening to radio advisories recorded similar on-time reliability performance to our simulated control subject, who ignores all forms of traveler information. During the afternoon peak period, when travel time variability is higher, the simulated radio listener recorded slightly better reliability performance than the simulated control subject. During other periods of the day, the on-time reliability performance of the simulated radio listener was worse than the simulated control subject.

KEYWORDS: Intelligent Transportation Systems, mobility benefits, HOWLATE, Advanced Traveler Information Systems, radio traffic advisories, simulated yoked trials, Washington, DC.

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EXECUTIVE SUMMARY

Commercial radio and television stations, providing broadcast traffic advisories throughout a metropolitan area, currently dominate the private sector traveler information market. In 2001, it was estimated that more than 2000 radio and 220 television stations broadcast traffic information to an audience of 100 million in 90 cities (1). Broadcast traffic advisories are provided at no cost to the motorist and are easily accessible, thereby making them the leading form of traveler information nationwide. Surveys have shown that commuters rely largely on commercial radio broadcasts to receive traffic information prior to leaving home and en route (2, 3, 4). Although radio traffic reports reach a wide audience, it remains an open research question whether they provide any tangible mobility benefits (e.g., improved trip reliability) to the commuter, above and beyond entertainment or serenity effects. Do advisories broadcast on radio or televisions provide enough detail for the motorist to make effective trip decisions? If so, are too many people receiving the same information and making similar detours causing congestion on alternative routes? While the private sector is primarily concerned with offering a valued service, regardless of the source of this perceived value (entertainment/serenity/mobility), the public sector has to focus on serenity, mobility and productivity improvements for its investments. Here, the main objectives are improving trip reliability and reducing driver stress. Do broadcast traffic reports fulfill these public sector goals? Do they serve only to increase serenity or are they also beneficial in terms of increasing trip reliability? Surveys conducted by the Michigan Department of Transportation, found that commuters in the Detroit area who used commercial radio as a source of traffic information felt that there was a need for more timely reports that offered route-specific information (5). To date, there has been no research on quantifying mobility benefits from media broadcasts of traffic reports. However, significant Advanced Traveler Information Services (ATIS) investments (sensors, cameras, etc.) have occurred without any comparison to broadcast traffic reports.

This report presents an approach to quantify trip reliability benefits from use of commercial radio as a source of traveler information using an analytical technique called the Heuristic On-line Web-Linked Arrival Time Estimator (HOWLATE) that Mitretek developed to evaluate user impacts of ATIS services using archived roadway travel time data. The principal objectives of this study are to quantify time savings and other mobility benefits from listening to radio traffic advisories, and to examine if radio advisories alone can have similar mobility benefits as a notification-based traveler information service offering personalized estimates of travel times.

A case study is presented for the Washington, DC area, the third most congested region in the United States (6), using route-specific travel times and advisories archived from the SmarTraveler web site (www.SmarTraveler.com), and radio advisory content from Westwood One.

Approach

Mitretek developed an automated process for acquiring commercial radio traffic reports and selected WMAL as the source for the Washington, DC case study. Traffic broadcasts on WMAL are provided by a separate entity, Westwood One, and last anywhere from under a minute to over two minutes.

Recording was performed every ten minutes from 6:30 AM to 9:30 AM and 3:00 PM to 7:00 PM, the times of day when WMAL broadcasts regular traffic reports. We were able to archive more than 4000 radio reports for 69 weekdays from 1 June 2001 to 17 January 2002. Of the 69 days, 48 days were determined to be of sufficient quality (both in terms of audio quality and completeness of reports across the AM and PM peak periods) to be coded for analysis.

Next, we transformed the audio broadcast traffic reports into a format suitable for use within HOWLATE. One of the candidate options for converting audio traffic reports into electronic format was use of speech-recognition software. This proved infeasible because the audio quality of the radio reports was often low and delivery of traffic news by on-air talent was too fast for the software to make sense of the content. Instead, we used a manual approach to process the audio reports. The manual processing of the recorded radio traffic reports proved to be extremely tedious and labor intensive. Hence, although we recorded radio traffic reports for 48 days, due to time and resource constraints, we were able to code the content for only 42 days.

Given that traffic broadcasts provide only qualitative information on the traffic conditions rather than estimated travel times, we collected concurrent travel time and incident data from the SmarTraveler web site. The HOWLATE methodology was enhanced to allow the assessment of reliability impacts of coded radio advisories against a prospective notification-based traveler information service, using concurrent archives of broadcast advisories and travel times reports.

The HOWLATE technique constructs synthetic trips of a pair of drivers, a habitual commuter who makes regular use of traveler information services (either broadcast advisories or ATIS), and a habitual commuter who ignores all traveler information sources, so that each pair has the same origin, destination and target time of arrival.

The HOWLATE process consists of four modules – the travel time archiver, the travel habituation module, the yoked study simulator, and the output post processor. In the first module, roadway travel-time reports are archived from the SmarTraveler traveler information web site using an automated process for archiving Internet postings (7).

In the second module, the travel habituation module, simulated commuters establish their habitual routes and determine their trip departure times that result in an acceptable frequency of on-time arrivals (specified in our study to be 95%), based on the travel times they experience over a number of days called the habituation or the training period. In addition, during this period, traveler information users adopt strategies for using the data based on prior experience. For example, ATIS users adjust for persistent bias in the predicted traveler information and the actual travel time that they experience. Radio listeners adopt strategies that correlate advisory content and experienced congestion. We model the simulated radio listener (or the radio archetype) as capable of making both pre-trip as well as en route trip decisions, and altering his route and/or trip departure time based on the reported congestion status on his route and available alternate routes. In the travel habituation module, the radio archetype learns how an advisory of a specific severity impacts his travel time. He does this by keeping a mental record of the radio advisories broadcast for his habitual route on each day of the training period. To translate the qualitative information mentioned in the advisories into measurable differences in travel times, we defined four scales to model the radio advisories: 0 corresponds to *no advisories mentioned* for the link, 1 corresponds to *conditions better than normal*, 2 corresponds to *usual delays*, and 3 corresponds to *worse than normal conditions*. The travel time that he experiences on his trip on each day of the training period is defined as a linear function of the average travel time for his trip over the entire training period and the number of unique advisories he hears for each link on his route. Linear regression is used to determine change in travel time associated with advisories of each of the four scales for each trip.

In the third module, simulated yoked trials are conducted between a pair of drivers, the traveler information user and the non user, so that they have the same origin, destination, and target arrival time. The radio archetype starts listening to radio traffic reports 30 minutes prior to the habitual trip departure time. The radio archetype calculates his expected travel time under current conditions by adjusting the normal (or average) travel time established during the training period to accommodate for traffic advisories. The change in travel time corresponding to an advisory of a certain severity is learned during the training period. If he determines that by taking the fastest route and leaving at the habitual trip departure time he will arrive at his destination more than ten minutes before his desired arrival time, he will postpone his trip by five minutes. The check is performed every five minutes. When he can no longer postpone the trip, he checks if the travel time on the fastest route is less than the travel time on the habitual route. If the difference is more than his indifference threshold (specified as three minutes in this study), he selects the fastest route. Otherwise, he takes his habitual route. Unlike the ATIS user, the radio archetype is also capable of altering his path en route.

Finally, in the fourth module, the effect of traveler information services is assessed.

The HOWLATE methodology was applied to 37 weekdays consisting of 4410 radio advisories. Although we coded the contents of radio advisories for 42 days, five were excluded from consideration due to gaps in the travel time data archive. The training period for this study was from 22 August 2001 to 9 October 2001, and composed of 19 weekdays.

The evaluation period was from 11 October 2001 to 11 January 2002, and composed of 18 weekdays. Simulated yoked trials between the simulated control subject and the two types of traveler information users (the ATIS user and the radio archetype) were conducted using five different random number seeds for each day in the evaluation period for the Washington, DC network, at 15-minute intervals between 6:30 AM and 6:30 PM.

Hypotheses and Key Findings

Hypothesis: Mobility benefits from radio traffic advisories will be lower than those from a prospective notification-based traveler information service that delivers pre-trip personalized estimates of route-specific travel times.

Findings: Our analysis showed that when taking into account both peak periods, the radio archetype performed worse than the ATIS user. In our study we found that on average, of the 33 segments modeled in the Washington, DC network, the number of roadway segments mentioned per radio traffic report ranged from one to 16, and averaged four. Given that there is only a 12% (4/33) probability of a roadway segment being mentioned in a traffic report and that the roadway segment may not be part of the chosen path, information available to the radio archetype is quite limited in comparison to the ATIS user who gets travel time estimates for his entire trip.

Table ES-1 lists the radio archetype's expectation of delays (or changes in travel time) in seconds for advisories of each of the four scales learned during the training period. For example, in the AM peak period, when an advisory refers to better than normal conditions on a roadway segment, the radio archetype expects the travel time on that roadway segment to be less by 41 seconds. Likewise, when no advisory is mentioned for a roadway segment his expectation is that the travel time will be less by six seconds. For simplicity, the delays or changes in travel time shown are the averages over all trips. We computed these delays for each trip in the training period. As anticipated, for both peak periods, average delays increase as the severity of the broadcast congestion increases.

Table ES-2 shows the average network travel times corresponding to the four advisory scales. Contrary to our expectation, in the training period when advisories referred to usual delays average travel times were found to be higher for both peak periods (22.3 minutes and 23.5 minutes) than when worse than normal conditions were mentioned (20.3 minutes and 21.3 minutes). However, in the evaluation period, the corresponding travel times under usual delays were lower than when conditions were worse than normal. In fact, travel times under usual delays were the lowest in the PM peak period (18.5 minutes). This contradicts the delays shown in Table ES-1. In addition, when no advisories were mentioned the travel times were lower than when conditions were better than normal, contradicting the delays computed for the two advisories (Table ES-1). Thus, there were inconsistent relationships between travel times and advisory scales from the training period to the evaluation period.

Table ES-1: Average Delay for Each Unique Advisory Mentioned for a Roadway Segment

Advisory Scale	Average Delays (seconds)	
	AM Peak	PM Peak
No advisories mentioned	-6	-8
Conditions better than normal	-41	-96
Usual delays	20	-18
Worse than normal conditions	46	49

Table ES-2. Average Network Travel Times in Minutes for the Four Advisory Scales

Radio Advisory Scale	Training Period		Evaluation Period	
	AM Peak	PM Peak	AM Peak	PM Peak
No advisories mentioned	18.2	19.2	19.5	20.3
Conditions better than normal	18.3	20.1	19.7	21.9
Usual delays	22.3	23.5	21.4	18.5
Worse than normal conditions	20.3	21.3	21.6	20.3

Table ES-3 shows the performance measures computed for the trips made by the pre-trip ATIS, the radio archetype, and the non-ATIS user in the AM and the PM peak periods. The radio archetype experienced higher travel disutility (defined as a function of in-vehicle travel time and the frequency and magnitude of early or late arrivals, based on the work done by (8) than the pre-trip ATIS for both peak periods. For the AM and PM peak periods, the radio archetype's travel disutility costs were $2.80 and $2.63, respectively, while the ATIS user's disutility costs were $2.52 for both peak periods. In the AM peak period the radio archetype had lower trip reliability (85.7%) than the ATIS user (98.5%), while in the PM peak period it was slightly higher (88.3% compared to 87.8% for the ATIS user). In the AM peak, the radio archetype had greater late schedule delay of 3.9 minutes compared to 2.5 minutes for the ATIS user, but in the PM peak both traveler information users had the same late schedule delays (3.4 minutes).

Table ES-3. Comparison of Performance Measures for the AM and PM Peak Periods

Aggregate Trip Metrics	AM Peak			PM Peak		
	Non-ATIS User	Pre-Trip ATIS User	Radio Archetype	Non-ATIS User	Pre-Trip ATIS User	Radio Archetype
Trip Time (minutes)	34.6	34.2	34.6	34.9	34.8	34.9
Travel Disutility Cost ($)	2.59	2.52	2.80	2.73	2.52	2.63
On-Time Reliability	88.0%	98.5%	85.7%	76.1%	87.8%	88.3%
% Early Trips	5.1%	15.5%	5.9%	23.9%	12.2%	11.7%
Late Schedule Delay (Minutes)	2.8	2.5	3.9	2.2	3.4	3.4
Early Schedule Delay (Minutes)	11.9	12.9	11.4	14.1	12.2	11.3

Hypothesis: A commuter listening to radio traffic advisories will have higher mobility benefits than a habitual commuter who does not make use of any form of traveler information service.

Findings: Our analysis of 37 days showed that this hypothesis was true for the PM peak period, but not for the AM peak period (Table ES-3). In the AM peak period, the radio archetype fared worse than the habitual commuter who does not make use of traveler information. When compared to the radio archetype, the non-ATIS user had higher trip reliability (88% versus 85.7%), lower travel disutility ($2.59 versus $2.80), and smaller late schedule delays (2.8 minutes versus 3.9 minutes). But in the PM peak period although the non-ATIS user had smaller late schedule delays (2.2 minutes versus 3.4 minutes), he had lower trip reliability (76.1% versus 88.3%) and higher travel disutility ($2.73 versus $2.63) than the radio archetype. The radio archetype's trip outcomes greatly depend on the number and timeliness of advisories heard for his route. Because of the limited time available for a broadcast traffic report, it is highly probable that the radio archetype fails to hear advisories mentioned for his route. This is further complicated by the inconsistent relationship between travel times and advisory scales from the training period to the evaluation period, as discussed in the previous section.

Conclusions and Future Extensions

Our analysis of the 37 weekdays consisting of 4410 advisories indicated that overall radio traffic advisories were less effective in improving traveler on-time reliability than a service offering route-specific travel time reports. This was expected given that the simulated ATIS user receiving estimates of travel times on his route could make more effective trip decisions compared to the simulated radio user who received comparatively incomplete, and vague advisories on prevailing congestion conditions from broadcast traffic reports, perhaps not on his chosen or desired route. Moreover, although we expected the simulated commuter listening to radio traffic advisories to experience higher mobility benefits than a habitual commuter who does not make use of any form of traveler information, our results showed that this was not always the case. This is because benefits of radio traffic advisories are highly dependent on the accuracy and timeliness of these advisories, and a commuter's interpretation of how these advisories may affect his travel times. In our study period, there were inconsistent relationships between travel times and advisory scales from the training period to the evaluation period.

This study is the first assessment of mobility benefits from radio advisories that we are aware of. However, one of the key caveats of this study was that it was conducted for only 37 days consisting of 4410 advisories and hence the benefits determined for the simulated commuters may not be indicative of long-term radio use. Moreover, we were also limited by a lack of detailed studies to guide our modeling of travelers listening to radio advisories, and how they process and react to broadcast congestion information.

Our study shows that ATIS services offering personalized route-specific travel time reports can have high mobility benefits, but such potential ATIS services are likely to be more expensive and less easily accessible than the radio. Increased investments can probably improve the precision of broadcast traffic reports, yet ultimately broadcast traffic reports are time-limited and can cover only a portion of the network. This inability of broadcast media to address personalized information needs is reflected in the limited reliability benefits accrued by the radio archetype in our study. However, this does not preclude improved serenity. Radio listeners may experience stress reduction and perceive value from an improved awareness of congestion sources and locations. Thus, although broadcast advisories have lower mobility benefits than ATIS, they are available for free and are more easily accessible, and so for now will continue to dominate the private traveler information market.

