On-Time Reliability Impacts of ATIS, Volume III:

Implications for ATIS Investment Strategies

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ABSTRACT

The effect of ATIS accuracy and extent of ATIS roadway instrumentation on the on-time reliability benefits to routine users of ATIS are evaluated through the application of Heuristic On-line Web-linked Arrival Time Estimation (HOWLATE) methodology. The HOWLATE methodology employs archived estimates of roadway travel times to recreate hypothetical, retrospective paired driving trials between travelers with and without ATIS. Previous research using this technique demonstrated that travelers who receive notification of current congestion prior to departure can realize substantial time management benefits from improved on-time reliability and trip predictability, and that these savings can be converted to a dollar-valued benefit. In this report, we expand the repertoire of applications of HOWLATE to investigate the impacts of ATIS accuracy and geographic coverage levels on the value of ATIS service, and how to best conduct ATIS evaluations using small data sets. We then examine the implications of these findings on the development of cost-effective ATIS deployment strategies.

Based on 12-month case studies in the cities of Washington DC, Minneapolis/St. Paul, and Los Angeles we predict that the net benefit from ATIS use across all potential trips in each network is positive only if the error in ATIS reporting is below the range of 10% to 21%. For ATIS services with worse accuracy, only certain subsets of the driving populations such as those with relatively long or highly variable trips may realize any benefit. Further, we observed that near-optimal geographical deployments of ATIS can garner as much as 50% to 80% of benefits from as little as the first 30% of deployment. Yet, identifying the near-optimal is not as simple as ATIS implementation on links with highest variability. In making effective tradeoff decisions about how to invest in improved ATIS, be it increasing geographic coverage or increasing accuracy, the findings of this report underscore the importance of understanding what levels of accuracy are required to generate ATIS user benefit based on regional day-to-day roadway variability.

KEYWORDS: Intelligent Transportation Systems, benefits, modeling, simulation, HOWLATE, Advanced Traveler Information Systems, accuracy, error, deployment, travel time, on-time reliability, variability, simulated yoked trials, Washington DC, Minneapolis/St. Paul MN, Twin Cities, Los Angeles, Cincinnati.

ACKNOWLEDGEMENTS

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EXECUTIVE SUMMARY

This report examines how on-time reliability benefits to users of Advanced Traveler Information Systems (ATIS) vary both by accuracy of the information provided by the ATIS and the geographic deployment of the ATIS. The method of analysis applied to conduct this evaluation is the Heuristic On-line Web-linked Arrival Time Estimation (HOWLATE) methodology, wherein simulated paired driver trials are conducted based on archives of roadway travel times to identify how ATIS use affects the trip outcome.

The HOWLATE methodology was documented and demonstrated using a small-scale test case in Volume I (Wunderlich, 1). In Volume II (Jung, 2), Mitretek applied HOWLATE in a large scale evaluation of a prospective pre-trip notification-based ATIS in two cities over a 15-month period and found that ATIS can benefit routine users by improving their on-time reliability without significantly reducing their in-vehicle travel time. Also in Volume II, Mitretek demonstrated how user savings in on-time reliability and in-vehicle travel time can be converted to a dollar-valued benefit.

In this report, Volume III, Mitretek Systems, at the request of the Intelligent Transportation Systems (ITS) Joint Program Office (JPO) of the U.S. Department of Transportation (USDOT), extends the HOWLATE methodology to investigate the impact of ATIS accuracy and geographic coverage levels on the value of ATIS service, and how to best conduct ATIS evaluations using small data sets. We then examine the implications of these findings on the development of cost-effective ATIS deployment strategies.

Background

Initiatives to evaluate the impact of traveler information services providing real-time congestion reports (hereafter, simply referred to ATIS in this report) in the 1990's indicated what appeared to be contradictory results with respect to the time savings of ATIS users: large *perceived* time savings reported by ATIS users in survey-based research, but marginal to no *observed* in-vehicle travel time savings when measured empirically in field operational tests. These quantitative findings proved problematic for justifying ATIS investment since public sector cost-benefit analysis was focused primarily on in-vehicle travel time savings.

In order to reconcile this apparent contradiction between *perceived* and *observed* ATIS benefits, Mitretek Systems developed the Heuristic On-line Web-Linked Arrival Time Estimation (HOWLATE) method, utilizing the concept of a *simulated yoked trial*. This technique efficiently reconstructs millions of hypothetical, retrospective paired driving trials using archives of roadway travel times wherein one driver uses ATIS in making commute decisions while the other driver does not deviate from normal departure time and route. Time management benefits to ATIS users such as reduction in in-vehicle travel time or arrival offset are quantified using the HOWLATE technique, while other more qualitative benefits such as trip serenity associated with knowledge of events are not explicitly addressed.

Using HOWLATE, Mitretek showed that routine users of personalized pre-trip ATIS can realize significant benefit in the form of improved trip reliability without a significant reduction in in-vehicle travel time (Wunderlich, 1; Jung, 2). Moreover, Mitretek demonstrated how these savings in trip reliability can translate into substantial monetary savings. It was demonstrated via case studies of Washington DC and Minneapolis/St. Paul, Minnesota that given an assumed level of accuracy of ATIS, benefits from improved trip reliability to a significant number of commuters would far exceed the cost of their subscription to a proposed personalized ATIS that provided current travel time on roadways. Thus, public investment in regional ATIS could prove cost-beneficial under the levels of ATIS accuracy employed in the study.

Predicated on the demonstration of potential benefit of ATIS to users and to improving transportation systems efficiency, significant ATIS investment has already occurred, particularly in the public sector. Within the United States, 26 metropolitan areas provide automated telephone services to distribute freeway travel times (Gordon and Trombly, 3). As of 2001, over 35 metropolitan areas provide freeway travel times or speeds via the internet (www.itsdeployment.ed.ornl.gov, 4). More recently, under the federal mandate for a national traveler information number (http://www.its.dot.gov/511/PDF/511_overview.pdf , 5), public transportation agencies continue their regional ATIS efforts with more significant investments planned toward larger, more comprehensive deployments. Yet, to date, little work has been done to help guide cost-effective ATIS investments.

The maximization of user benefit is fundamentally predicated on engendering a large user base that experiences benefit from the service. However, user benefit is highly dependent on the accuracy and the level of coverage of ATIS. If the information does not cover significant portions of a commuter's trip or the information is not reliably accurate, then the commuter will not use it. But at what point does an ATIS become accurate enough or provide enough coverage to garner a net user benefit?

In making deployment decisions, planners need to understand these issues and be able to assess where their system is now, what investments are likely to result in the largest benefit, and how to make these decisions in an environment of limited data. In this report we apply the HOWLATE methodology to assess the sensitivity of user benefits to the accuracy of the ATIS system, and to explore how benefit varies across some basic coverage deployment strategies.

Approach

As in the field experiments conducted in the 1990s, HOWLATE mimics the conduct of a paired driving trial between a simulated ATIS user and a comparable, simulated non-user. Unlike the field trials where subjects departed trip origins simultaneously, the HOWLATE pairing is based on trip origin, trip destination and target time arrival at the destination. Using an extensive archive of roadway travel times and a measure of the accuracy of the ATIS, a Monte Carlo technique is employed to generate realized roadway travel times. The difference between the original archive of ATIS estimated travel times and a realization of actual travel times is a function of the level of ATIS accuracy specified in the experiment.

The decisions of when to start a trip and which route to take are made differently for the ATIS user and the non-user. The ATIS user waits for notification to start a trip from an ATIS service, which scans the realization-based travel time archive every five minutes and relays the expected travel time on the fastest route under current conditions. The non-user, conversely, does not adjust trip timing or route based on current conditions, but rather relies on past experience to establish a habitual time of departure and habitual route. The yoked study simulator in HOWLATE, referencing the travel times on a particular work day in the study period, plays out what would have happened in millions of such synthetic paired trials.

Simulated travelers are designated as arriving *late* (1 second or more after the target arrival time), *early* (10 minutes or more earlier than the target arrival time), or *just-in-time* (not late and up to 10 minutes early) in each trial. These thresholds are selected to reflect commute scenarios where trip arrival timing is very important –for example workers at factories with stringent arrival requirement. Travelers who are not late are considered *on-time*, regardless of whether they are just-in-time or early. HOWLATE collects statistics on each trial and calculates whether, on average, the simulated ATIS user experiences fewer late arrivals and less wasted time by arriving too early than the simulated counterpart who does not use ATIS. A dollar-valued benefit of reductions in travel disutility based on the work of Small (Small et al., 6) is calculated from the reductions in the frequency and magnitude of early or late arrivals as well as in-vehicle travel time.

For this analysis, case studies are conducted using observed data for the cities of Washington, DC, Minneapolis/St. Paul (hereafter, Twin Cities), and Los Angeles to test the hypotheses of the project related to ATIS accuracy and coverage level. The Washington metropolitan area and Twin Cities analyses were conducted using a study period from June 2000 to May 2001 with data from SmarTraveler.com, a product of SmartRoute Systems corporation. In Los Angeles, the analyses were conducted using a study period from January 2002 to July 2002 with data from the California Freeway Performance Measurement System (PeMS).

Measuring ATIS Accuracy Impacts

In evaluating how ATIS user benefit varies by ATIS information accuracy, we conduct sets of simulations wherein the level of error in the ATIS information is varied from 0% (perfect information) to 25%. Consequently, the gap between estimated travel times provided by ATIS and the realized roadway travel times grows as the level of error is increased. The error introduced is that of random error, causing information sometimes to be higher than true roadway times and sometimes to be lower than true roadway times, but overall, without any recurrent bias in the ATIS information. We conduct analyses based on zero recurrent bias because ATIS providers can relatively effectively correct for recurrent bias, but day-to-day randomness is more difficult to address. Moreover, a routine ATIS user would be aware of

recurrent bias and would adjust ATIS information to align with trip experience, thereby mitigating the effect of recurrent reporting bias.

Measuring ATIS Geographic Coverage Impacts

In a variant to the HOWLATE process developed to modeled partial deployments of traffic monitoring systems, the ATIS provider uses historic data to fill in data gaps that exist because real-time coverage is not deployed on particular links. We evaluate an incremental deployment strategy where links with highest observed travel time variability are deployed first. This strategy, called the *travel time variability ranked strategy*, represents an analytical process by which regional planners might design deployment, wherein the roads with highest travel time variability are instrumented for ATIS first. The effectiveness of this plausible strategy is then compared to two benchmarks. First, the *most effective link first strategy* is our benchmark for near-optimal deployment. This strategy is implemented by an experiment in which each portion of the network is instrumented individually and the efficiency of the network is evaluated based on that individual instrumentation. The second strategy, *randomly ranked deployment* represents the worst case scenario for regional planners where no information is available in making incremental deployment decisions. Links are randomly ranked and traffic monitoring systems for ATIS are deployed based on the ranking.

For each strategy, deployments are evaluated from zero ATIS instrumentation to 100% network instrumentation at increments of approximately 10% based on roadway miles. We use the metric of ATIS users' dollar-valued benefit at specific levels of deployment as a percent of benefit associated with 100% ATIS deployment.

Hypotheses and Key Findings

Hypotheses Regarding ATIS Accuracy: There exists a unique value level of error, called the crossover point of error, below which ATIS provides positive travel reliability benefits on aggregate for a region. The crossover point of error is higher for cities with higher day-to-day variability, and similarly is higher during peak periods for a city given that day-to-day variability is greater during periods of greater congestion. Further, we hypothesize that cities currently providing ATIS are at or above their crossover points of error and therefore may not be generate positive reliability benefits for potential ATIS users in the region.

*Findings: **Crossover points of error were found to range from 10% to 21% based on city (St. Paul/Minneapolis, MN; Washington, DC; and Los Angeles, CA) and time of day.** This signifies that if a trip is made from each origin to each destination for each 15-minute interval in the day, the net benefit from ATIS use for all trips would be positive only if the ATIS reporting error is below the range of 10% to 21%, depending on the city and time of day. For ATIS services higher than these levels of error, only certain subsets of the driving populations such as those with relatively long or highly variable trips may realize benefit.*

The marginal benefit from ATIS accuracy improvements decreases at lower levels of ATIS errors. Figure ES-1 illustrates the relationship of utility from improved trip reliability versus travel time error for the Los Angeles region. In Los Angeles, the crossover point of error ranges from 14% to 21%. ***Once regional ATIS reaches a level of error near or below the range of 5%, benefits from further improvements to ATIS accuracy may outweigh the costs associated with these improvements.*** The curves for the cities of Washington, DC and St. Paul/Minneapolis have the same shape as that of Los Angeles.
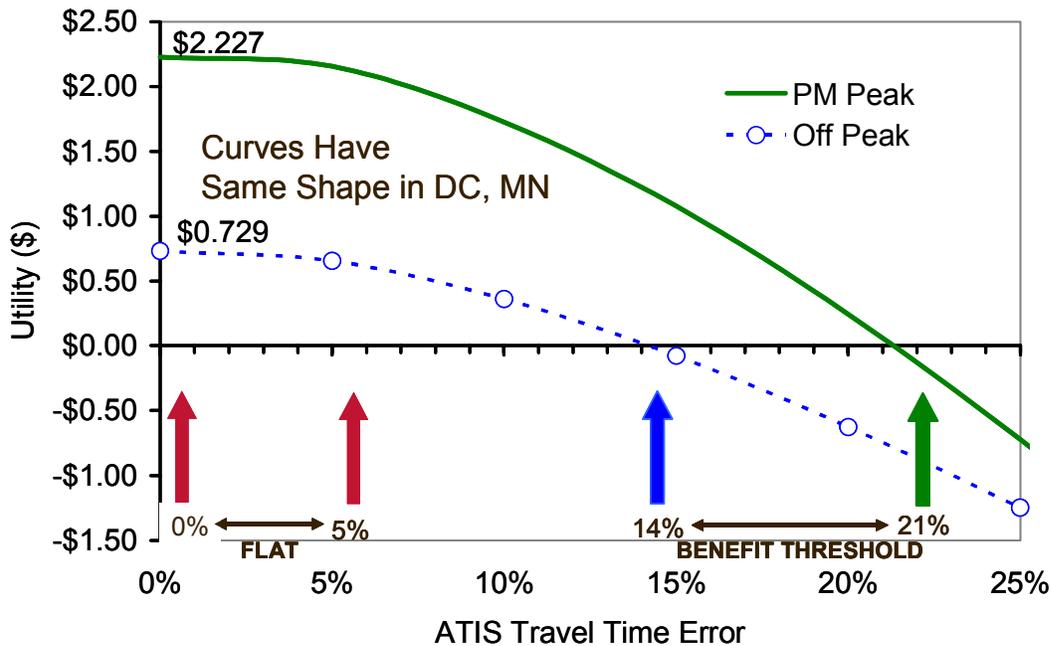
Figure ES-1   Los Angeles Network Utility Curve by ATIS Error Level