In order to make more robust conclusions about potential mobility benefits we propose to analyze the outcomes of simulated commuter trips for a longer period of time, such as a year. However, as coding of advisories is highly labor-intensive, we propose constructing radio advisories from available web advisories posted on the SmarTraveler web site, given that the contents of both sets of advisories are provided by the same entity, Westwood One. Our analysis of the two sets of advisories to recreate radio advisories from those available on the web showed that, although many of the radio advisories were also mentioned on the web, the contents of the two advisory sets were not always consistent. No linear relationship was observed between the contents of the two sets of advisories.

We propose to use artificial neural networks to construct radio advisories from the web advisories since they are particularly useful in detecting trends or patterns in data that are non-linear or are not explicit. We will examine mobility benefits based on the constructed radio advisories. Another potential extension is to examine the effect of radio advisories in improving the serenity of travelers, as although radio advisories may not be as effective as ATIS in improving mobility benefits, radio listeners are likely to benefit from improved serenity, which, to date has not been quantified. Once we have a better understanding of both serenity and mobility impacts of broadcast advisories, another interesting extension is assessing improvements in traveler trip outcomes from public sector investments in improved network surveillance. Even if the public sector itself provides no ATIS service, it is likely that better surveillance results in more accurate advisories, which is an improvement that can be analyzed and quantified in a future HOWLATE study.

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1. INTRODUCTION

1.1 Background

Commercial radio and television stations, carrying broadcast traffic advisories throughout a metropolitan area, currently dominate the private sector traveler information market. In 2001, it was estimated that more than 2000 radio and 220 television stations broadcast traffic information to an audience of 100 million in 90 cities (1). Radio and television stations put together traffic advisories from sources such as state and local police agencies, phone calls from passing motorists, aerial surveillance, and video cameras. Alternatively, stations may swap airtime for traffic report services from providers such as Westwood One, who provide regional traffic reports and on-air talent for multiple broadcasts.

Broadcast traffic advisories are free to the motorist and are easily accessible, thereby making them the leading form of traveler information nationwide. A study conducted in California found that commuters rely largely on commercial radio broadcasts to receive traffic information prior to leaving home and en route (2). Results from a phone survey conducted by Leflein Associates nationwide in June 2003 indicated that 51% of all commuters switch stations to listen to radio traffic reports, and commuters with a trip time of more than 45 minutes are 58% more likely to switch to a desired radio station (3). Another survey conducted in the Washington, DC, metropolitan area found that almost all participants obtained traffic information on the radio prior to leaving home or work and while driving (4). In comparison, relatively few participants (8%) accessed the Internet or the telephone for traffic information, although both services were available. Thus, for now the radio is the dominant source of traffic information.

Although radio traffic reports reach a wide audience, it remains an open research question if they provide any tangible mobility benefits (e.g., improved trip reliability) to the commuter, above and beyond entertainment or serenity effects. An example of the entertainment value during a traffic report is when the on-air talent makes a witty off-hand comment without any direct bearing on current traffic conditions. These types of comments encourage the listener to stay tuned for additional reports. An example of serenity benefits is when a motorist is made aware of congestion without being able to take action on the information to reduce delay. This may reduce stress but does not change trip outcomes. This leads to a number of questions: Can advisories broadcast on radio or televisions provide enough detail so that the motorist can make effective trip decisions? Are too many people receiving the same sketchy information and making similar detours causing congestion on alternative routes? While the private sector is primarily concerned with offering a valued service, regardless of the source of this perceived value (entertainment/serenity/mobility), the public sector has to focus on serenity, mobility and productivity improvements for its investments. Here, the main objectives are improving trip reliability and reducing driver stress. Do broadcast traffic reports fulfill these public sector goals? Do they serve only to increase serenity or are they also beneficial in terms of increasing trip reliability? Surveys conducted by the Michigan Department of Transportation, found that commuters in the Detroit area who used commercial radio as a source of traffic information felt that there was a need for more timely reports that offered route-specific information (5). To date, there has been no research on quantifying mobility benefits from media broadcasts of traffic reports. However, significant Advanced Traveler Information Services (ATIS) investments (sensors, cameras, etc.) have occurred without any comparison to broadcast traffic reports. When making these comparisons it is important to point out that ATIS investments have likely improved the accuracy and timeliness of broadcast traffic reports.

This report presents an approach to quantify mobility benefits from use of commercial radio as a source of traveler information using an analytical technique called the Heuristic On-line Web-Linked Arrival Time Estimator (HOWLATE) that Mitretek developed to evaluate user impacts of ATIS services using archived roadway travel time data. The objectives of the study are presented in Section 1.2, followed by the hypothesis of the study in Section 1.3. Section 2 gives an overview of the HOWLATE methodology. Sections 3.1 and 3.2 describe the process used for acquiring traffic reports from the radio and the data processing that was required to transform it into a suitable format. Section 4 analyzes the content of the traffic reports. Section 5 describes an enhancement made to the HOWLATE methodology to emulate a commuter listening to radio traffic reports. Section 6 presents a description of the data used in the study, including the geographic area, and compares the mobility benefits of radio traffic reports with those of a notification-based traveler information service offering estimates of route-specific travel times. Finally, the key findings and future work are summarized in Section 7.

In this study, a *radio traffic report* is defined as traffic related news that is broadcast every ten minutes, throughout the day. A *radio traffic advisory* corresponds to travel conditions on a *single* roadway segment. Thus, each radio traffic report contains multiple radio traffic advisories for various roadway segments.

1.2 Objective and Scope of the Study

Studies using the HOWLATE technique have found that commuters in case studies conducted in Washington, DC, Minneapolis/St. Paul, and Cincinnati are able to increase trip reliability through use of a prospective notification-based traveler information service that delivers pre-trip estimates of route-specific travel times (9, 10, 11). However, it remains an open question if radio traffic advisories can provide similar quantifiable mobility benefits. Thus, the principal objectives of this study are to see if we can quantify time savings and other mobility benefits from listening to radio traffic advisories, and to examine if radio advisories alone can have similar mobility benefits as the prospective ATIS service considered in the previous HOWLATE studies.

To meet this objective, we have developed an analytical approach to evaluate commuter utilization of radio traffic advisories to improve on-time reliability in congested urban areas. A case study is presented for the Washington, DC area, the third most congested region in the United States (6), using route-specific travel times and advisories archived from the SmarTraveler web site (www.SmarTraveler.com), and radio advisory content from Westwood One.

1.3 Study Hypothesis

The main hypothesis of this study is that mobility benefits from radio traffic advisories will be lower than those from a prospective notification-based traveler information service that delivers pre-trip personalized estimates of route-specific travel times. This is based on our expectation that a commuter receiving quantitative estimates of travel times on relevant roadways can make more effective trip decisions than a commuter who receives comparatively incomplete, irregular and vague advisories on prevailing congestion conditions from broadcast traffic reports, perhaps not on his chosen or desired route.

In addition, we also hypothesize that a commuter listening to radio traffic advisories will have higher mobility benefits than a habitual commuter who does not make use of any form of traveler information service. However, it should be noted that the benefits of radio traffic advisories are highly dependent on the number, accuracy and timeliness of these advisories, and a commuter's interpretation of how these advisories may affect his travel times.

2. OVERVIEW OF THE HOWLATE METHODOLOGY

The HOWLATE process constructs synthetic trips and records trip decisions and outcomes of travelers who make routine commutes at various times of the day. It consists of four modules: (i) the travel time archiver, (ii) the travel habituation module, (iii) the yoked study simulator, and (iv) the output post processor.

In the first module of the HOWLATE process travel-time reports are archived from the SmarTraveler traveler information web site using an automated web mining process for archiving Internet postings (7). The SmarTraveler web site lists by facility, real-time travel-time information as well as information on accidents, construction, and special events, for a number of cities in the United States. Travel times on each facility are archived at five-minute intervals from 6:30 AM to 6:30 PM (145 time intervals) over a period of several days.

In the second module, the travel habituation module, commuters establish their habitual routes and determine their trip departure times that result in an acceptable frequency of on-time arrivals (specified in our study to be 95%), based on the travel times they experience during the habituation period. This period of habituation is called "the training period". The "actual travel times" are constructed using Monte Carlo techniques from the archived travel times and the error distributions between the archived travel-time reports and the observed travel times. The observed travel times are based on a field study conducted by Hardy *et al.* (12). In addition, during this period, users of traveler information service also learn to adjust for persistent bias in the predicted traveler information and the actual travel time that they experience.

In the third module, simulated yoked trials are conducted between a pair of habitual commuters, one who does not use ATIS (the non-ATIS user), and the other who uses ATIS offering pre-trip estimates of travel times (the pre-trip ATIS user). A simulated yoked trial is the technique where hypothetical pairs of driving trials are constructed using “actual travel times”. Pairs of drivers are yoked together so that each pair of simulated drivers (one who uses pre-trip ATIS and the other who does not) has the same origin, destination and desired arrival time. Yoked pairs of trips or driving trials are simulated for each origin-destination pair throughout the day for the period when archived travel-time reports are available.

The intent of each pair of simulated drivers is to arrive on time at their destinations 95% of the time, rather than reduce travel times. The non-ATIS user leaves at his habitual time and takes his customary route. In contrast, the pre-trip ATIS user is notified by the ATIS service of his trip departure time and route based on the existing travel times. The ATIS service starts checking thirty minutes before the habitual departure time of the pre-trip ATIS user. If the user is expected to arrive at his destination more than ten minutes before the desired arrival time, the trip is postponed by five minutes. The check is performed every five minutes. When the trip can no longer be postponed, the ATIS service determines if the travel time on the fastest route is less than the travel time on the user’s habitual route. If travel-time savings is more than a pre-determined indifference threshold (3 minutes; 13), the ATIS service recommends the alternate fastest route; otherwise the user is advised to take the habitual route. The postponement is done until a limit is reached, which is thirty minutes after the habitual start time. Once the route and trip departure time are, the pre-trip ATIS user does not alter the route, even if he faces congestion on the chosen route.

Finally, in the fourth module, the effect of pre-trip traveler information services is assessed. A more detailed description of the HOWLATE process can be found in Wunderlich *et al.* (14) and Shah *et al.* (10).

3. ACQUISITION OF RADIO TRAFFIC REPORTS

3.1 Recording Radio Traffic Reports

This section describes an automated process that Mitretek developed for acquiring commercial radio traffic reports for the Washington, DC case study. Typically, radio stations broadcast traffic conditions every ten minutes throughout the day or at least during peak travel periods. We chose WMAL as the source for traffic reports for the Washington, DC metropolitan area as it is one of the most popular local News/Talk radio stations. The WMAL station gets its traffic reports through use of aerial surveillance as well as from Westwood One. WMAL broadcasts traffic related news on the “6’s”. For example, traffic reports are broadcast at the 6th minute after the hour, with the subsequent broadcasts at the 16th minute, and so on.

We developed an automated process, illustrated in Figure 1, to ensure consistent acquisition of traffic reports from WMAL over a period of several weeks. A radio, tuned into WMAL, was connected to a computer using an audio cable. Using a timer, audio segments containing the traffic reports were fed into the computer sound card where they were repeated through the computer speakers. This automatic recording of traffic reports during the AM and PM peak travel periods were carried out using Total Recorder software, a product of High Criteria, Inc. (http://www.highcriteria.com). One of the attractive features of Total Recorder is that it has a built-in scheduler that allows scheduling of recordings. The Total Recorder software records the audio file in WAV format. WAV files store sound in a digitized format and can be played by nearly all Windows applications that support sound, but are very large and unmanageable. As our intent was to acquire traffic reports for each weekday during the AM and PM peak periods, we realized that archiving traffic reports in the existing WAV format would consume a significant amount of computer disk space. Hence, for an optimal use of our resources, we decided to convert the large WAV files into MP3 format using an add-on function for Total Recorder called blade.dll. MP3 files are compressed files that, unlike the WAV files, do not contain the superfluous information, which the human ear cannot hear, and are significantly smaller. It should be mentioned that we were able to reduce the size of a file by more than ten times by converting its format from WAV to MP3.

Traffic broadcasts on the WMAL station last anywhere from under a minute to over two minutes. Moreover, automatic recording of broadcasts requires synchronizing the computer clock with the WMAL station clock. Hence, to ensure full coverage of the traffic report, using the Total Recorder we scheduled recording of traffic reports thirty seconds before the traffic report was scheduled to start and continued for a total of four minutes. The recorded data was converted to the MP3 format using the blade.dll. Recording was performed every ten minutes from 6:30 AM to 9:30 AM and 3:00 PM to 7:00 PM, the times of day when WMAL broadcasts regular traffic reports. On an average, each four-minute report in the MP3 format was about 1.4 MB, and the daily storage was 59 MB. We systematically downloaded traffic reports from the WMAL radio station on each weekday starting in March 2001. Testing of the automated recording process lasted from March to June 2001.

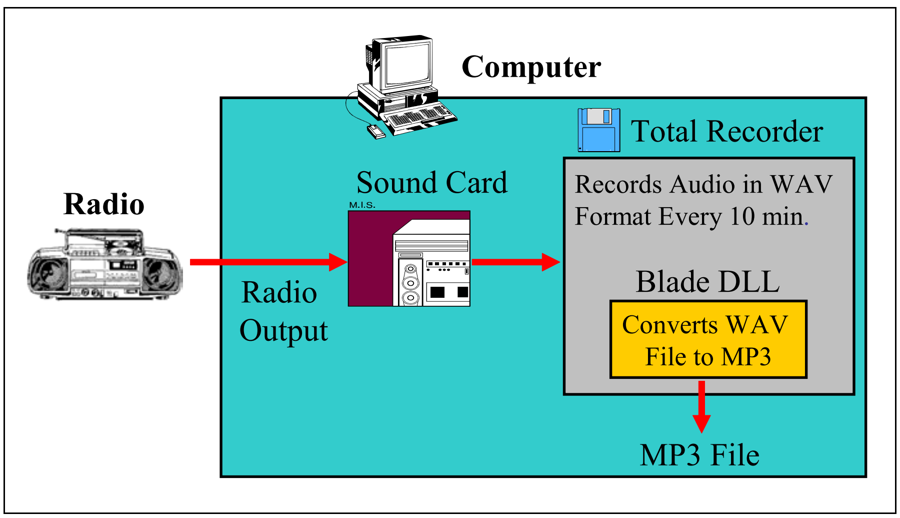


Figure 1. Recording Radio Traffic Reports

Given that traffic broadcasts provide only qualitative information on the traffic conditions rather than estimated travel times, we collected concurrent travel time and incident data from the SmarTraveler web site. Note that both SmarTraveler and WMAL use the same source for traffic reports, Westwood One. We were able to archive more than 4000 radio reports for 69 weekdays from 1 June 2001 to 17 January 2002. Gathering of reports was suspended on 18 January 2002 when access to the SmarTraveler web site was lost, due to technical problems at the SmarTraveler web site. Of the 69 days, only 48 days had complete data. The remaining

21 days were not used in the study, due to gaps in the recording of radio traffic reports, which were caused due to problems in our automated recording process.

3.2 Processing Data

This section describes the processing done to transform the audio broadcast traffic reports into a format suitable for use within HOWLATE. One of the candidate options for converting audio traffic reports into electronic format was use of speech-recognition software. This was found to be infeasible since the audio quality of the radio reports was often low and delivery of traffic news by on-air talent was too fast for the software to make sense of the content. Instead, we used a human-in-the-loop approach to process the audio reports. The processing of the recorded radio traffic reports proved to be extremely tedious and labor intensive. Hence, although we recorded radio traffic reports for 48 days, due to schedule constraints, we were able to code the content for only 42 days.