Figure ES-2 presents a graph of crossover error point by variability in link speeds, disaggregated by city and congestion period. St. Paul/Minneapolis and Washington DC, the cities with lower day-to-day speed variability, have a significantly lower crossover points compared to Los Angeles, a city with greater speed variability. Thus, ATIS in the cities of Washington DC and St. Paul/Minneapolis needs to be more accurate than in Los Angeles to achieve a net positive ATIS user benefit. Also, the PM peak period for all cities tends to have greatest speed variability, and consequently highest thresholds for ATIS error.

Note that the relationship between the crossover point of error and system-level travel speed variability can be shown to be linear with a R-square value of 0.92 and a slope of 1.55*%. **This suggests that as regional trip variability decreases by 1 minute, the system needs to decrease ATIS error by 1.55% to maintain the same level of potential user benefit.**

With respect to the current level of accuracy of actual ATIS implementations, we identified two corridor studies for the cities of Washington DC and St. Paul/Minneapolis. In Washington DC the error of ATIS excluding recurrent bias in reporting ranged from 9% to 17% for freeways and 6% to 26% for arterials (Hardy et al., 7). This report identifies the crossover point of error to range between 9% and 14% for Washington DC. In St. Paul/Minneapolis the error of ATIS excluding bias ranged from 24% to 33% depending on peak versus off-peak periods (Cambridge Systematics, 8; Toppen et al., 9). This report identifies the crossover point of error to range between 10% and 15%. These ranges of current accuracy are illustrated in Figure ES-2.

Based on this single study to measure ATIS accuracy in Washington DC, the ranges of measured ATIS error and crossover point overlap, leaving the status of net aggregate impact from ATIS use ambiguous. In St. Paul/Minneapolis, the net impact of ATIS would clearly be negative (measured error > crossover point) had all trips on the network used ATIS. Still, the Twin Cities deployment may be cost-beneficial taken as a whole, given that commuters who do not benefit would not have used ATIS, and that for commuters with very long or highly variable trips benefits would be significant from ATIS use even at these high levels of error.

Crossover Point of Error = 0.0155 x (Avg. Stdev. In Link Speed) + 0.0471

$R^2 = 0.9234$
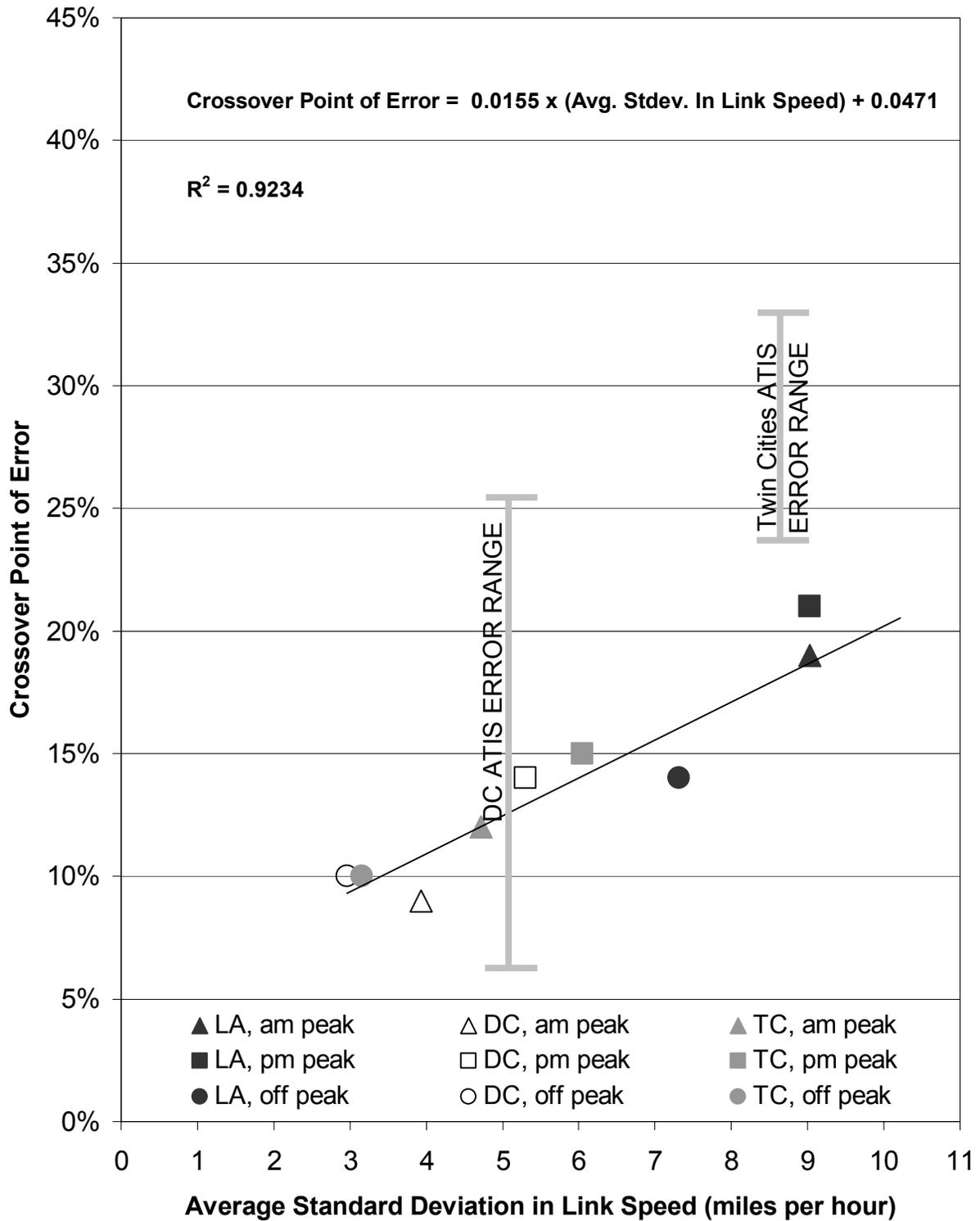
Figure ES-2   Crossover Point of Error by Average Link Speed Standard Deviation

Hypotheses Regarding Incremental Geographic Deployment: For near-optimal incremental deployment strategies of ATIS, an overwhelming percentage of the benefit associated with full deployment can be achieved through efficient deployment of travel time surveillance over a relatively limited set of a few key roadway segments. Incremental deployment strategies based on the observable roadway condition, link travel time variability, will be relatively closer to near-optimal efficiency compared to a random deployment strategy. The geometric form of the regional roadway network will affect the magnitude of benefit achieved by the first few levels in an incremental deployment strategy. More deployment always implies more benefit.

Findings: **The most effective link ranked strategy, offered as a benchmark for near-optimal incremental deployment, generates deployment plans wherein 30% of network miles deployed account for as much as 93%, 80%, and 56% of the full deployment benefit.** This is based on the trip disutility reductions in the cities of Washington DC, St. Paul/Minneapolis, and Los Angeles, respectively. However implementing this strategy would require an experiment in which a single link in the network is instrumented with ATIS while all other links have no ATIS capability. This would be repeated for each link in the network along with a measure of the efficiency of the network based on that individual link instrumentation. Figure ES-3 presents the percent of total benefit garnered by percent of roadway miles covered using the most effective link ranked strategy. As demonstrated from the evaluations, ATIS real-time coverage on key facilities in the region has the potential to generate the majority of ATIS user benefits associated with full deployment.

Our hypothesis regarding the effectiveness of partial deployment plans based on observed link variability was not supported*. Deployments based solely on the criterion of link travel time variability proved no better and sometimes even less efficient than the randomly ranked link deployment strategy, and in all cases far less efficient than the most effective link ranked strategy.* Incremental deployments based on the randomly ranked strategy were on average 68% to 76% as efficient as our near-optimal benchmark across the three cities. In contrast, incremental deployments based on the travel time variability ranked strategy were on average 57% to 75% as efficient as the near-optimal strategy across the three cities. Table ES-1 presents the relative efficiency of the travel time variability strategy and the random strategy compared to the near-optimal strategy of most effective link first.

One reason the travel time variability strategy may have performed poorly can be seen in the Washington DC case study. Here arterial links tend to have greater variability compared to freeway links. Yet freeways are far more likely to be utilized for network-wide travel. It may be that an incremental deployment strategy of first placing instrumentation on freeways with high variability may return patterns more similar to the near-optimal benchmark.
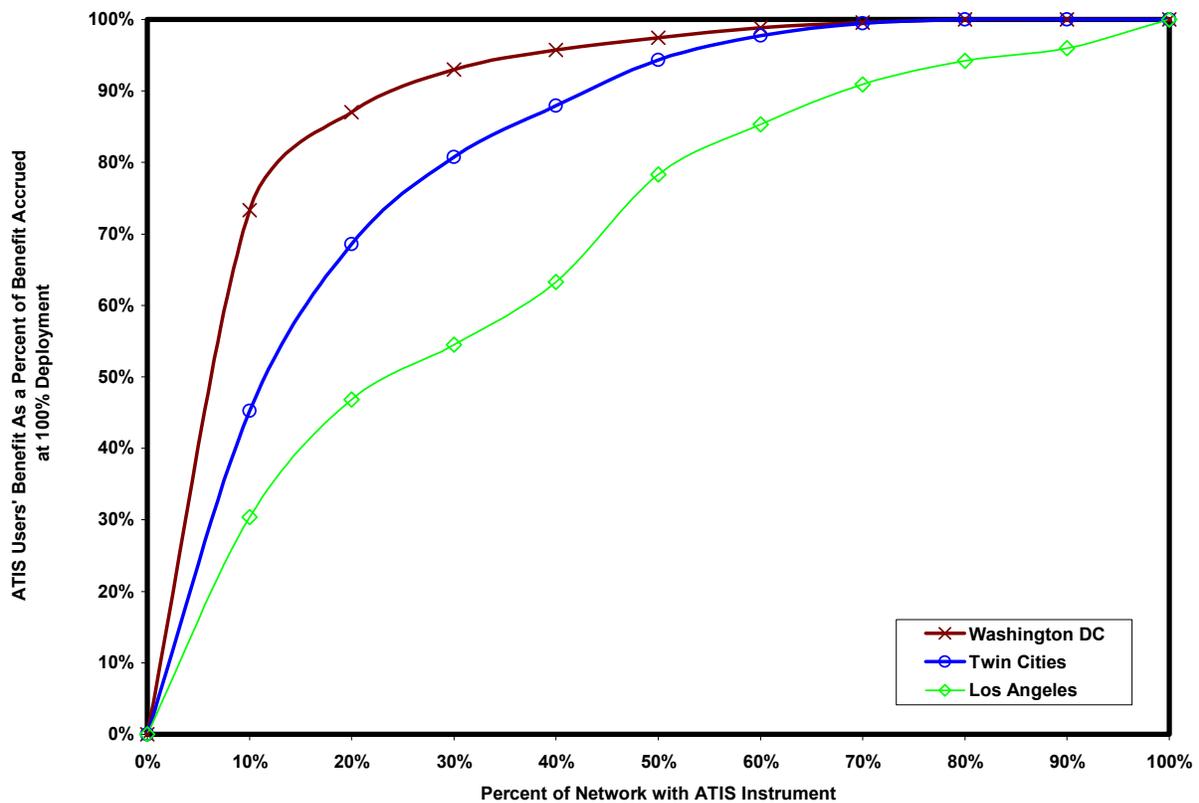
Figure ES-3   Benefit of Incremental Deployments based on Near-Optimal Deployment Strategy

Table ES-1   Relative Efficiency of Deployment Strategies Compared to the Benchmark Near-Optimal Plan

STRATEGY	Washington, DC	Twin Cities	Los Angeles
Most Effective Link Ranked	Set to 100% Effectiveness		
Travel Time Variability Ranked	57.2%	73.7%	74.8%
Average of 10 Randomly Ranked	68.1%	67.7%	75.6%
Best of 10 Randomly Ranked	85.7%	77.7%	87.7%
Worst of 10 Randomly Ranked	42.7%	57.9%	62.9%

In addition, poor performance of the travel time variability strategy compared to a random deployment (even in all freeway networks like Los Angeles) may be attributed to the fact that the demand pattern weights trips from each origin to each destination equally. We expect in reality that the freeway sections with greatest variability will be those most used, and that weighting trips by demand will prove that incremental deployments based on travel-time variability will be more efficient than random deployments. We will investigate these and other incremental deployment strategies in future work.

Washington DC, a mixed radial network, has the highest potential for planned, incremental deployment, followed by Twin Cities as illustrated in Figure ES-3. ***Based on the near-optimal strategy, deployments beyond the first most effective 70% of the networks in Washington, DC and Twin Cities generated no benefit. This is because the accuracy of the ATIS was not high enough compared to the variability of links instrumented to make ATIS useful or beneficial. In Los Angeles, however, the hypothesis that more deployment means more benefit holds true.***

Implications

Public sector investment in ATIS is predicated on the expectation of mobility and productivity benefits to both users of ATIS and the transportation system. For aggregate user benefits to be realized, the ATIS service must perform at or above a specific level of accuracy, or conversely, provide information below a certain level of error. Thus, the first step toward efficient ATIS investment decision-making for regions with existing ATIS is to evaluate the accuracy of the current ATIS system.