The captured audio reports were four minutes in length. In addition to traffic news, the files also contained advertisements, on-air banter and other information that was not traffic-related. We used the Cool Edit 2000 software to clean the sound files to isolate traffic news. The files were also processed to reduce background noise and control the volume (http://www.syntrillium.com). An MP3 player Winamp was used to listen to the cleaned radio reports and the speed of the reports was slowed by 50% without affecting the pitch. This was done to facilitate capturing of data using Winamp's Slow Me Down plug-in software (http://www.winamp.com). The slowing down of the audio was critical for the human-in-the-loop operation to capture and code traffic information given the exceptionally rapid delivery of the professional traffic reporters.

We created an Excel form with Visual Basic macros to configure the radio reports into a functional format by mapping them to SmarTraveler roadway segments containing reported travel times. One of the fields featured in the form was the reported congestion on the roadway segment. Possible options for the congestion status were: *much better than normal, mentioned better than normal, usual delays/normal congestion, mentioned, slow, heavy congestion, stop-and-go, and standstill/closed*. Other fields in the form were presence of an accident in the radio report and quality of the radio report in terms of completeness and broadcast information. Figure 2 illustrates the Excel form for processing information from the radio report. Data was entered in the Excel form for each traffic report. Whenever a roadway segment was mentioned in the radio report, the corresponding fields in the Excel form were checked and a record created. This process required listening to each traffic report numerous times despite slowing the speed using the Slow Me Down software. On average, it took nine hours to listen to and code peak-period radio reports for one day. Thus, it took approximately 47 days (9 x 42 = 378 staff hours) to listen to and code the 42 days of data. This is highly labor-intensive given that the automated acquisition and archiving of travel time data is nearly labor-free. We estimate only two hours of labor for quality control for 42 days of data.

Travel time information, incident logs and references to slow traffic, road closures, and weather-related items for each roadway segment by time and date were acquired from the SmarTraveler web site for the aforementioned three weeks to support our analysis. Once data was entered in the form given in Figure 2, it was imported into an Excel Worksheet. This worksheet was mapped to a database containing the SmarTraveler advisory data using SQL queries. A sample worksheet is given in Figure 3.

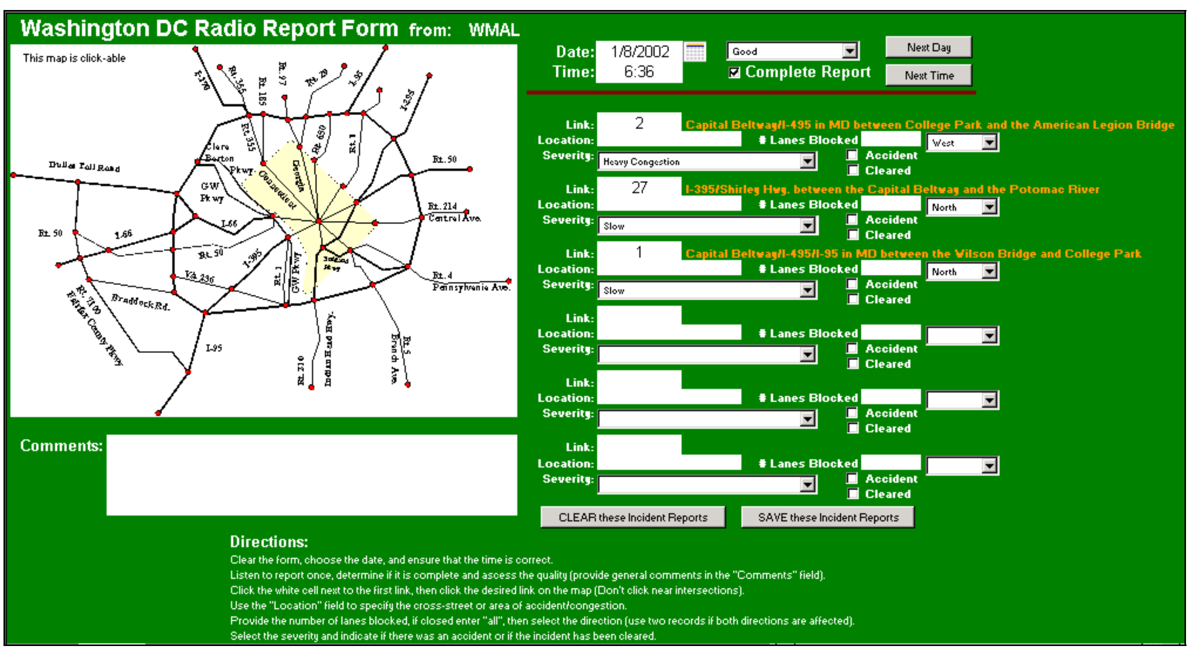
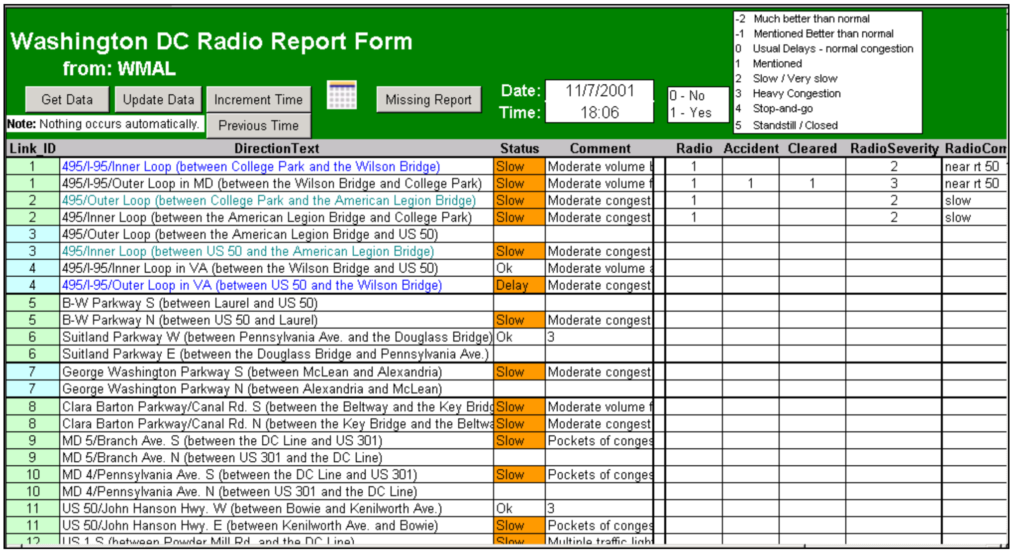


Figure 2. Radio Report Form



Washington DC Radio Report Form
from: WMAL

Get Data | Update Data | Increment Time | Previous Time | Missing Report

Note: Nothing occurs automatically.

Date: 11/7/2001
Time: 18:06

0 - No
1 - Yes

-2 Much better than normal
-1 Mentioned Better than normal
0 Usual Delays - normal congestion
1 Mentioned
2 Slow / Very slow
3 Heavy Congestion
4 Stop-and-go
5 Standstill / Closed

Link_ID	DirectionText	Status	Comment	Radio	Accident	Cleared	RadioSeverity	RadioCom
1	495/I-95/Inner Loop (between College Park and the Wilson Bridge)	Slow	Moderate volume	1			2	near rt 50
1	495/I-95/Outer Loop in MD (between the Wilson Bridge and College Park)	Slow	Moderate volume	1	1	1	3	near rt 50
2	495/Outer Loop (between College Park and the American Legion Bridge)	Slow	Moderate congest	1			2	slow
2	495/Inner Loop (between the American Legion Bridge and College Park)	Slow	Moderate congest	1			2	slow
3	495/Outer Loop (between the American Legion Bridge and US 50)							
3	495/Inner Loop (between US 50 and the American Legion Bridge)	Slow	Moderate congest					
4	495/I-95/Inner Loop in VA (between the Wilson Bridge and US 50)	Ok	Moderate volume					
4	495/I-95/Outer Loop in VA (between US 50 and the Wilson Bridge)	Delay	Moderate congest					
5	B-W Parkway S (between Laurel and US 50)							
5	B-W Parkway N (between US 50 and Laurel)	Slow	Moderate congest					
6	Suitland Parkway W (between Pennsylvania Ave. and the Douglass Bridge)	Ok	3					
6	Suitland Parkway E (between the Douglass Bridge and Pennsylvania Ave.)							
7	George Washington Parkway S (between McLean and Alexandria)	Slow	Moderate congest					
7	George Washington Parkway N (between Alexandria and McLean)							
8	Clara Barton Parkway/Canal Rd. S (between the Beltway and the Key Bridg	Slow	Moderate volume					
8	Clara Barton Parkway/Canal Rd. N (between the Key Bridge and the Beltwa	Slow	Moderate congest					
9	MD 5/Branch Ave. S (between the DC Line and US 301)	Slow	Pockets of conges					
9	MD 5/Branch Ave. N (between US 301 and the DC Line)							
10	MD 4/Pennsylvania Ave. S (between the DC Line and US 301)	Slow	Pockets of conges					
10	MD 4/Pennsylvania Ave. N (between US 301 and the DC Line)							
11	US 50/John Hanson Hwy. W (between Bowie and Kenilworth Ave.)	Ok	3					
11	US 50/John Hanson Hwy. E (between Kenilworth Ave. and Bowie)	Slow	Pockets of conges					

Figure 3. Excel Worksheet to Map Radio Advisories to SmarTraveler Advisory Data

4. CONTENT ANALYSIS

This section compares the radio traffic advisories and the corresponding web-based advisories that were compiled for peak-periods of 42 weekdays. There were a total of 5070 radio traffic advisories mentioned during this period. Table 1 shows a break up of the 5070 advisories with respect to traffic congestion status. More than 76% of the radio advisories referred to extreme congested conditions (i.e., congestion status of slow, heavy congestion, stop-and-go or standstill/closed).

Table 1. Summary of Radio Traffic Advisories with respect to Congestion Status

Traffic Congestion Status	No. of Radio Traffic Advisories
Much better than normal	45
Mentioned better than normal	506
Usual delays - normal congestion	416
Mentioned	229
Slow	1622
Heavy congestion	1642
Stop-and-go	484
Standstill / Closed	126

Traffic broadcasts were mostly focused around regional bottlenecks at the expense of other roadways. Figure 4 illustrates the roadway segments that were mentioned most frequently. Approximately 40% of the traffic advisories were dedicated to the four segments of the Capital Beltway. Table 2 summarizes for each segment the total number of traffic advisories referenced in the analysis period and the number of advisories corresponding to extreme congestion. Roadway segments mentioned most frequently were also the ones that had the most number of references to extreme congestion. The Capital Beltway in Virginia between the American Legion Bridge and US 50 had the most number of references to extreme congestion.

The traffic reporter is allocated a limited amount of time for each broadcast, and can only mention a few locations. The average number of roadway segments mentioned per radio report was four, with a standard deviation of two. The maximum number of roadway segments mentioned in a report was 16. One traffic report was dedicated to a single incident. The average length of traffic-related content per report was 63 seconds.

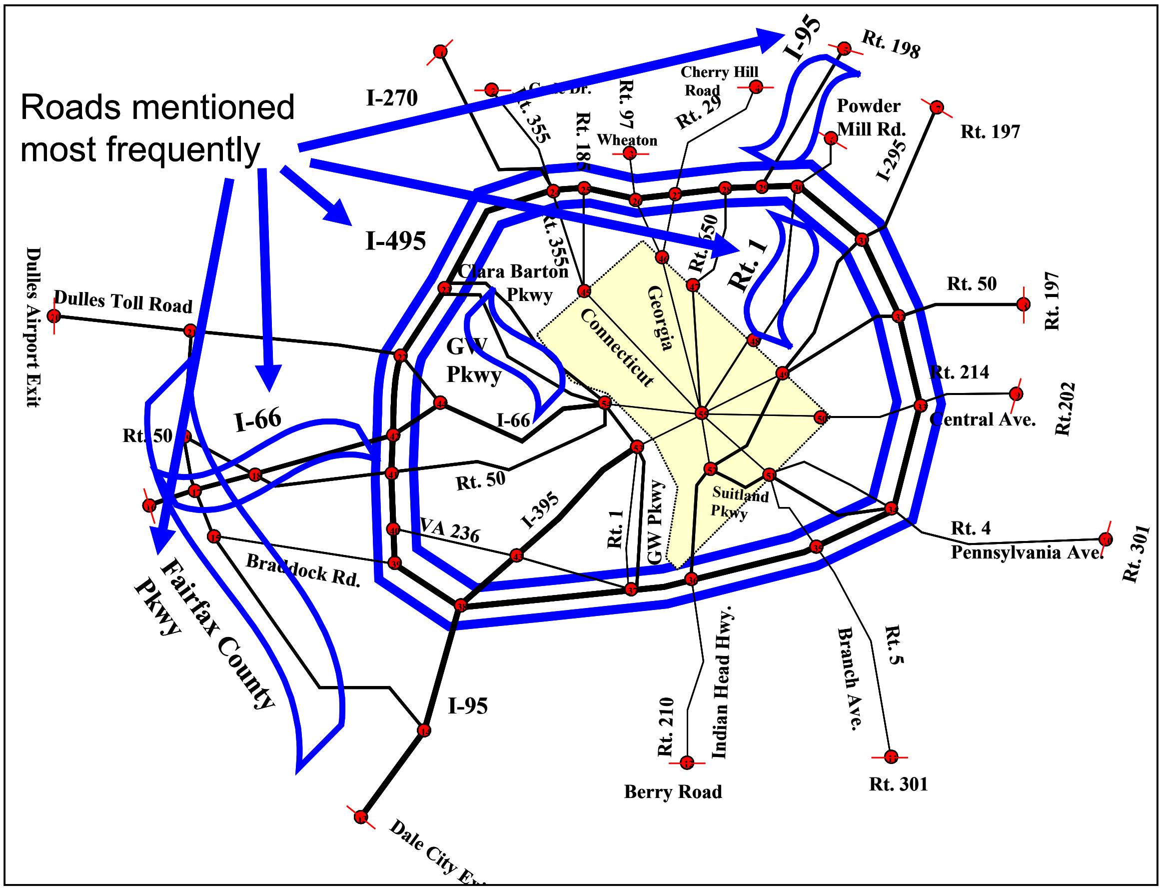


Figure 4. Most Frequently Mentioned Roadway Segments

There were 1181 traffic reports referring to 552 distinct incidents; of these, 292 incidents were mentioned as cleared and the remaining 260 were not specifically stated as cleared. Moreover, incidents were mentioned only sporadically. If there had not been any time constraints, radio advisories, like web advisories, would have alluded to incidents for the duration that they lasted. In our study period, we estimate from the web advisory data that there would have been 2308 traffic reports dedicated to the 552 incidents. However, due to limited broadcast time, there is more than 50% chance that the traffic reporter will neglect mentioning an incident. In our analysis period, only 1181 reports referred to incidents. Thus, when there is an incident, it is quite likely that a commuter tuning into a radio station will wrongly presume that traffic conditions are normal on his route. In such situations, radio traffic broadcasts will not be useful to the commuter in making alternate trip choices. It was also observed that on days when roadway segments were universally congested, the quality of the broadcast traffic information suffered. The information relayed was either vague or incomplete. Specific days when this happened in our study period were during the AM peak period of 9 January 2002, and PM peak periods of 7 January 2002 and 31 October 2001. Heavy congestion on the two days in January was mainly due to icy conditions and incidents, while on 31 October it was caused by incidents.