For regions with existing ATIS as well as for regions in the planning stages of ATIS, decision-makers also need to assess how accurate their ATIS needs to be to generate positive user benefit in their region. The crossover point of error, the value below which ATIS yields a net regional benefit, ranged from 10% to 21% based on the three cities evaluated in this report. More importantly, the crossover point of error proved to have a linear relationship with day-to-day roadway variability of the region. Thus, ATIS planners can use measured roadway variability to gauge how accurate ATIS in their region needs to be to garner user benefit.

Across the three cities we found that once ATIS error is reduced to a 5% level, benefits from improvements in accuracy are minimal. Having an understanding of the range within which a region's ATIS level of error is acceptable may have significant implications in identifying the types of sensor technologies selected for deployment. For example, in Los Angeles where the crossover point of error ranges from 14% to 21%, detectors using certain technologies with an error range around 12% may be most cost effective. Those same detectors may not be adequate in Washington DC where the crossover point of error ranges from 9% to 14%. The key finding is that if the regional variability is relatively low, the accuracy of ATIS required to realize regional user benefit must be relatively high. Conversely, if the regional variability is relatively high, ATIS accuracy to realize aggregate regional user benefits can be relatively lower.

An equally important step toward efficient ATIS investment decision-making for regions is smarter geographic deployment of ATIS coverage. We observed that near-optimal geographic deployments of ATIS can garner as much as 50% to 80% of benefits from as little as the first 30% of deployment. Yet, identifying the near-optimal is not as straightforward as ATIS implementation on links with highest variability. Travel demand is expected to play a significant role in the deployment selection process as is facility type (eg. freeway versus arterial).

In making effective tradeoff decisions about how to invest in improved ATIS —be it increasing geographic coverage or increasing accuracy, the findings of this report underscore the importance of understanding what levels of accuracy are required to generate ATIS user benefit based on regional day-to-day roadway variability. Figure ES-4 presents a notional nomograph based on the findings of this report that illustrates some fundamental concepts in planning cost-effective investments in ATIS deployments. Decision makers in regions with low travel time variability considering investments in ATIS systems with poor accuracy (the "don't deploy" region) should not consider deployment unless they can implement a system with relatively low error in reporting of ATIS. That is, the net user benefit from ATIS is likely to be greater than zero once their ATIS system is either in the "get better sensors" or "add coverage" regions. Conversely, sufficiently accurate ATIS services (the "add coverage" region) should consider geographic expansion rather than further refinement of ATIS accuracy. At higher levels of coverage or ATIS information error, decision makers again find themselves in the "get bettor sensors" region and may need to consider further improvements in ATIS accuracy that may

come at the expense of better sensors or information processing technologies. Continued investment in ATIS service coverage or accuracy reaches a natural end point in the "stand pat" region where both geographic coverage and accuracy of the ATIS service is at a level where the marginal benefits from additional improvements do not warrant the cost of such improvements.
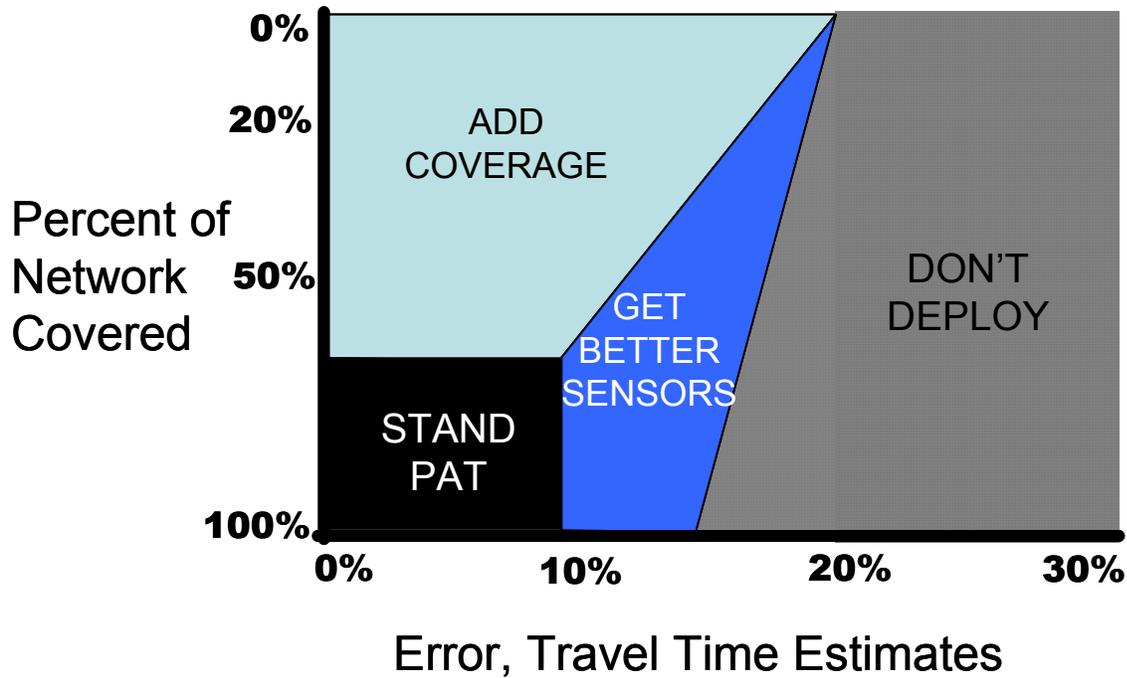
Figure ES-4   Notional Nomograph of Potential Decision Making Regimes

Across the dozens of existing deployed ATIS services, overwhelmingly, the level of error in the information they provide is poorly known. A review of literature on the accuracy of ATIS or speed/travel time sensor devices provided limited data on ATIS accuracy. Based on these reviews and the notional nomograph (Figure ES-4) presented earlier in this section, we derive a nomograph (Figure ES-5) of the current state of ATIS in the United States and the direction in which ATIS decision-makers should move. Our findings from this study suggest that the initial focus should be on accuracy, followed by an expansion of geographic deployment.
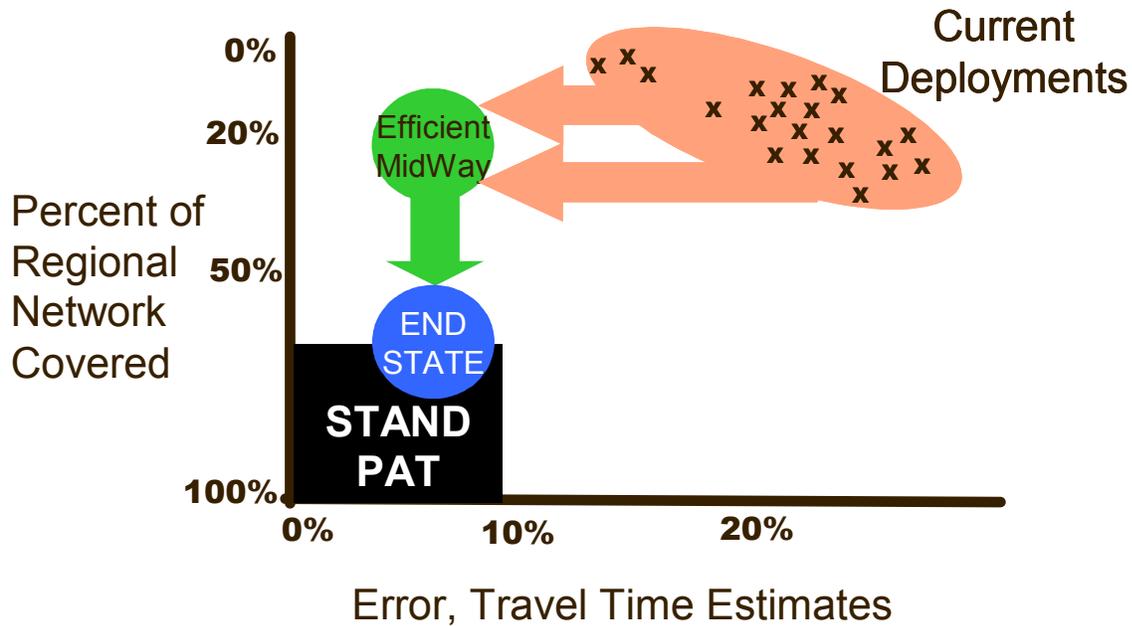
Figure ES-5 Suggested Direction for ATIS Investment

CONCLUSIONS AND NEXT STEPS

By extending the HOWLATE methodology, we successfully evaluated how ATIS user benefits of on-time reliability and travel time vary by ATIS accuracy and deployment coverage. The implications for field managers considering ATIS investment strategies, based on the findings from case studies in the cities of Los Angeles, Washington DC, and Minneapolis/St. Paul are noteworthy. Implications for decision makers in regions with existing ATIS are:

- Before considering further ATIS investments, first gain an understanding of the accuracy of your current posted travel time information and of the day-to-day variability of travel on roadways instrumented with ATIS.

- If the accuracy of the existing service is poor in relation to day-to-day travel variability, then focus investment into improving accuracy. The variability-accuracy relationship is demonstrated in Figure ES-2.

- Once system accuracy is relatively good in relation to day-to-day travel time variability, then, focus on increasing ATIS geographic coverage (Figure ES-4).

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- Keep in mind that more deployment does not always mean more benefit. There exists an end-state wherein deployment on roadways may not generate additional benefit to users of the ATIS.

For decision makers in regions considering ATIS:

- First identify the day-to-day variability of travel on major regional roadways.

- Select technologies and data processing techniques with a level of accuracy that is appropriate considering the magnitude of variability in your region.

- A good deployment plan can generate significant benefit from minimal investment. Identifying such a plan is difficult if only limited data is available. Deployments of ATIS based on both travel demand and roadway variability data are likely to be a good start in developing an efficient deployment plan.

Case studies in the three cities identified that for ATIS to generate user benefits of on-time reliability, the level of error in information delivered by ATIS needs to meet a minimum range of 10% to 21%. Further, regions with greater day-to-day roadway variability can generate ATIS user benefits at higher levels of error in ATIS information compared to regions with lesser day-to-day roadway variability. We also confirmed that near-optimal, incremental ATIS geographic deployment plans can garner as much 50% to 80% of benefit associated with full deployment with as little as 20% to 30% of the full geographic deployment.

Based on these findings, we have presented notional nomographs aimed at assisting ATIS decision-makers in developing effective investment strategies that provide the highest possible value of service to their constituencies. In future work, we expect to expand on these nomographs to deliver decision-makers more detailed graphs that identify efficient directions for investment based on their specific situation. In expanding the notional nomograph, we also expect to expand on the various accessible metrics upon which to base incremental geographic deployments of ATIS. In this report, we evaluated deployments based solely on travel time variability. In future work we hope to consider other factors such as annual average daily traffic, travel demand, or other metrics readily available to transportation planners.

1   INTRODUCTION

In 1999, at the request of the Intelligent Transportation Systems (ITS) Joint Program Office of the United States Department of Transportation (USDOT), researchers at Mitretek Systems developed a new technique for the evaluation of user impacts of Advanced Traveler Information Systems (ATIS) services based on the analysis of archived roadway travel time data, the Heuristic On-line Web-linked Arrival Time Estimation (HOWLATE) methodology. This methodology of simulated paired driver trails was documented and demonstrated using a small-scale test case in Volume I (Wunderlich, 1).

Mitretek then applied HOWLATE in a large scale evaluation of a prospective pre-trip notification-based ATIS in two cities over a 15-month period. The evaluation focused on the potential of ATIS in reducing trip variability and travel time in the cities of Washington DC and St. Paul/Minneapolis, MN. Mitretek also demonstrated how user savings in on-time reliability and in-vehicle travel time can be translated to a monetary savings. These efforts are documented in Volume II (Jung, 2). Key findings from Volumes I and II are that:

- ATIS does benefit travelers who need to be on–time,

- ATIS benefits are overwhelmingly from improvements in trip reliability and minimally from improvements in in-vehicle travel time,

- benefits are highly concentrated both by time of day and by geography of trips,

- the magnitude of user benefits rises proportionally with a rise in the region's level of congestion, and

- users of ATIS for both unfamiliar and routine trips can benefit from ATIS use.

In this report, Volume III, we expand the repertoire of applications of the HOWLATE methodology to assist ATIS decision-makers in developing effective investment strategies that provide the highest possible value of service to their constituencies. As jurisdictions work toward cost-effective plans for ATIS deployment many basic questions pertaining to deployment strategies have yet to be addressed. For example, are their existing or planned ATIS accurate

enough to be beneficial to users? How accurate does their ATIS need to be to provide user benefit? At what point is geographic coverage sufficient for commuters in the region to begin to experience noticeable benefits.

In this report, we explore the implications of ATIS accuracy and geographic coverage levels on the value of ATIS service. We also explore how to make the best of limited data sets in conducting ATIS evaluations. Specifically, we explore the relationship between improved ATIS accuracy and the trip reliability benefit to routine users from a pre-trip ATIS. We also explore the relationship between increasing geographic deployment of ATIS and the reliability benefits to users for these geographical levels of ATIS deployment.

This introductory section is intended to provide the reader with the necessary background regarding the HOWLATE methodology to be able to read and understand this full report as a stand-alone document without the prerequisite of having read Volumes I (Wunderlich, 1) or II (Jung, 2). First, a brief summary of the background and motivation on the history of ATIS evaluations and the role of HOWLATE are presented in Section 1.1. An overview of the HOWLATE methodology is presented in Section 1.2. Section 1.3 outlines the hypotheses of the new HOWLATE research covered as a part of this document. Readers familiar with HOWLATE may wish to skip forward to Section 1.3.

Section 2 of this report presents modifications and extensions to the HOWLATE methodology developed to address study hypotheses. Sections 3 and 4 present the methodologies and findings from the ATIS accuracy and geographic coverage studies, respectively. Findings are based on case studies of three cities: Washington, DC; Minneapolis/St. Paul, MN, and Los Angeles, CA. Section 5 summarizes the findings of these studies with respect to the hypotheses presented in Section 1.3 and outlines the roadmap of future work that builds upon the findings of this research.