Table 2. Radio Traffic Advisories Referring to Extreme Congestion

Roadway Segment Name	Length of Roadway Segment (miles)	Number of Radio Traffic Records					
		Total	Worse than Normal Congestion				
			Slow	Heavy congestion	Stop-and-go	Standstill/ Closed
Capital Beltway/I-495 in MD between College Park and the American Legion Bridge	17.4	470	157	133	35	0
Capital Beltway/I-495 in VA between the American Legion Bridge and US 50	8.3	733	254	212	87	15
Capital Beltway/I-495/I-95 in MD between the Wilson Bridge and College Park	25	376	112	126	62	9
Capital Beltway/I-495/I-95 in VA between US 50 and the Woodrow Wilson Bridge	13.2	432	125	162	34	1
I-66 between Centreville and the Capital Beltway	12.5	220	86	74	17	5
I-95 in VA between Dale City and the Capital Beltway	14	17	7	2	0	0
I-270 between Gaithersburg and the Capital Beltway	9.1	77	17	30	3	2
I-395/Shirley Hwy. between the Capital Beltway and the Potomac River	9.5	29	6	3	3	4
Baltimore/Washington Parkway between Laurel and US 50	10.9	36	11	13	2	6
Dulles Toll Rd./VA 267 between Dulles Airport and I-66	14.4	34	8	9	0	9
I-95 in MD between Laurel and the Capital Beltway	6.1	164	83	31	10	1
MD 210/Indian Head Hwy. between Berry Road and the DC Line	8.4	25	10	8	2	0
George Washington Parkway between Alexandria and McLean	16.5	171	59	46	12	0
US 50 between Bowie and Kenilworth Ave.	11.1	59	19	10	3	0
I-66 between the Capital Beltway and the Roosevelt Bridge	9.9	43	8	10	5	11
MD 355/Rockville Pike/Wisconsin Ave. between Gude Dr. and the DC Line	12	59	7	14	1	25
US 1 in VA between North Kings Hwy. and the 14th Street Bridge	5.6	347	102	93	33	5
US 29 in MD between Cherry Hill Road and the DC Line	6.9	7	6	0	0	0
MD 97/Georgia Ave. between Wheaton and the DC Line	4.8	12	6	2	0	0
Clara Barton Parkway/Canal Road between the Capital Beltway and the Key Bridge	8.6	4	3	0	0	0
MD 5/Branch Ave. between US 301 and the DC Line	12.8	180	54	47	20	11
MD 4/Pennsylvania Ave. between US 301 and the DC Line	12.6	22	5	7	2	1
US 50 in VA between the Fairfax County Parkway and the Capital Beltway	9.7	17	5	7	0	0
US 1 in MD between Powder Mill Road and the DC Line	8	392	131	147	29	8
US 50 in VA between the Capital Beltway and the Potomac River	9.3	84	26	26	11	3
VA 7100/Fairfax County Parkway between Springfield Metro and the Dulles Toll Road	23.8	449	120	175	59	4
Suitland Parkway between the Douglass Bridge and Pennsylvania Ave.	10.7	349	109	154	35	4
MD 650/New Hampshire Ave. between the Capital Beltway and the DC Line	4.1	37	10	13	3	1
I-295/Anacostia Freeway between the Capital Beltway and US 50	10.3	19	9	9	0	0
VA 620/Braddock Road between the Fairfax County Parkway and the Capital Beltway	8.9	35	9	18	1	0
VA 236 between the Capital Beltway and King St. Metro	9.3	126	49	41	12	1
MD 214/Central Ave. between MD 202 and the DC Line	4.7	18	6	7	1	0
MD 185/Connecticut Ave. between the Capital Beltway and the DC Line	2.6	33	6	10	1	1

5. MODELING USE OF RADIO ADVISORIES IN HOWLATE

The HOWLATE methodology was enhanced to include a new archetype (henceforth referred to as the "radio archetype") emulating a commuter who uses radio as the source of traveler information. In the real-world, a typical commuter who listens to radio traffic advisories may have a fixed departure time and may occasionally make use of advisories to alter his path en route. Due to lack of information on the behavior of commuters listening to radio advisories, we tried to model this type of commuter in our study as capable of making both pre-trip as well as en route trip decisions, and altering his route and/or trip departure time based on the congestion status reported for his current (or chosen, if pre-trip) route and alternate routes, and his knowledge of the travel times on these routes. Please note that there may be instances when the radio archetype is unaware of the congestion status on either his chosen route or the alternate route or both. Enhancements were made to the travel habituation module and the yoked study simulator.

During the training period, the radio archetype, like the non-ATIS and pre-trip ATIS users, establishes his habitual route and trip departure time that result in an acceptable frequency of on-time arrivals. In addition, he also learns how an advisory of a specific severity impacts his travel time. He does this by keeping a mental record of the radio advisories broadcast for his habitual route on each day of the training period. To translate the qualitative information mentioned in the advisories into measurable differences in travel times, we defined four scales to model the radio advisories: 0 corresponds to *no advisories mentioned* for the link, 1 corresponds to *conditions better than normal*, 2 corresponds to *usual delays*, and 3 corresponds to *worse than normal conditions*. During the course of his trip, the radio archetype only pays heed to unique advisories of the same scale mentioned for each roadway segment (or link) traversed on his route. The travel time that he experiences on his trip on each day of the training period is defined as a linear function of the average travel time for his trip over the entire training period and the number of unique advisories he hears for each link on his route. Linear regression is used to determine change in travel time or delay associated with advisories of each of the four scales for each trip.

In the third module, the radio archetype starts listening to radio traffic reports 30 minutes prior to the habitual trip departure time. The expected travel time is the sum of the average travel time experienced on the trip during the training period and his learned expectation of changes in travel time or delays associated with each unique advisory for each link. If he determines that by taking the fastest route and leaving at the habitual trip departure time he will arrive at his destination more than ten minutes before his desired arrival time, he will postpone his trip by five minutes. The check is performed every five minutes. When he can no longer postpone the trip, he checks if the travel time on the fastest route is less than the travel time on the habitual route. If the difference is more than the indifference threshold, he selects the fastest route. Otherwise he takes his habitual route. Unlike the pre-trip ATIS user, the radio archetype is also capable of altering his path en route.

An algorithmic description of the HOWLATE methodology along with enhancements made to the travel habituation module and the yoked study simulator to model the commuter listening to radio traffic advisories is given in Appendix A.

6. MOBILITY BENEFITS OF RADIO ADVISORIES USING HOWLATE

This section quantifies the time savings and other mobility benefits from radio advisories using the HOWLATE methodology. The geographic area covered under this study is presented in Section 6.1, followed by a discussion on the archived travel time data and the training and evaluation periods used in the study in Section 6.2. Section 6.3 presents the definitions of the measures of effectiveness examined in the study. Section 6.4 compares the mobility benefits of radio traffic advisories with those of a notification-based traveler information service offering estimates of route-specific travel times.

6.1 Geographic Network

The study was conducted for the Washington, DC metropolitan area. The geographic coverage by SmarTraveler for the Washington region ranges from Laurel and Gaithersburg in Maryland, to Centreville and Dale City in Virginia. Figure 5 presents the SmarTraveler map and the corresponding HOWLATE network for the Washington, DC area.

The Washington, DC network, for which travel time reports are posted on the SmarTraveler web site, consists of 33 facilities (18 freeways and 15 major arterials), with a total of 711.8 directed miles. The 18 freeway facilities constitute 472.4 of the 711.8 miles, and the 15 arterial facilities constitute the remainder (239.4 miles). The average facility length is 10.8 miles, with the longest and shortest lengths being 25.0 and 2.6 miles, respectively.

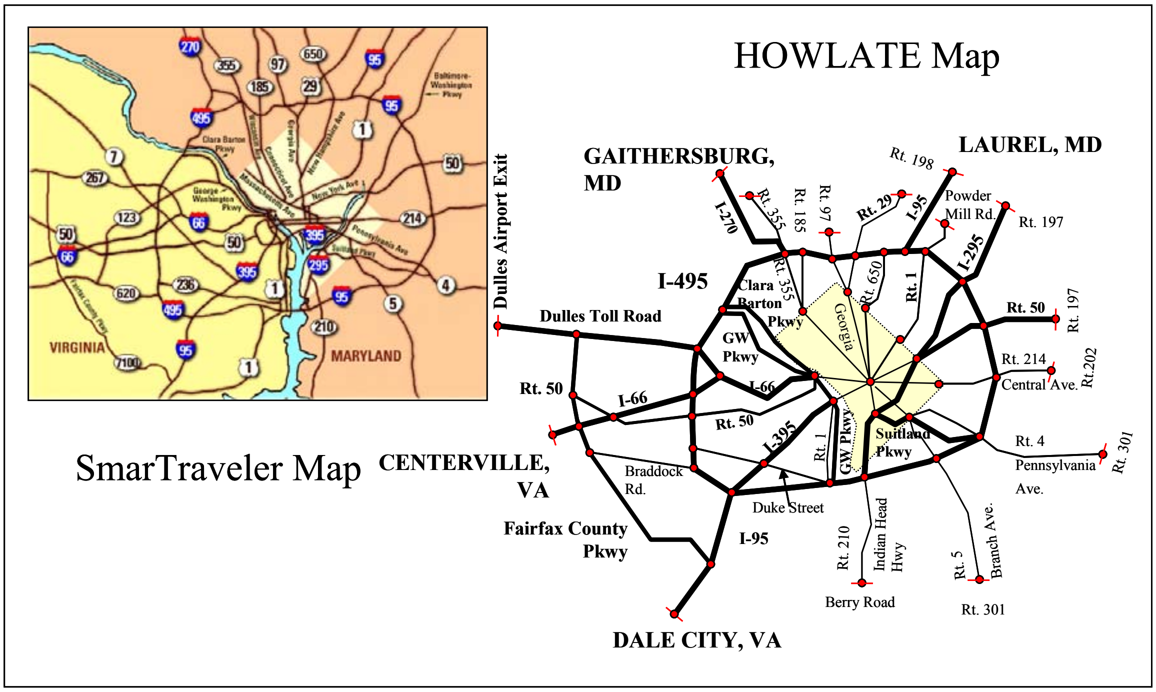


Figure 5. Washington, DC Network

The 33 facilities were divided into 75 links (150 directed links), for use in the HOWLATE network. The average link length for the HOWLATE network was 4.6 miles. The longest link was 13.5 miles while the shortest link was 1.0 mile. As SmarTraveler does not post any travel time information for the arterial facilities within the District of Columbia, an additional 18 links were modeled since these facilities were important in representing the available route choice options. A total of 55 nodes (potential trip origin or trip destination) were modeled in the HOWLATE network; thus, there were a total of 55 x 54 origin-destination pairs. A detailed description of the process used to construct the HOWLATE network is presented elsewhere (14).

6.2 Archived Travel Time Data

The travel time data used for the analysis was based on an automated process developed by Mitretek Systems for archiving Internet postings by SmarTraveler (7). The HOWLATE analysis was done for the period starting on 22 August 2001 and ending on 11 January 2002. As mentioned earlier, we were restricted to performing our analysis for this short period since coding of radio advisories was highly labor intensive. Although we coded the contents of radio advisories for 42 days, five were excluded from consideration due to gaps in the travel time data archive. If on any day travel time data on a facility was not archived for duration of more than 20 minutes, that day was not used. The absence in the archiving was due to the following factors: the SmarTraveler site was down, Internet connectivity for the Mitretek site was down, or SmarTraveler modified significantly the format and/or content of the web pages causing problems with the automated download process.

Data was archived every five minutes from 6:30 AM to 6:30 PM (145 time intervals) for each of 33 facilities for each day. Thus, there were a total of 4785 (145 x 33) archived travel time reports for each day. The travel time for each facility was then divided among its corresponding HOWLATE network links based on the assumption of a uniform speed.

The training period for this study was from 22 August 2001 to 9 October 2001, and composed of 19 weekdays. The evaluation period was from 11 October 2001 to 11 January 2002, and composed of 18 weekdays. Simulated yoked trials between the non-ATIS user and the two types of traveler information users (the pre-trip ATIS user and the radio archetype) were conducted using five different random number seeds for each day in the evaluation period for 55 x 54 origin-destination pairs in the Washington, DC HOWLATE network, for target arrival times (49 target arrival times) at 15-minute intervals between 6:30 AM and 6:30 PM.

Table 3 shows the average network travel time and travel variability in the training and evaluation periods. In the AM peak (7:00 AM to 9:30 AM), the training period had lower travel times and travel variability than the evaluation period. In the PM peak (4:15 PM to 6:30 PM), the evaluation period had higher travel times and lower variability than the training period. Thus, overall, the PM peak had higher travel times and travel variability than the AM peak. However, the AM peak showed a greater increase in travel times and variability from the training period to the evaluation period. Given that, we hypothesized that in the AM peak the non-ATIS user would be less conservative and leave a smaller buffer for on-time arrivals, thereby experiencing on-time arrivals less frequently than his targeted expectation of being on-time on 95% of the trips. However, in the PM peak, although the travel times are lower in the training period since the variability is higher the non-ATIS user may be able to meet his targeted expectation of being on-time 95% of the time.

Table 3. Average Network Travel Times and Travel Variability

Peak Periods	Training Period		Evaluation Period	
	Average (minutes)	Standard Deviation (minutes)	Average (minutes)	Standard Deviation (minutes)
AM Peak	18.2	1.7	19.6	1.8
PM Peak	19.2	2.4	20.3	2.3

Table 4 lists the radio archetype's expectation of delays in seconds for advisories of each of the four scales learned during the training period. For simplicity, the shown delays are the averages over all trips for the AM and PM peak periods. Please note that these delays are determined for each trip in the peak periods. Thus, on a specific trip the delays may be much higher or lower depending on how frequently the links traversed on the trip are mentioned on the radio, and how well the broadcast advisories reflect the experienced travel times archived from the SmarTraveler web site. For example, for the trip from Laurel to Dale City with a target arrival time of 6:30 pm, the delays for advisories of each of the four scales, *no advisories mentioned for the link*, *conditions better than normal*, *usual delays*, and *worse than normal conditions*, were found to be -2 minutes, -5 minutes, 5 minutes and 7 minutes, respectively. On this trip, when the radio archetype takes his habitual route, he traverses four links on the network. This implies that in the evaluation period, whenever the radio archetype hears an advisory being mentioned for a link on his route which refers to conditions worse than normal he adds 7 minutes to his expected trip time, which is learned during the training period. Thus, if an advisory is mentioned for each of the four links on his route with worse than normal conditions, the radio archetype adds 28 minutes to his expected trip time. If advisories referring to worse than normal conditions are repeated for the same links, the radio archetype disregards them, i.e., he ignores advisories that reinforce the traffic conditions on a link. He does not add additional delays of 7 minutes. When no advisories are mentioned on a link on his route, he subtracts 2 minutes from his expected trip time. It should be noted that when the radio archetype hears that conditions are better than normal his expectation is of lower travel time than when he does not hear any advisory being mentioned.

Table 4: Average Delay for Each Unique Advisory Mentioned for a Link

Advisory Scale	Average Delays (seconds)	
	AM Peak	PM Peak
No advisories mentioned	-6	-8
Conditions better than normal	-41	-96
Usual delays	20	-18
Worse than normal conditions	46	49

Table 5 shows the average network travel times corresponding to the four advisory scales. Our expectation was that whenever an advisory referred to *worse than normal conditions* on a link, the travel time reported for the link would be more than the travel time experienced under *usual delays* or when *conditions were mentioned as better than normal*. Contrary to our expectation, in the training period when advisories referred to usual delays average travel times were found to be higher for both peak periods (22.3 minutes and 23.5 minutes) than when worse than normal conditions were mentioned (20.3 minutes and 21.3 minutes). However, in the evaluation period, the corresponding travel times under usual delays were lower than when conditions were worse than normal. In fact, travel times under usual delays were the lowest in the PM peak period (18.5 minutes). This contradicts the delays shown in Table 4. In addition, when no advisories were mentioned the travel times were lower than when conditions were better than normal, contradicting the delays computed for the two advisories. Computation of the delays using linear regression technique was complicated by inconsistencies between the advisories and the corresponding travel times. However, since this is the average over the network, it is likely that on some trips the advisories may be more representative of the travel times. Hence, we expect the radio archetype to outperform the non-ATIS user on some trips, but overall the radio archetype will only do as well as the non-

ATIS user as his trip outcomes are dependent on how he translates the qualitative information mentioned in the advisories into measurable delays.

Table 5. Average Network Travel Times in Minutes for the Four Advisory Scales

Radio Advisory Scale	Training Period		Evaluation Period	
	AM Peak	PM Peak	AM Peak	PM Peak
No advisories mentioned	18.2	19.2	19.5	20.3
Conditions better than normal	18.3	20.1	19.7	21.9
Usual delays	22.3	23.5	21.4	18.5
Worse than normal conditions	20.3	21.3	21.6	20.3

6.3 Measures of Effectiveness

The following measures of effectiveness were defined to evaluate the benefits of radio advisories compared to a personalized pre-trip traveler information service:

Trip time is defined as the difference between the actual time of arrival at the destination and the departure time.

On-time reliability is defined as the proportion of simulated yoked trials wherein a traveler arrives at the destination node at or prior to the target arrival time.

Late schedule delay is the time in minutes by which the traveler is delayed in reaching the destination. It is computed as the difference between the actual arrival at the destination and the target time of arrival.

Early schedule delay is defined as the difference between the actual arrival time at the destination and the target time of arrival, when the traveler arrives before the target time of arrival.

The dollar-valued travel disutility is a measure of disutility associated with a trip by assigning a cost to the duration of travel time and how early or late one reaches one's destination based on the work of Small *et al.* (8). The cost function is linear in in-vehicle travel time, quadratic in the magnitude of early arrivals, and linear in the magnitude of late arrival with an additional penalty for arriving late. Note that the cost of late or early arrival is not sensitive to the duration of the trip, i.e., being five minutes late has equal disutility, or cost, regardless of the fact that the trip may be five or 50 minutes long. The disutility function is defined as follows:

$$c = \alpha T + \beta_{SDE}(SDE) + 2\ \beta_{SDE2}(SDE)^2 + \gamma(SDL) + \theta D_L$$

T: Travel Time

SDE: Schedule delay early

SDL: Schedule delay late

D_L: Late arrival index $= \begin{cases} 1 & \text{if } \ SDL > 0 \\ 0 & \text{otherwise} \end{cases}$

The estimates of the parameters, determined through a survey of travelers in Southern California by Small *et al*., are:

α: \$0.0564/min (linear cost of in-vehicle travel time)

β_{SDE}: \$-0.023/min (linear component of quadratic early cost)

β_{SDE2}: \$0.005/min (quadratic component of quadratic early cost)

γ: \$0.310/min (linear cost of late arrival)

θ: \$2.87 (one step penalty for arriving late)

These measures are a direct measurement of trip outcomes and were computed for all three types of users. It should be noted that all metrics were computed for unitary trips, as there was no data on network flows.

6.4 Results

This section compares the peak period results of the simulated yoked trials conducted between the radio archetype and the non-ATIS user, with those of the yoked trials conducted between the pre-trip ATIS user and the non-ATIS user. The trip decisions made by the pre-trip ATIS user and the radio archetype are discussed in Section 6.4.1. Section 6.4.2 presents the outcomes of the simulated trips of the three types of users, and compares the results.

6.4.1 Trip Decisions

This section presents the choices made by the two traveler information users (the pre-trip ATIS user and the radio archetype) with respect to changes in their habitual trip start time and/or route. Table 6 illustrates the trip decisions made by the pre-trip ATIS user and the radio archetype when compared to the non-ATIS user for the AM and PM peak periods.

During both peak periods, the personalized traveler information service recommended a change in departure time more often than a change in route for the pre-trip ATIS user. Overall, in the AM peak period, the pre-trip ATIS user altered his habitual route and/or trip departure times 68.4% of the time, while the radio archetype deviated from his habitual behavior on 49.3% of the trips. In the AM peak period, the pre-trip ATIS user changed his departure times on 67.4% of the trips and routes on 2.5% of the trips. In comparison, the radio archetype changed his departure times on 47.3% of the trips and routes on 2.5% of the trips. When changing the departure time, the pre-trip ATIS user left earlier than normal by 6.3 minutes or later by 5.3 minutes. The corresponding changes made by the radio archetype were 5.1 minutes and 5.4 minutes. The maximum early departure that the pre-trip ATIS user made during the AM peak was 30 minutes prior to the habitual departure time. On this trip, from Dale City to the 14th Street Bridge with a target arrival time of 8:15 AM, the pre-trip ATIS user left at 7:05 AM and arrived at his destination on-time at 8:10 AM, whereas the radio archetype left at the habitual departure time of 7:35 AM and was late by 13 minutes. Thus, the pre-trip ATIS user who receives estimates of travel times on his route is able to make more intelligent trip decisions than the radio archetype.

During the PM peak period, the pre-trip ATIS user deviated from his habitual behavior on 65.4% of the trips and the radio archetype on 55.9% of the trips. As was observed for the AM peak period, both commuters altered their departure times more often than their routes. This is because, although the Washington, DC network has a well-connected system of arterials and surface streets, we were unable to model them in our study due to lack of travel time data on these arterials and surface streets. Hence, both the radio archetype and the pre-trip ATIS user had limited route choices. Improvements to trips could mostly be made by changing the departure times. The radio archetype and the pre-trip ATIS user altered their departure times on 52.9% and 63.7% of the trips.

The pre-trip ATIS user is restricted by trip decisions made prior to the start of the trip, while the radio archetype has the ability to changes routes en route. Route changes made by the radio archetype were rare (only 2.5% of the AM peak trips and 3.7% of the PM peak trips). When they occurred, they usually occurred en route (73% of the AM peak route changes and 82% of the PM peak route changes). These changes were made based on his learned expectation of delay associated with an advisory heard for a link on his chosen route. When making route changes, both traveler information users typically took longer routes than the habitual route.

Table 6. Trip Decisions of the Radio Archetype and the Pre-Trip User Compared to the Non-ATIS User

Travel Choice Category	AM Peak		PM Peak	
	Pre-Trip ATIS User	Radio Archetype	Pre-Trip ATIS User	Radio Archetype
Trips with Both Route and Departure Time Changes	1.6%	0.5%	3.0%	0.7%
% Pre-Trip Path Changes	100%	95%	100%	90%
% En route Path Changes	-	5%	-	10%
Trips with Only Route Changes	0.9%	2.0%	1.6%	3.0%
% Pre-Trip Path Changes	100%	27%	100%	17%
% En route Path Changes	-	73%	-	83%
Trips with Only Departure Time Changes	65.8%	46.8%	60.7%	52.2%
Trips with No Change	31.6%	50.7%	34.6%	44.0%
Trips with Route Changes:				
% Resulting in Shorter Routes (with respect to length)	1.2%	1.1%	1.5%	1.1%
% Resulting in Longer Routes (with respect to length)	1.3%	1.4%	3.1%	2.6%
Avg. Miles Route is Shorter (when taking shorter route)	6.3	4.4	7.2	6.5
Avg. Miles Route is Longer (when taking longer route)	5.3	4.6	4.0	7.0
Trips with Departure Time Changes:				
% With Early Departure	92.7%	70.1%	60.6%	46.2%
% With Late Departure	7.3%	29.9%	39.4%	53.8%
Avg. Minutes Early Departure (when departing early)	6.3	5.1	5.8	5.1
Avg. Minutes Late Departure (when departing late)	5.3	5.4	6.9	6.8

6.4.2 Trip Outcomes

This section discusses the experiences of the three types of users, and compares the benefits of the personalized traveler information service with those from the radio advisories. Table 7 shows the performance measures computed for the trips made by the non-ATIS user, the pre-trip ATIS user and the radio archetype in the AM and the PM peak periods.

When compared to the trip outcomes of the non-ATIS user, personalized traveler information service proved to be beneficial to the pre-trip ATIS user in reducing travel disutility and increasing on-time arrivals for both peak periods, while the radio archetype had mixed results considering both peak periods. In the AM peak, the pre-trip ATIS user was able to reduce his travel disutility by 2.4% and increase his on-time arrivals by 10.5%. In the PM peak, the travel disutility cost for the pre-trip ATIS user reduced by 7.9% and on-time arrivals increased by 3%. In contrast, in the AM peak the radio archetype experienced an increase in travel disutility by 8.4% and a decrease in on-time arrivals of 2.3%. In the PM peak, however, the radio archetype experienced a reduction of 3.9% in the travel disutility cost, despite a decrease in on-time arrivals of 2.2%. This is because the radio archetype was able to reduce his early arrivals from 23.9% to 11.7%.

The pre-trip ATIS user made departure time changes based on his knowledge of estimates of existing travel times, whereas the radio archetype's decisions were based on his expectation of the delay corresponding to the qualitative information that he received via the radio. However, the non-ATIS user does not have any quantitative or qualitative knowledge of the travel times. Hence, in the AM peak period, while the non-ATIS user is often late (12% of the time), the pre-trip ATIS user is late only 1.5% of the time by departing earlier than his habitual departure time 62.5% of the time. However, the radio archetype who departed earlier on 33.2% of the trips was late more often than his non-ATIS counterpart possibly due to an inaccurate assessment of delays corresponding to advisories mentioned for links on his route. Similar trend was observed in the PM peak period. This could be due to inconsistent relationships between the travel times and the advisory scales from the training period to the evaluation period (Table 5).

From the table it can be seen that since the pre-trip ATIS user departed earlier than the non-ATIS user or the radio archetype, he arrived early at his destination more often (15.5% in the AM peak and 12.2% in the PM peak) as all trip choices made by him were pre-trip. He was early by 12.9 minutes in the AM peak period and 12.2 minutes in the PM peak period. The radio archetype was early by 11.4 minutes in the AM peak and 11.3 minutes in the PM peak. In the AM peak period, the radio archetype had a higher late schedule delay than the pre-trip ATIS user, while in the PM peak period both traveler information users had similar delays. It should be noted that both traveler information users experienced slightly higher late schedule delays than their non-ATIS counterpart. However, the trip times experienced by the three types of users were comparable for both peak periods.

Thus, as hypothesized our analysis showed that when taking into account both peak periods, the radio archetype performed worse than the pre-trip ATIS user. The radio archetype experienced higher travel disutility than the pre-trip ATIS for both peak periods. In the AM peak period trip reliability was lower for the radio archetype, while in the PM peak period it was negligibly higher (an increase of 0.5%). In the AM peak, the radio archetype had greater late schedule delay, but in the PM peak both traveler information users had the same late schedule delays.

However, our second hypothesis that a commuter listening to radio traffic advisories will have higher mobility benefits than a habitual commuter who does not make use of any form of traveler information service was not entirely satisfied. In the AM peak, the radio archetype fared worse than the habitual commuter and had lower trip reliability, higher travel disutility and greater late schedule delays. But in the PM peak, although the radio archetype still had greater late schedule delays, he had higher trip reliability and lower travel disutility because he was able to reduce his early arrivals. The radio archetype's trip outcomes greatly depend on the number and timeliness of advisories heard for his route. On average only four of the 33 roadway segments were mentioned in a traffic report. Hence, it is highly probable that the radio archetype fails to hear advisories mentioned for his route. This is further complicated by the inconsistent relationship between the travel times and the advisories from the training period to the evaluation period.

Table 7. Comparison of Performance Measures for the AM and PM Peak Periods

Aggregate Trip Metrics	AM Peak			PM Peak		
	Non-ATIS User	Pre-Trip ATIS User	Radio Archetype	Non-ATIS User	Pre-Trip ATIS User	Radio Archetype
Trip Time (minutes)	34.6	34.2	34.6	34.9	34.8	34.9
Travel Disutility Cost ($)	2.59	2.52	2.80	2.73	2.52	2.63
On-Time Reliability	88.0%	98.5%	85.7%	76.1%	87.8%	88.3%
% Early Trips	5.1%	15.5%	5.9%	23.9%	12.2%	11.7%
Late Schedule Delay (Minutes)	2.8	2.5	3.9	2.2	3.4	3.4
Early Schedule Delay (Minutes)	11.9	12.9	11.4	14.1	12.2	11.3

7. CONCLUSIONS

This report examined the mobility benefits of radio traffic advisories with that of a personalized traveler information service that delivers estimates of travel times pre-trip in a Washington, DC case study. Our analysis of the 37 weekdays consisting of 4410 advisories indicated that overall radio traffic advisories were less effective in improving traveler on-time reliability than a service offering route-specific travel time reports.

7.1 Hypotheses and Key Findings

This section examines our main study hypotheses presented in Section 1.3 and discusses our findings from the study.

Hypothesis: Mobility benefits from radio traffic advisories will be lower than those from a prospective notification-based traveler information service that delivers pre-trip personalized estimates of route-specific travel times.

Findings: Our analysis showed that when taking into account both peak periods, the radio archetype performed worse than the ATIS user. In our study we found that on average, of the 33 segments modeled in the Washington, DC network, the number of roadway segments mentioned per radio traffic report ranged from 1 to 16, and averaged four. Given that there is only a 12% (4/33) probability of a roadway segment being mentioned in a traffic report and that the roadway segment may not be part of the chosen path, information available to the radio archetype is quite limited in comparison to the ATIS user who gets travel time estimates for his entire trip.

Additionally, we observed an inconsistent relationship between travel times and advisory scales from the training period to the evaluation period (Table 5). Contrary to our expectation, in the training period when advisories referred to usual delays average travel times were found to be higher for both peak periods than when worse than normal conditions were mentioned. However, in the evaluation period, the corresponding travel times under usual delays were lower than when conditions were worse than normal. In fact, travel times under usual delays were the lowest in the PM peak period (18.5 minutes). This contradicts the delays shown in Table 4. In addition, when no advisories were mentioned the travel times were lower than when conditions were better than normal, contradicting the delays computed for the two advisories (Table 4).

Table 7 shows the performance measures computed for the trips made by the pre-trip ATIS, the radio archetype, and the non-ATIS user in the AM and the PM peak periods. The radio archetype experienced higher travel disutility than the pre-trip ATIS for both peak periods. For the AM and PM peak periods, the radio archetype's travel disutility costs were $2.80 and $2.63, respectively, while the ATIS user's disutility costs were $2.52 for both peak periods. In the AM peak period the radio archetype had lower trip reliability (85.7%) than the ATIS user (98.5%), while in the PM peak period it was slightly higher (88.3% compared to 87.8% for the ATIS user). In the AM peak, the radio archetype had greater late schedule delay of 3.9 minutes compared to 2.5 minutes for the ATIS user, but in the PM peak both traveler information users had the same late schedule delays (3.4 minutes).