1.1   ATIS Evaluation and the Role of HOWLATE

ATIS users overwhelmingly expressed that their use of ATIS saves commute time and reduces commute stress. Independent survey studies undertaken in Boston, Seattle, Washington DC, and other metropolitan areas (Englisher, 10; Jensen, 11; Schintler, 12; Lappin, 13) show that between

85% and 95% of respondents in each of these surveys reported high confidence that their use of ATIS helped them to save time. Other potential user benefits of ATIS include stress reduction and better time management; while transportation systems benefits include quicker accident congestion dispersion, increased throughput, and reductions in the potential of secondary accidents.

Later work using simulation models (Bunch, 14; Wunderlich, 15; Carter, 16) showed that significant travel time savings accrue to ATIS users under conditions of intense, unexpected congestion, but total in-vehicle travel time savings on an annualized basis for ATIS users is often not statistically significant. Moreover, field trials from in-vehicle navigation systems such as Pathfinder, TravTek, and ADVANCE proved minimal to non-existent in-vehicle travel time benefit from ATIS use (JHK and Assoc., 17, Inman, 18, and Schofer, 19). These quantitative findings proved problematic for justifying ATIS investment since public sector cost-benefit analysis was focused on in-vehicle travel time savings.

Mitretek showed using HOWLATE that routine users of personalized pre-trip ATIS can realize significant benefit in the form of improved trip reliability with a marginal benefit in the form of in-vehicle travel time savings (Jung, 2). Moreover, Mitretek demonstrated how these savings in trip reliability can translate into monetary savings, and that monetary savings are potentially substantial. Volume II demonstrated via case studies of Washington DC and Minneapolis/St. Paul, Minnesota that given an assumed level of accuracy of ATIS, benefits from improved trip reliability to a significant number of commuters would far exceed the cost of their subscription to a proposed personalized ATIS using current travel time data sources. Thus, public funding toward regional ATIS can prove cost-beneficial under the levels of ATIS accuracy employed in the study.

Predicated on the demonstration of potential benefit of ATIS to users and to improving transportation systems efficiency, significant ATIS investment has already occurred, particularly in the public sector. Within the United States, 26 metropolitan areas provide automated telephone services to distribute freeway travel times (Gordon and Trombly, 3). As of 2001, over 35 metropolitan areas provide freeway travel times or speeds via the internet (www.itsdeployment.ed.ornl.gov, 4). More recently, under the federal mandate for a national

traveler information number (http://www.its.dot.gov/511/PDF/511_overview.pdf , 5), public transportation agencies continue their regional ATIS efforts with more significant investments planned toward larger, more comprehensive deployments. Estimates of the cost of implementing and maintaining a 511 traveler information service range from $60,000 to $600,000 per year, only considering the telecommunications costs.(ICDN 2001 http://www.nawgits.com/icdn/511_wright.html, 20) Yet, to date, little work has been done to help guide cost-effective ATIS investments.

Aiming for greatest user benefits is fundamentally predicated on fostering a sufficiently large user base that experiences a benefit from the service. However, user benefit is highly dependent on the accuracy and the level of coverage of ATIS. That is, given commuters can easily get traffic information, then the accuracy and coverage of the information will dictate whether commuters will be able to realize improved travel reliability and predictablility. If the information does not cover significant portions of a commuter's trip, or the information is not reliably accurate; then, the commuter will not use it. But at what point does an ATIS become accurate enough or provide enough coverage to garner a net user benefit?

In making deployment decisions, planners need to understand these issues and be able to assess where their system is now, where it needs to be to prove useful, and how to make these decisions in an environment of limited data. In this volume we apply the same fundamental methodology of HOWLATE to assess the sensitivity of user benefits to the accuracy of the ATIS system and to explore how benefit varies across some basic coverage deployment strategies.

1.2   Overview of the HOWLATE Methodology

The HOWLATE methodology brings together the necessary data for the implementation and analysis of large-scale simulated yoked studies. The simulated yoked study is an experiment wherein the trips of two drivers; having the same origin, destination, desired arrival time and normal route; are repeated in simulation across many days. The commute of one driver remains fixed while the commute of the other driver varies based on information he receives from an ATIS. The objective of both of these commuters is to arrive at their destination on-time.

The HOWLATE methodology consists of four modules (Figure 1), the first of which is the travel time archiver. The archiver is a software application that monitors ATIS link travel time reports via the Internet and stores these reports at five-minute intervals. The archiver compiles and saves a daily profile of link travel time by roadway, by time of day, and date over a period of several months.

A key input required for simulated yoked studies is statistical distributions of error between the ATIS link travel time reports and observed travel times. The distributions of error, combined with the ATIS travel time report profiles collected by the travel time archiver, facilitate the construction of multiple "actual day" profiles through independent Monte Carlo trials. Since we cannot know precisely what the actual travel times were on the roadway links, we randomly sample from a set of likely values. Each random sample is analyzed as if it were the actual travel times, and is called a realization of the Monte Carlo trial. Multiple realizations are constructed from each day in the travel time archive and passed to the yoked study simulator.

In order to conduct a simulated yoked study trial, habitual time of trip start and route choice must be determined for the non-ATIS traveler. To facilitate the identification of habitual time of trip start and route choice, the ATIS travel time archive is separated into two periods: training and evaluation. The training period represents the time period in which non-ATIS drivers settle into habitual travel choices that meet a target on-time reliability threshold. This is modeled in the travel habituation module (Figure 1) by obtaining a single realization ("actual day profile") for each of the days in the training period data. Average link travel times at five-minute intervals are obtained across all days in the training period using the actual day profiles. Fastest time-variant paths and associated path travel times are then identified using the technique of (Kaufman, 21) with respect to each origin-destination-target time of arrival. These fastest paths with respect to average travel times are selected as the habitual route for ATIS non-users. Using average travel times to determine habitual route choice is straightforward and computationally efficient. We do not know, however, how realistically this assumption mirrors this aspect of traveler behavior. More complex habituation modeling can be incorporated as a component of HOWLATE when additional empirical data become available.

EXTERNAL INPUTS TO THE HOWLATE PROCESS

ATIS Travel Time Reports

Travel Time Error Distributions

Roadway Network Data

HOWLATE MODULES

TRAVEL TIME ARCHIVER

TRAVEL HABITUATION MODULE

YOKED STUDY SIMULATOR

OUTPUT POST-PROCESSOR

training period data

Habitual Trip Timing and Route Choice

September 3
September 2
September 1

Travel Time and On-Time Reliability Performance Record for Each Yoked Pair

Day 3
Day 2
Day 1

Link Travel Time Profiles by Time-of-Day and Date

evaluation period data

ATIS impacts such as trip time, lateness, etc...

HOWLATE GENERATED INPUTS /OUTPUTS

Figure 1-1   Overview of HOWLATE Methodology

We estimate travel time variability for each habitual path by computing the variability of its travel time over the days in the training period. To determine the time of habitual trip start we first subtract the average habitual path time from the target arrival time. We then subtract an additional time buffer proportional to the amount of travel time variability and level of on-time arrival confidence. The buffer size is computed under the assumption that day-to-day variation in travel times in the training period is normally distributed. Travelers who are very concerned about being late choose larger time buffers to produce a higher probability of being on-time. Thus, a traveler with a 95% on-time reliability requirement has a larger time buffer for variability than traveler with an 80% on-time reliability requirement.