Hypothesis: A commuter listening to radio traffic advisories will have higher mobility benefits than a habitual commuter who does not make use of any form of traveler information service.

Findings: Our analysis of 37 days showed that this hypothesis was true for the PM peak period, but not for the AM peak period (Table 7). In the AM peak period, the radio archetype fared worse than the habitual commuter who does not make use of traveler information. When compared to the radio archetype, the non-ATIS user had higher trip reliability (88% versus 85.7%), lower travel disutility ($2.59 versus $2.80), and smaller late schedule delays

(2.8 minutes versus 3.9 minutes). But in the PM peak period although the non-ATIS user had smaller late schedule delays (2.2 minutes versus 3.4 minutes), he had lower trip reliability (76.1% versus 88.3%) and higher travel disutility ($2.73 versus $2.63) than the radio archetype. The radio archetype's trip outcomes greatly depend on the number and timeliness of advisories heard for his route. Because of the limited time available for a broadcast traffic report, it is highly probable that the radio archetype fails to hear advisories mentioned for his route. This is further complicated by the inconsistent relationship between travel times and advisory scales from the training period to the evaluation period, as discussed in the previous section.

7.2 Implications

This study is the first assessment of mobility benefits from radio advisories that we are aware of. However, one of the key caveats of this study was that it was conducted for only 37 days consisting of 4410 advisories and hence the benefits determined for the simulated commuters may not be indicative of long-term radio use. Moreover, we were also limited by a lack of detailed studies to guide our modeling of travelers listening to radio advisories, and how they process and react to broadcast congestion information.

Our study shows that ATIS services offering personalized route-specific travel time reports can have high mobility benefits, but such potential ATIS services are likely to be more expensive and less easily accessible than the radio. Increased investments can probably improve the precision of broadcast traffic reports, yet ultimately broadcast traffic reports are time-limited and can cover only a portion of the network. This inability of broadcast media to address personalized information needs is reflected in the limited reliability benefits accrued by the radio archetype in our study. However, this does not preclude improved serenity. Radio listeners may experience stress reduction and perceive value from an improved awareness of congestion sources and locations. Thus, although broadcast advisories have lower mobility benefits than ATIS, they are available for free and are more easily accessible, and so for now will continue to dominate the private traveler information market.

7.3 Future Extensions

In order to make more robust conclusions about potential mobility benefits we propose to analyze the outcomes of simulated commuter trips for a longer period of time, such as a year. However, as coding of advisories is highly labor-intensive, we propose constructing radio advisories from available web advisories posted on the SmarTraveler web site, given that the contents of both sets of advisories are provided by the same entity, Westwood One.

To recreate radio advisories from web advisories, we compared radio advisories broadcast on 15 weekdays to traffic advisories posted on the SmarTraveler web site with the aim of detecting when a web advisory had the greatest likelihood of being broadcast. Our analysis showed that more than 85% (1720) of the radio traffic advisories also appeared on the SmarTraveler web site. The 1720 traffic advisories were only 6% of the web advisories posted on the SmarTraveler web site. There were more than 27,000 traffic advisories posted on the SmarTraveler web site during the peak periods of the 15 weekdays. Although the proportion of radio traffic advisories that was also mentioned on the web was high, the content (or the congestion status) of the radio advisories was not always consistent with the advisories posted on the web. No linear relationship was observed between the contents of the two sets of advisories.

We propose to use artificial neural networks to construct radio advisories from the web advisories since they are particularly useful in detecting trends or patterns in data that are non-linear or are not explicit (15, 16). We will examine mobility benefits based on the constructed radio advisories. Another potential extension is to examine the effect of radio advisories in improving the serenity of travelers, as although radio advisories may not be as effective as ATIS in improving mobility benefits, radio listeners are likely to benefit from improved serenity, which, to date has not been quantified. Once we have a better understanding of both serenity and mobility impacts of broadcast advisories, another interesting extension is assessing improvements in traveler trip outcomes from public sector investments in improved network surveillance. Even if the public sector itself provides no ATIS service, it is likely that better surveillance results in more accurate advisories, which is an improvement that can be analyzed and quantified in a future HOWLATE study.

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APPENDIX A: Enhancement to the HOWLATE (Heuristic On-Line Web-Linked Arrival Time Estimator) Algorithm to Model the Radio Archetype

Overview

Step 1. Expectation Under Training Period
Step 2. Optimal Paths and Travel Times in Evaluation Period
Step 3. Determine Performance of Non-Users in Evaluation Period
Step 4. Determine Performance of Traveler Information Users in Evaluation Period
OPTION 1: Pre-Trip Travel Time Service
OPTION 2: Pre-Trip and En Route Travel Time Service
OPTION 3: Pre-Trip and En Route Travel Advisory Service

A. Forward A-STAR Dynamic Program: D'
B. Reverse Time Dynamic Program: $`\mathrm{D}$
C. Forward Path Traversal Under Estimated Travel Times: $\mathrm{T}'\left(\Lambda\ , \bar{c}_{\lambda}(t)\right)$
D. Forward Path Traversal Under Actual Travel Times: $\mathrm{T}'\left(\Lambda\ , \breve{c}_{\lambda}(t)\right)$
E. Evaluating Arc Costs Between Lattice Points

STEP 1. EXPECTATION-SETTING UNDER TRAINING PERIOD

Network Structure File:

For each link $\lambda \in L$, the network of directed arcs:

$\lambda:(a,b)$	link λ defined as unidirectional arc from node a to node b
f_λ	facility type (currently arterial or freeway)
ξ_λ	congestion threshold time (seconds)
δ_λ	distance along link (miles)

Archived Daily Link Travel Time Files, Training Period

For each day $k = 1, 2, 3 \Lambda N$ in the training period of N days, one file containing:
For each link $\lambda \in L$, and 5-minute time slice day $k: t = 0, 1, 2\Lambda T$;

$\bar{c}_\lambda^k(t)$	archived link travel time for link λ for arc traversal beginning at time t, day k

Monte Carlo Parameters from Control Parameter File:

μ_f^κ	offset for link travel time value by facility type and congestion
σ_f^κ	standard deviation of link travel time value by facility type and congestion

Experimental Control Parameters:

ϕ yoked trial toggle. Set = 1 if this is a yoked trial between ATIS users and habitual travelers who are FAMILIAR with congestion conditions;
Set = 0 if this is a yoked trial between UNFAMILIAR subjects.

χ FAMILIAR parameter: subject on-time arrival requirement (scaredy/macho factor)

ρ UNFAMILIAR parameter: estimated peak period travel time premium
for DC, use TTI mobility index: 1.41.

$\mathbf{T}^p$ UNFAMILIAR parameter: set of time intervals designated as "peak" period
for DC, use: 7:00-9:30 AM, 3:30-6:00 PM.

PROCEDURE:

1. Monte Carlo sampling to produce actual travel times in each day of the training period $\breve{c}_\lambda^k(t)$:

   a. compute congestion factor based on λ, t:

$$\kappa = \begin{cases} 1 & \bar{c}_\lambda^k(t) > \xi_\lambda \\ 0 & \bar{c}_\lambda^k(t) \le \xi_\lambda \end{cases}$$

   b. compute estimates based on link characteristics, time of arc traversal, and adjustment factors:

$$\breve{c}_\lambda^k(t) = \mathrm{M}(\lambda, t) = \mathrm{NORMAL}\left(\bar{c}_\lambda^k(t) - \mu_f^\kappa, \sigma_f^\kappa\right)$$

   c. enforce consistency in actual travel time profiles, enforcing FIFO for arc costs in time:
   if $\breve{c}_\lambda^k(t) - \breve{c}_\lambda^k(t+1) > 300$ then set $\breve{c}_\lambda^k(t+1) = \breve{c}_\lambda^k(t) - 300$.

   d. if $\phi = 1$ then proceed to substep 2 to compute FAMILIAR training, else proceed to substep 5.

2. FAMILIAR TRAINING

   Generate profile of average experienced conditions during training period $\breve{c}_{\lambda}(t)$:

$$\breve{c}_{\lambda}(t) = \frac{\sum_{k} \breve{c}_{\lambda}^{k}(t)}{N}$$

3. For each destination node d and target arrival-at-destination time τ,
   where τ: $1, 2, 3 \Lambda \; T_{\tau}$, a lattice of 15 minute target arrival times during the day,
   perform DP recursively from d at time τ using average arc costs to find:

   $`\mathrm{D}\left(d, \tau, \breve{c}_{\lambda}(t)\right) \rightarrow \overline{\mathbf{P}}_{o,d,\tau}$, the habitual path established for o, d, τ and

   $\overline{p}_{o,d,\tau}^{1}$, the expected travel time for this path (1st estimate)

4. For each day k in the training period; for each o, d, τ :
   a. traverse $\overline{\mathbf{P}}_{o,d,\tau}$ forward at time $\tau - \overline{p}_{o,d,\tau}^{1}$ using training day k arc costs:

   $\mathrm{T}'\left(\overline{\mathbf{P}}_{o,d,\tau}, \tau - \overline{p}_{o,d,\tau_{\tau}}^{1}, \breve{c}_{\lambda}^{k}(t)\right) \rightarrow \quad \overline{p}_{o,d,\tau}^{k}$, the travel time on the habituated path

   b. from the vector series $\left\{\overline{p}_{o,d,\tau}^{k} : k = 1, 2, \Lambda \; N\right\}$, compute $\overline{p}_{o,d,\tau}$, the average path travel time and $\overline{\sigma}_{o,d,\tau}^{\overline{\mathbf{P}}}$, the standard deviation of the series of days of travel on the habitual path

   c. compute the habituated time of trip start, $t_{o,d,\tau}^{0} \forall \, o, d, \tau$:
   $t_{o,d,\tau}^{0} = \tau - \left(\overline{p}_{o,d,\tau} + Z_{\chi} \overline{\sigma}_{o,d,\tau}^{\overline{\mathbf{P}}}\right)$, where Z_{χ} is the Z-statistic for χ %, normal dist.
   Note: $t_{o,d,\tau}^{0}$ cannot take values between lattice points, so $t_{o,d,\tau}^{0}$ should be marked down to the previous five minute interval point, i.e., set $t_{o,d,\tau}^{0} = t_{o,d,\tau}^{0} - REM\left(\frac{t_{o,d,\tau}^{0}}{\Delta}\right)$, where REM() is the remainder after integer division.

   d. compute the average travel distance on the habitual path $\overline{\delta}_{o,d,\tau} = \sum_{\lambda \in \overline{P}_{o,d,\tau}} \delta_{\lambda}$.

e. OPTION 1: ATIS TRAVEL TIME SERVICE (CORRECTION FACTOR)

This option identifies the savvy ATIS user correction factor, $\omega_{o,d,\tau}$, for travel time services.

For each day k of the training period,
traverse $\overline{\mathbf{P}}_{o,d,\tau}$ forward with ATIS-estimated arc costs fixed at time $t' = \tau - \overline{p}^{1}_{o,d,\tau}$:

$\mathrm{T}'\left(\overline{\mathbf{P}}_{o,d,\tau}, t', \tilde{c}^{k}_{\lambda}(t')\right) \rightarrow \tilde{p}^{k}_{o,d,\tau}$, the pre-trip estimate of travel time on the habituated path.

Let $\omega_{o,d,\tau} = \dfrac{\overline{p}_{o,d,\tau}}{\sum_{k} \tilde{p}^{k}_{o,d,\tau}}$, the ratio of experienced to predicted travel times in the period.

e. OPTION 2: ATIS ADVISORY SERVICE (ENROUTE)

Let $x^{k}_{\lambda}(\tilde{t})$ the advisory on day k of the training period on link λ at non-lattice time $\tilde{t}$,
taking values $x^{k}_{\lambda}(t) = \{\varnothing, 1, 2, 3\}$ where value $\varnothing$ indicates no advisory broadcast.

Let e^{-}_{a} be the amount of time before trip start that the user begins to listen for advisories.

For each o, d, τ :

Identify the set of advisories heard each day in the training period while on the habitual path,

$$\mathbf{X}^{k} = x^{k}_{\lambda}(\tilde{t}) \quad \text{such that } \lambda = \overline{\mathbf{P}}_{o,d,\tau} \quad \text{(links on the habitual path)}$$

$$\text{and } \tau - \overline{p}^{1}_{o,d,\tau} - e^{-}_{a} \leq \tilde{t} \leq \tau - \overline{p}^{1}_{o,d,\tau} + \overline{p}^{k}_{o,d,\tau} \quad \text{(advisories heard)}$$

Let x^{k}_{s} be the count of unique link advisories with value s in $\mathbf{X}^{k}$, i.e., we disregard repeated advisories of the same severity on the same link.

Fit via linear regression the set of k equations:

$$\overline{p}_{o,d,\tau} + b_{\varnothing} x^{k}_{\varnothing} + b_{1} x^{k}_{1} + b_{2} x^{k}_{2} + b_{3} x^{k}_{3} = \overline{p}^{k}_{o,d,\tau},$$

These parameters derive the learned (absolute) delay by advisory severity function:

$$\hat{\mathrm{B}}_{o,d,\tau}\left[x_{\lambda}(t)\right] = \begin{cases} b_{\varnothing} & \mathit{if}\ x_{\lambda}(t) = \varnothing \\ b_{1} & \mathit{if}\ x_{\lambda}(t) = 1 \\ b_{2} & \mathit{if}\ x_{\lambda}(t) = 2 \\ b_{3} & \mathit{if}\ x_{\lambda}(t) = 3 \end{cases}$$

. Retain this function by o, d, τ for Step 4, Option 3.

f. skip forward to Step 2., Optimal Paths in Evaluation Period.

5. UNFAMILIAR TRAINING

Generate profile of roadway congestion estimated by unfamiliar travelers, $\widetilde{c}_\lambda(t)$:

$$\widetilde{c}_\lambda(t) = \begin{cases} \rho\, \hat{c}_\lambda(0) & t \in \mathbf{T}^p \\ \hat{c}_\lambda(0) & t \notin \mathbf{T}^p \end{cases}$$

6. For each destination node d and target arrival-at-destination time τ, where $\tau :\ 1, 2, 3\,\Lambda\ \ T_\tau$, a lattice of 15 minute target arrival times during the day, perform DP recursively from d at time τ using average arc costs to find:

$`\mathrm{D}(d, \tau, \widetilde{c}_\lambda(t)) \rightarrow \overline{\mathbf{P}}_{o,d,\tau}$, the habitual path established for o, d, τ and

$\overline{p}_{o,d,\tau}$, the expected travel time for this path

7. Compute the habituated time of trip start, $t^0_{o,d,\tau}\ \forall\, o, d, \tau$:

$t^0_{o,d,\tau} = \tau - \overline{p}_{o,d,\tau}$,

Note: $t^0_{o,d,\tau}$ cannot take values between lattice points, so $t^0_{o,d,\tau}$ should be marked down to the previous five minute interval point, i.e., set $t^0_{o,d,\tau} = t^0_{o,d,\tau} - REM\left(\frac{t^0_{o,d,\tau}}{\Delta}\right)$, where REM() is the remainder after integer division.

8. Set $\omega_{o,d,\tau} = 1\ \forall\, o, d, \tau$.

Skip forward to Step 2, Optimal Paths and Travel Times.

STEP 2. OPTIMAL PATHS AND TRAVEL TIMES IN EVALUATION PERIOD

NEW INPUT FILES:

Archived Daily Link Travel Time Files, Evaluation Period

For each day $j = 1, 2, 3 \Lambda\ M$ in the evaluation period of M days, one file containing:
For each link $\lambda \in L$, and observed 5-minute time slice in day $j : t = 0, 1, 2\Lambda\ T$;

$\bar{c}_\lambda^j(t)$ archived link travel time for link λ for arc traversal beginning at time t, day j

PROCEDURE:

1. Monte Carlo sampling to produce actual travel times in each day of the evaluation period $\hat{c}_\lambda^j(t)$:
   For each $\lambda \in L,\ t \in T$:
   a. compute congestion factor based on λ, t as in Step 1.1.
   b. compute estimates based on link characteristics, time of arc traversal, and adjustment factors:
   $$\hat{c}_\lambda^j(t) = \mathrm{M}(\lambda, t) = \mathrm{NORMAL}\left(\bar{c}_\lambda^j(t) - \mu_f^\kappa, \sigma_f^\kappa\right)$$
   c. enforce consistency in actual travel time profiles, enforcing FIFO for arc costs in time:
   if $\hat{c}_\lambda^j(t) - \hat{c}_\lambda^j(t+1) > 300$ then set $\hat{c}_\lambda^j(t+1) = \hat{c}_\lambda^j(t) - 300$.

2. Find fastest paths based on actual data from the evaluation period:

   For each destination node d, target arrival time of τ, and day j:

   a. perform DP recursively for d, τ, j under actual evaluation period conditions to establish:

   `D$\left(d, \tau, \hat{c}_\lambda^j(t)\right) \rightarrow$ $\hat{\mathbf{P}}_{o,d,\tau}^j$, the optimal path on day j for the o, d, τ; and
   $\hat{p}_{o,d,\tau}^j$, the travel time on $\hat{\mathbf{P}}_{o,d,\tau}^j$.

   b. find path distance on the optimal route as $\hat{\delta}_{o,d,\tau}^j = \sum_{\lambda \in \hat{\mathbf{P}}_{o,d,\tau}^j} \delta_\lambda$.

STEP 3. DETERMINE PERFORMANCE OF NON-USERS IN EVALUATION PERIOD

NEW INPUT FILES:

None.

PROCEDURE:

1. Recover habituated paths and trip start times from Step 1, $\overline{\mathbf{P}}_{o,d,\tau}$ and $t^{0}_{o,d,\tau} \forall\, o, d, \tau$

2. For each day j in the evaluation period, for each o, d, τ:

   a. traverse $\overline{\mathbf{P}}_{o,d,\tau}$ forward from time $t^{0}_{o,d,\tau}$, using actual arc costs for day j:

   $\mathrm{T}'\left(\overline{\mathbf{P}}_{o,d,\tau}, t^{0}_{o,d,\tau}, \breve{c}^{j}_{\lambda}(t)\right) \rightarrow \breve{p}^{j}_{o,d,\tau}$, actual experienced travel time on the habituated path

STEP 4. DETERMINE PERFORMANCE OF TRAVELER INFORMATION USERS IN EVALUATION PERIOD

OPTION 1: Pre-Trip ATIS, Concurrent Time-Shift and Route Choice

NEW INPUTS:

From Control File:

e^{+}	Maximum late departure, expressed in multiples of 300 seconds
e^{-}	Maximum early departure, expressed in multiples of 300 seconds
ε	Route diversion indifference threshold

PROCEDURE:

1. Recover archived and actual link travel time files for the evaluation period.

2. For each o, d, τ :
   a. set $t' = t^{0}_{o,d,\tau} - e^{-}$.
   b. perform forward DP from t' with arc costs fixed at $t = t'$;
   $\mathrm{D}'\left(o, d, t', \bar{c}^{j}_{\lambda}(t')\right) \rightarrow \dot{\mathbf{P}}^{j}_{o,d,\tau}$, a candidate fastest path with predicted travel time $\dot{p}^{j}_{o,d,\tau}$
   c. check to see if trip start can be safely postponed five minutes longer
   CHECK#1: $t' + \omega_{o,d,\tau}\, \dot{p}^{j}_{o,d,\tau} < \tau - \Delta$ (predicted to be early?)
   CHECK#2: $t' < t^{0}_{o,d,\tau} + e^{+}$ (still have flexibility to postpone trip?)
   If CHECK#1 and CHECK#2 are true,
   then set $t' = t' + \Delta$ and GOTO step b;
   Otherwise we have determined the time of trip start, set $\tilde{t}^{\,j}_{o,d,t} = t'$.
   d. Check if candidate path is the habitual path;
   If $\dot{\mathbf{P}}^{j}_{o,d,\tau} = \overline{\mathbf{P}}_{o,d,\tau}$, set $\bar{\bar{p}}^{j}_{o,d,\tau} = \dot{p}^{j}_{o,d,\tau}$ and GOTO step h.
   e. forward traverse the habitual path, $\overline{\mathbf{P}}_{o,d,\tau}$, using arc costs fixed at $\tilde{t}^{\,j}_{o,d,\tau}$;
   $\mathrm{T}'\left(\overline{\mathbf{P}}_{o,d,\tau}, \tilde{t}^{\,j}_{o,d,\tau}, \bar{c}^{j}_{\lambda}\left(\tilde{t}^{\,j}_{o,d,\tau}\right)\right) \rightarrow \bar{\bar{p}}^{j}_{o,d,\tau}$, the predicted travel time on the habitual path.
   f. perform check to see if the alternative route is attractive enough to warrant diversion
   CHECK#3: $\bar{\bar{p}}^{j}_{o,d,\tau} - \dot{p}^{j}_{o,d,\tau} > \varepsilon$
   If CHECK #3 is false, then GOTO step h.
   g. SWITCH to the alternative path:
   Traverse $\dot{\mathbf{P}}^{j}_{o,d,\tau}$ forward from time, using actual arc costs for day j , departing at $\tilde{t}^{\,j}_{o,d,t}$:
   $\mathrm{T}'\left(\dot{\mathbf{P}}^{j}_{o,d,\tau}, \tilde{t}^{\,j}_{o,d,\tau}, \hat{c}^{j}_{\lambda}(t)\right) \rightarrow \tilde{p}^{j}_{o,d,\tau}$, experienced travel time for the ATIS user.
   Set pre-trip switch indicator $z^{j}_{o,d,\tau} = 1$, and trip distance $\tilde{\delta}^{\,j}_{o,d,\tau} = \sum_{\lambda \in \dot{\mathbf{P}}^{j}_{o,d,\tau}} \delta_{\lambda}$.
   Set $y^{j}_{o,d,\tau} = 0$. GOTO step i.

h. STICK with habituated path:

traverse $\overline{\mathbf{P}}_{o,d,\tau}$ forward from time, using actual arc costs for day j, departing at $\tilde{t}^{\,j}_{o,d,t}$:

$\mathrm{T}'\left(\overline{\mathbf{P}}_{o,d,\tau}, \tilde{t}^{\,j}_{o,d,\tau}, \hat{c}^{\,j}_{\lambda}(t)\right) \rightarrow \tilde{p}^{\,j}_{o,d,\tau}$, experienced travel time for the ATIS user.

Set pre-trip switch indicator $x^{j}_{o,d,\tau} = 0$, trip distance $\tilde{\delta}^{\,j}_{o,d,\tau} = \sum_{\lambda \in \overline{\mathbf{P}}^{j}_{o,d,\tau}} \delta_{\lambda}$. Set $y^{j}_{o,d,\tau} = 0$.

h. Generate performance record (by day j):

o	trip origin
d	trip destination
τ	target time of trip end at destination
$\hat{p}^{\,j}_{o,d,\tau}$	optimal travel time
$\hat{\delta}^{\,j}_{o,d,\tau}$	travel distance on optimal path
$t^{0}_{o,d,\tau}$	habitual time of trip start
$\check{p}^{\,j}_{o,d,\tau}$	non-user experienced travel time (leaves at habitual trip start time)
$\overline{\delta}_{o,d,\tau}$	travel distance on habitual path
$\tilde{t}^{\,j}_{o,d,\tau}$	ATIS user time of trip start
$\overline{\overline{p}}_{o,d,\tau}$	predicted travel time on habitual path at trip start
$\dot{p}^{\,j}_{o,d,\tau}$	predicted fastest travel time for ATIS user at trip start
$\tilde{p}^{\,j}_{o,d,\tau}$	experienced travel time, ATIS user
$\tilde{\delta}^{\,j}_{o,d,\tau}$	experienced travel distance, ATIS user
$z^{j}_{o,d,\tau}$	number of pre-trip route changes by ATIS user
$y^{j}_{o,d,\tau}$	number of en route path changes by ATIS user
$\omega^{j}_{o,d,\tau}$	savvy ATIS user correction factor

OPTION 2 En Route ATIS, Travel Time Service

PROCEDURE:

1. Recover archived and actual link travel time files for the evaluation period $\bar{c}^j_\lambda(t), \hat{c}^j_\lambda(t) : \forall\ t, j.$.

2. For each o, d, τ : (Establish Time of Trip Start)
   a. set $t' = t^0_{o,d,\tau} - e^-$.
   b. perform forward DP from t' with arc costs fixed at $t = t'$;
   $\mathrm{D}'\left(o, d, t', \bar{c}^j_\lambda(t')\right) \rightarrow\ \hat{\mathbf{P}}^j_{o,d,\tau}$, a candidate fastest path with predicted travel time $\hat{p}^j_{o,d,\tau}$

   c. check to see if trip start can be safely postponed five minutes longer
   CHECK#1: $t' + \omega_{o,d,\tau}\hat{p}^j_{o,d,\tau} < \tau - \Delta$ (predicted to be early?)
   CHECK#2: $t' < t^0_{o,d,\tau} + e^+$ (still have flexibility to postpone trip?)
   If CHECK#1 and CHECK#2 are true,
   then set $t' = t' + \Delta$ and GOTO step b;
   Otherwise we have determined the time of trip start, set $\tilde{t}^j_{o,d,t} = t'$.

3. Continue with the o, d, τ by establishing en route behavior
   a. Initialize intermediate travel time $\alpha = \tilde{t}^j_{o,d,\tau}$, intermediate location $i = o$, and current path $\mathbf{P}_{i,d,\tau}(\alpha) = \overline{\mathbf{P}}_{o,d,\tau}$. Define $\mathrm{I}(\mathbf{P})$, a function which recovers the first link in a path, and $\mathrm{B}(\lambda)$, a function that recovers the b-node of a link.
   Set the path taken by the traveler $\tilde{\mathbf{P}} = \varnothing$, and set $x^j_{o,d,\tau} = y^j_{o,d,\tau} = 0$.
   b. forward traverse the current path, $\mathbf{P}_{i,d,\tau}(\alpha)$, using arc costs fixed at $t = \alpha$;
   $\mathrm{T}'\left(\mathbf{P}_{i,d,\tau}(\alpha), \alpha, \bar{c}^j_\lambda(\alpha)\right) \rightarrow\ p^j_{i,d,\tau}(\alpha)$, the predicted remaining travel time on the current path.
   c. If $i = o$, set $\bar{p}^j_{i,d,\tau} = p^j_{i,d,\tau}(\alpha)$.
   d. perform forward DP from i at α with arc costs fixed at $t = \alpha$;
   $\mathrm{D}'\left(i, d, \alpha, \bar{c}^j_\lambda(\alpha)\right) \rightarrow\ \bar{\mathbf{P}}^j_{i,d,\tau}(\alpha)$, the fastest predicted intermediate path and $\bar{p}^j_{o,d,\tau}(\alpha)$, the predicted remaining travel time on $\bar{\mathbf{P}}^j_{i,d,\tau}(\alpha)$.
   If $\mathrm{I}\left(\bar{\mathbf{P}}^j_{i,d,\tau}(\alpha)\right) = \mathrm{I}\left(\mathbf{P}_{i,d,\tau}(\alpha)\right)$, GOTO Step g.

   e. Check to see that the alternative route saves more time than the indifference threshold
   If $p^j_{i,d,\tau}(\alpha) - \bar{p}^j_{i,d,\tau}(\alpha) < \varepsilon$, GOTO Step g.

   f. Switch to the alternative path:
   Let $\lambda' = \mathrm{I}\left(\bar{\mathbf{P}}^j_{i,d,\tau}(\alpha)\right)$ next link to be traversed from alternative path
   If $i = o$, then set $z^j_{o,d,\tau} = z^j_{o,d,\tau} + 1$; increment route switch counter
   Else set $y^j_{o,d,\tau} = y^j_{o,d,\tau} + 1$

Set $\mathbf{P}_{i,d,\tau}(\alpha) = \breve{\mathbf{P}}^{j}_{i,d,\tau}(\alpha)$, the alternative path is now the current path
GOTO step h.

g. Stick with the current path:
Let $\lambda' = \mathrm{I}\left(\mathbf{P}_{i,d,\tau}(\alpha)\right)$ next link to be traversed from current path

h. Set $\widetilde{\mathbf{P}} = \widetilde{\mathbf{P}} + \lambda'$, update list of traversed links
Set $i = \mathrm{B}(\lambda')$, update current position
Set $\alpha = \alpha + \breve{c}^{j}_{\lambda'}(\alpha)$, update current time
Set $\mathbf{P}_{i,d,\tau}(\alpha) = \mathbf{P}_{i,d,\tau}(\alpha)$ update path given we have advanced to a new node
If $i \neq d$ GOTO b.

i. Let $\widetilde{p}^{j}_{o,d,\tau} = \alpha - \widetilde{t}^{j}_{o,d,\tau}$, the experienced travel time on $\widetilde{\mathbf{P}}$, and $\widetilde{\delta}^{j}_{o,d,\tau} = \sum_{\lambda \in \widetilde{\mathbf{P}}} \delta_{\lambda}$.

k. Generate performance record (identical to OPTION 1)

OPTION 3 En Route Advisory Service Evaluation

PROCEDURE:

1. Recover average link travel times in the training period $\breve{c}_\lambda(t)\,\forall t.$,
   and actual link travel time files for the evaluation period $\breve{c}_\lambda^j(t)\,\forall t, j.$
   Prepare an the advisory report content profile, $x_\lambda^j(\hat{t})$,
   for each day j of the evaluation period referencing link λ at non-lattice time $\hat{t}$,
   taking severity values $x_\lambda^j(\hat{t}) = \{\varnothing, 1, 2, 3\}$ where value $\varnothing$ indicates no advisory broadcast.
   Recover learned advisory impact functions, $\hat{\mathrm{B}}_{o,d,\tau}\left[x_\lambda(t)\right]$, (see Step 1.4.e Option 2)

2. For each o, d, τ : (Establish Time of Trip Start)
   a. set $t' = t^0_{o,d,\tau} - e^- + 30$ (listens to advisories for 30 minutes)
   b. Identify the set of advisories heard each day while on the habitual path,

   $\mathbf{X}^j(t')$, the set of $x_\lambda^j(\hat{t})$ such that $\lambda = \overline{\mathbf{P}}_{o,d,\tau}$ (links on the habitual path)
   and $t^0_{o,d,\tau} - e^- \le t \le t'$ (advisories heard up to current time)

   Let $x_s^j(t')$ be the count of unique link advisories with value s in $\mathbf{X}^j(t')$, i.e.,
   we disregard repeated advisories of the same severity on the same link.

   Calculate $\hat{c}_\lambda^j(t') = \breve{c}_\lambda(t') + \hat{\mathrm{B}}_{o,d,\tau}\left[x_s^j(t')\right]\forall\lambda.$ (expected travel times under advisory)

   perform forward DP from t' with arc costs fixed at $t = t'$;
   $\mathrm{D}'\left(o, d, t', \hat{c}_\lambda^j(t')\right) \rightarrow \hat{\mathbf{P}}^j_{o,d,\tau}$, a candidate fastest path with predicted travel time $\hat{p}^j_{o,d,\tau}$

   c. check to see if trip start can be safely postponed five minutes longer
   CHECK#1: $t' + \hat{p}^j_{o,d,\tau} < \tau - \Delta$ (predicted to be early?)
   CHECK#2: $t' < t^0_{o,d,\tau} + e^+$ (still have flexibility to postpone trip?)
   If CHECK#1 and CHECK#2 are true,
   then set $t' = t' + \Delta$ and GOTO step b;
   Otherwise we have determined the time of trip start, set $\tilde{t}^j_{o,d,t} = t'$.

3. Continue with the o, d, τ by establishing en route behavior
   a. Initialize intermediate travel time $\alpha = \tilde{t}^j_{o,d,\tau}$, intermediate location $i = o$, and current path $\mathbf{P}_{i,d,\tau}(\alpha) = \overline{\mathbf{P}}_{o,d,\tau}$. Define $\mathrm{I}(\mathbf{P})$, a function which recovers the first link in a path, and $\mathrm{B}(\lambda)$, a function that recovers the b-node of a link.
   Set the path taken by the traveler $\tilde{\mathbf{P}} = \varnothing$, and set $x^j_{o,d,\tau} = y^j_{o,d,\tau} = 0$.
   b. forward traverse the current path, $\mathbf{P}_{i,d,\tau}(\alpha)$, using arc costs fixed at $t = \alpha$;
   $\mathrm{T}'\left(\mathbf{P}_{i,d,\tau}(\alpha), \alpha, \hat{c}_\lambda^j(\alpha)\right) \rightarrow p^j_{i,d,\tau}(\alpha)$, the predicted remaining travel time on the current path.

c. If $i = o$, set $\breve{p}^{j}_{i,d,\tau} = p^{j}_{i,d,\tau}(\alpha)$.

d. perform forward DP from i at α with arc costs fixed at $t = \alpha$;
$\mathrm{D}'\left(i, d, \alpha, \breve{c}^{j}_{\lambda}(\alpha)\right) \rightarrow \breve{\mathbf{P}}^{j}_{i,d,\tau}(\alpha)$, the fastest predicted intermediate path
and $\breve{p}^{j}_{o,d,\tau}(\alpha)$, the predicted remaining travel time on $\breve{\mathbf{P}}^{j}_{i,d,\tau}(\alpha)$.
If $\mathrm{I}\left(\breve{\mathbf{P}}^{j}_{i,d,\tau}(\alpha)\right) = \mathrm{I}\left(\mathbf{P}_{i,d,\tau}(\alpha)\right)$, GOTO Step g.

e. Check to see that the alternative route saves more time than the indifference threshold
If $p^{j}_{i,d,\tau}(\alpha) - \breve{p}^{j}_{i,d,\tau}(\alpha) < \varepsilon$, GOTO Step g.

f. Switch to the alternative path:
Let $\lambda' = \mathrm{I}\left(\breve{\mathbf{P}}^{j}_{i,d,\tau}(\alpha)\right)$ next link to be traversed from alternative path
If $i = o$, then set $z^{j}_{o,d,\tau} = z^{j}_{o,d,\tau} + 1$; increment route switch counter
Else set $y^{j}_{o,d,\tau} = y^{j}_{o,d,\tau} + 1$
Set $\mathbf{P}_{i,d,\tau}(\alpha) = \breve{\mathbf{P}}^{j}_{i,d,\tau}(\alpha)$, the alternative path is now the current path
GOTO step h.

g. Stick with the current path:
Let $\lambda' = \mathrm{I}\left(\mathbf{P}_{i,d,\tau}(\alpha)\right)$ next link to be traversed from current path

h. Set $\widetilde{\mathbf{P}} = \widetilde{\mathbf{P}} + \lambda'$, update list of traversed links
Set $i = \mathrm{B}(\lambda')$, update current position
Set $\alpha = \alpha + \breve{c}^{j}_{\lambda'}(\alpha)$, update current time
Set $\mathbf{P}_{i,d,\tau}(\alpha) = \mathbf{P}_{i,d,\tau}(\alpha)$ update path given we have advanced to a new node

Update expectation based on advisories based on current time update.
$\mathbf{X}^{j}(\alpha)$, the set of $x^{j}_{\lambda}(t)$
such that $\lambda = \mathbf{P}_{i,d,\tau}(\alpha)$ (links on the remaining path)
and $t^{0}_{o,d,\tau} - e^{-} \le t \le \alpha$ (advisories heard up to current time)
Let $x^{j}_{s}(\alpha)$ be the count of unique link advisories with value s in $\mathbf{X}^{j}(\alpha)$, i.e., we disregard repeated advisories of the same severity on the same link.

Calculate $\hat{c}^{j}_{\lambda}(\alpha) = \hat{c}_{\lambda}(\alpha) + \hat{\mathrm{B}}_{o,d,\tau}\left[x^{j}_{s}(\alpha)\right] \forall \lambda$. (revised expected travel times)

If $i \neq d$ GOTO b.

i. Let $\widetilde{p}^{j}_{o,d,\tau} = \alpha - \widetilde{t}^{j}_{o,d,\tau}$, the experienced travel time on $\widetilde{\mathbf{P}}$, and $\widetilde{\delta}^{j}_{o,d,\tau} = \sum_{\lambda \in \widetilde{\mathbf{P}}} \delta_{\lambda}$.

k. Generate performance record (identical to OPTION 1)

A. Forward A-STAR Dynamic Program: D'

$\mathrm{D}'\left(o, d, t^0, c_\lambda(t)\right)$: The subroutine takes the following arguments:

o	trip origin
d	trip destination
t^0	time of trip start
$c_\lambda(t)$	set of estimated arc costs to be used, defined $\forall\, \lambda, t$

Plus, it uses the following array already constructed:

$H'_d(n)$	heuristic estimate of minimum time required to go from n to d.

1. Define the following:

$\mathbf{O}$	the set of open nodes, set $\mathbf{O} = o$.
$\mathbf{C}$	the set of closed nodes, set $\mathbf{C} = \varnothing$.
$\mathrm{F}(n)$	estimate of fastest path time from o to d through n, departing n at earliest possible time, $\mathrm{F}(n) = G(n) + H'_d(n)$
$\mathrm{G}(n)$	earliest possible arrival time at node n, $G(o) = t^0$.
$\mathrm{S}(n)$	set of successor nodes for n, i.e., nodes reached in one arc from n
$\breve{N}(n)$	pointer for node n to previous node along fastest path

2. if $\mathbf{O} = \varnothing$, exit with FAILURE. Otherwise, recover or calculate $\mathrm{F}(n) \forall n \in \mathbf{O}$.

3. a. find $n = \min\limits_{n' \in \mathbf{O}} \{\mathrm{F}(n')\}$; $\alpha = \mathrm{G}(n)$.

   b. if $n = d$, then GOTO Step 5.

   c. for each $n' \in \mathrm{S}(n)$:

      Let $\lambda = (n, n')$ and $\alpha' = \alpha + c_\lambda(\alpha)$.

      if $n' \notin \mathbf{O} \cup \mathbf{C}$ then

         Set $\mathbf{O} = \mathbf{O} + n'$, GOTO (*).

      if $n' \in \mathbf{O}$ AND $\alpha' < G(n')$ then GOTO (*).

      if $n' \in \mathbf{C}$ AND $\alpha' < G(n')$ then

         Set $\mathbf{C} = \mathbf{C} - n'$, $\mathbf{O} = \mathbf{O} + n'$, GOTO (*).

      Else GOTO (**).

      (*) Set $G(n') = \alpha'$ and $\breve{N}(n') = n$.

      Update $F(n') = G(n') + H'_d(n')$.

      (**) Next n'.

   d. Set $\mathbf{C} = \mathbf{C} + n$, $\mathbf{O} = \mathbf{O} - n$.

4. GOTO Step 2.
5. DONE. Retrace pointers to find optimal path, path travel time is $G(d) - t^0$.

B. Reverse-Time Dynamic Program: `D

`D$\left(d, \tau, c_\lambda(t)\right)$: The subroutine takes the following arguments:

d	trip destination
τ	target time of arrival at d
$c_\lambda(t)$	set of actual arc costs to be used, defined $\forall\, \lambda, t$

Plus, it uses the following array already constructed:

c_λ^0	free-flow arc travel times $\forall\, \lambda$

1. Define the following:

$\mathbf{O}$	the set of open nodes, set $\mathbf{O} = d$.
$\mathbf{C}$	the set of closed nodes, set $\mathbf{C} = \varnothing$.
$\mathrm{G}(n)$	latest possible departure time from node n to get to d at time τ, $G(d) = \tau$.
$P(n)$	set of predecessor nodes for n, i.e., nodes from which n is reached in one arc
$\vec{N}(n)$	pointer for node n to next node along fastest path

2. if $\mathbf{O} = \varnothing$ and $\mathbf{C}$ contains all nodes in the network, GOTO Step 5.
   Otherwise, recover or calculate $G(n) \forall n \in \mathbf{O}$.

3. a. find $n = \max_{n' \in \mathbf{O}} \{G(n')\}$; set $\alpha = \mathrm{G}(n)$.

   b. for each $n' \in P(n)$:

   Let $\lambda = (n', n)$ and $\alpha'' = \alpha - c_\lambda^0 - REM\left(\dfrac{\alpha - c_\lambda^0}{\Delta}\right)$.

   (b*) if $\alpha'' + c_\lambda(\alpha'') \le \alpha$ then

   $$\alpha' = \alpha'' + \frac{\left[\alpha - \alpha'' - c_\lambda(\alpha'')\right]\Delta}{\Delta + c_\lambda(\alpha'' + \Delta) - c_\lambda(\alpha'')}$$

   else set $\alpha'' = \alpha'' - \Delta$, GOTO (b*).

   if $n' \notin \mathbf{O} \cup \mathbf{C}$ then

   Set $\mathbf{O} = \mathbf{O} + n'$, GOTO (*).

   if $n' \in \mathbf{O}$ AND $\alpha' > G(n')$ then GOTO (*).

   if $n' \in \mathbf{C}$ AND $\alpha' > G(n')$ then

   Set $\mathbf{C} = \mathbf{C} - n'$, $\mathbf{O} = \mathbf{O} + n'$, GOTO (*).

   Else GOTO (**).

   (*) Set $G(n') = \alpha'$ and $\vec{N}(n') = n$.

   (**) Next n'.

   e. Set $\mathbf{C} = \mathbf{C} + n$, $\mathbf{O} = \mathbf{O} - n$.

4. GOTO Step 2.

5. DONE. Retrace pointers to find optimal path, latest departure from any node is $G(n)$, travel time on optimal path from any node is $\tau - G(n)$.

C. Forward Path Traversal Under Estimated Travel Times: $\mathrm{T}'\left(\Lambda\ ,\bar{c}_{\lambda}(t)\right)$

$\mathrm{T}'\left(\mathbf{P}_{o,d}, t^0, c_\lambda\left(t^0\right)\right)$: The subroutine takes the following arguments:

$\mathbf{P}_{o,d}$	Path to be traversed from origin to destination, an array of links
t^0	time of trip start
c_λ	set of estimated arc costs fixed at time t^0, defined $\forall\,\lambda$

Return $p_{o,d} = \sum_{\lambda \in \mathbf{P}_{o,d}} c_\lambda$, defined as the total path cost from origin to destination.

D. Forward Path Traversal Under Actual Travel Times: $\mathrm{T}'\left(\Lambda\ ,\hat{c}_{\lambda}(t)\right)$

$\mathrm{T}'\left(\mathbf{P}_{o,d}, t^0, c_\lambda(t)\right)$: The subroutine takes the following arguments:

$\mathbf{P}_{o,d}$	Path to be traversed from origin to destination, an array of links
t^0	time of trip start
$c_\lambda(t)$	set of actual arc costs, defined $\forall\,\lambda, t$

1. Set $p_{o,d} = 0$, defined as the cumulative path cost from origin to destination.

   Set the intermediate time $\alpha = t^0$.

2. Find $\lambda \in \mathbf{P}_{o,d}$, the next link in sequence from origin to destination.

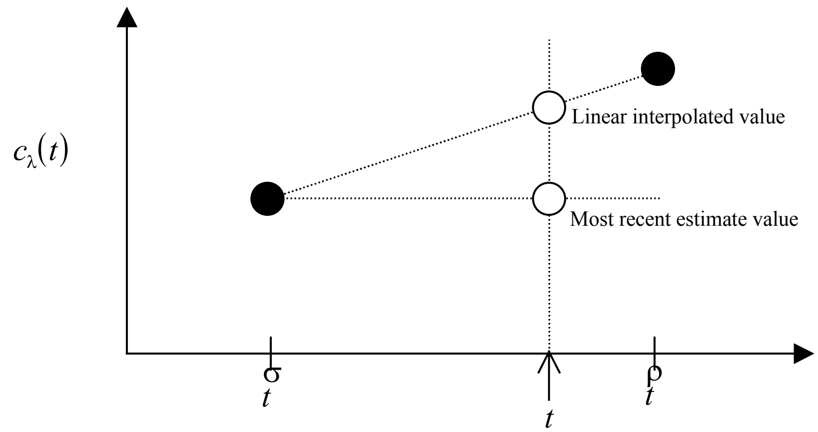
   $$\hat{c}_\lambda(t) = \hat{c}_\lambda\left(\overleftarrow{t}\right) + \left(t - \overleftarrow{t}\right)\frac{\left(\hat{c}_\lambda\left(\overrightarrow{t}\right) - \hat{c}_\lambda\left(\overleftarrow{t}\right)\right)}{\left(\overrightarrow{t} - \overleftarrow{t}\right)} \qquad \text{(see E)}$$

   $$p_{o,d} = p_{o,d} + c_\lambda(\alpha)$$

3. If $\lambda \equiv (a, b); b \neq d$ then set GOTO step 2 with $\alpha = p_{o,d} + t^0$.

   Else return $p_{o,d}$ as the travel time on the path.

E. Evaluating Arc Costs Between Lattice Points



1. For traversals and DP applications using estimated data, let $\bar{c}_\lambda(t) = c_\lambda\left(\overset{\upsilon}{t}\right)$.
2. For traversals and DP applications using actual data, $\overset{)}{c}_\lambda(t)$, use linear interpolation:

$$\overset{)}{c}_\lambda(t) = \overset{)}{c}_\lambda\left(\overset{\sigma}{t}\right) + \left(t - \overset{\sigma}{t}\right)\frac{\left(\overset{)}{c}_\lambda\left(\overset{\rho}{t}\right) - \overset{)}{c}_\lambda\left(\overset{\sigma}{t}\right)\right)}{\left(\overset{\rho}{t} - \overset{\sigma}{t}\right)}.$$