After habitual routes and trip start timings are determined in the travel habituation module, one realization of travel congestion in each day of the evaluation period is generated. Details of the experimental (ATIS) and control (non-ATIS) travel behavior policies are set for all origin-destination-target time of arrival combinations in the network. Details include the on-time requirement for the ATIS non-user, as well as the desired flexibility of the ATIS user to adjust trip starts in real time. ATIS user preference to remain on the habitual route is modeled using a travel time threshold. The ATIS service does not contact the user about diversion from the habitual path unless a faster alternative path is predicted to result in greater time savings than the threshold value.

In addition, ATIS users discounts or inflates the estimates of travel time provided by the ATIS service based on the observed accuracy of those reports in the training period. For example, if reports during the early morning periods frequently underestimated the experienced travel time of the commuter during the training period, that user would likely begin to adopt the position of "when they say it's going to be 45 minutes, I know that it's really going to be 60 minutes." For each origin-destination and time of arrival, an ATIS adjustment factor is computed based on experience in the training period.

Simulated yoked trials are conducted using a single Monte Carlo realization for each day in the evaluation period. The ATIS non-user departs from the origin at the habitual trip start time and traverses the network on the habitual path (no diversion). The ATIS service identifies a suggested trip start time by checking the travel time on the current fastest path. The first check is initiated at a set time (e.g., 30 minutes) prior to the habitual start time. The service postpones notifying the user about a trip start by five minutes if taking the current fastest path is projected to provide an arrival at the destination earlier than a set arrival window (e.g. 10 minutes) compared to the scheduled arrival time. When a trip can no longer be postponed, the service alerts the user of the projected trip start time and the fastest path (subject to the habitual route preference threshold). HOWLATE assumes that the ATIS user adopts the suggested trip start time and traverses the network on the suggested path. Note that the service may also contact the traveler to suggest trip start timing later than the habitual start time if congestion conditions are lighter than normal during that particular day. An en route guidance supplement to the basic pre-trip service can also be modeled.

In-vehicle travel time, arrival time, and other metrics are computed for both the ATIS user and the ATIS non-user by traversing the roadway network using the time-variant travel times associated with the actual day realizations. For comparison, an optimal travel time duration and trip start timing (corresponding to a perfectly timed arrival at the destination) is also determined in a separate calculation by applying the method of (Kaufman, 21). by fixing the time of trip end at the destination at the target arrival time and working backward in time until the origin is reached. A record for each yoked trial is generated and these records are assembled into daily profiles, one for each day in the evaluation period.

These records of each simulated yoked trial are then analyzed in the output post-processor module. (Figure 1-1) The post-processor accumulates performance measures such as on-time reliability and in-vehicle travel time for ATIS users and ATIS non-users. These performance measures can be separated out by records from peak or off-peak periods, or by trip features such as trip length. A full description of the set of performance measures developed is presented in Section 2.3

Additional realizations of traffic conditions in the evaluation can be analyzed by generating a new set of "actual" conditions through random trial. Note that because of the randomness inherent in the Monte Carlo technique, a traveler may be on-time in one realization and late in another, even though they are both representations of what might have happened on a particular day in the evaluation period.

1.3   Study Hypotheses

The first set of hypotheses for this study is that there exists a unique value level of error at which ATIS information becomes useful, called the "crossover" point of error, and that this crossover point will be higher for cities with greater day-to-day travel time variability than for cities with relatively stable travel times from day-to-day. Moreover, the crossover point of error will be higher during peak periods as compared to the off-peak periods of travel. This set of hypotheses is based on the expectation that with greater trip variability from day-to-day, the lesser the accuracy of the ATIS information needs to be to maintain a given level of user benefit. We also hypothesize that many ATIS systems are likely to be above their crossover point of error and will

test this hypothesis based on limited accuracy data from two cities: Minneapolis/St. Paul, and Washington DC.

A second set of hypotheses pertains to the geographic coverage of ATIS. We hypothesize that there exists near-optimal plans for incremental ATIS deployment wherein the lion's share of the total potential user benefit associated with full deployment can be achieved by an efficient partial deployment at a 20% or 30% level. Identifying a near-optimal plan, however, is expected to be a difficult task based on the set of data accessible to transportation planners considering ATIS deployment. We also hypothesize that incremental deployments based on strategies likely to be used by planners will not be pareto optimal, but will be relatively efficient. We will test this hypothesis through the simulation of an incremental deployment based on observed link travel time variability. Finally, we hypothesize that beyond some level, the marginal benefit of increasing coverage may be minimal. These hypotheses associated with incremental ATIS deployment are explored in Section 4 of this report.

To test these two sets of hypotheses, certain aspects of the HOWLATE methodology had to be altered. For example, the ability to model and evaluate partial ATIS network deployments had to be designed and implemented. Section 2 presents revisions and extensions made to the HOWLATE process from the algorithm initially implemented in Jung et al, (2). In addition Section 2 provides an overview of the parameters varied or held constant throughout the tests and the measures of effectiveness used to determine benefit. Special attention is paid to the process by which various measures are addressed in the computation of dollar-valued disutility (Small, et al., 6).

2 EXTENSIONS AND REVISIONS TO THE HOWLATE METHODOLOGY

In order to test the hypotheses posed in Section 1.3 and to incorporate more realistic travel behaviors for ATIS users, the HOWLATE methodology required two modifications and an enhancement. This section provides detail on those enhancements as well as key parameter settings held in common or varied across experiments presented in Sections 3 and 4.

2.1 Variable ATIS User Target Arrival Window

In modeling the ATIS notification service, once the sum of the current clock time and the ATIS calculated current trip time generates an expected trip completion within a target arrival window, the ATIS service notifies the user to depart. The ATIS target arrival window does not vary by trip duration or trip variability in the previous HOWLATE method. The target arrival window in Wunderlich and Jung (1, 2) was set at 10 minutes to be in sync with a key performance measure, the just-in-time arrival reliability. The just-in-time reliability measures the frequency of being neither very early (10 or more minutes early) or late.

Based on this regime of a constant target arrival window, very short trips tend to routinely arrive a few minutes early. For example, assume a trip with scheduled arrival at 8:00am required 5 minutes for travel, and the habitual departure time is 7:55am—indicating that the travel time does not change from day to day. The ATIS scans departures and suggests the ATIS user to depart at 7:45 given this would project an arrival within the target arrival window of 7:50am to 8:00am. Thus, the ATIS user would consistently arrive 10 minutes early.

To mitigate this recurrent early arrival effect of the fixed 10-minute arrival window, the arrival window we will set to vary by origin, destination, and time of day while remaining the same from day to day. The target arrival window for ATIS notification is now calculated during the training period, in a similar fashion to the calculation of the habitual commuter buffer. The habitual traveler's buffer time, B_H, is a function of his trip time variability in the training period, σ_H , and his lateness tolerance, i.e., the percentage of trips he needs to be on time. This is shown in Equation 1 where $z_{95\%}$ is the z-statistic corresponding to the probability of an on-time arrival 95% of the time assuming a normal distribution of travel time from day to day. The σ_H is based

on the variability of travel times across the training period for a specific trip defined by origin, destination, and scheduled arrival.

$$B_H = \sigma_H \cdot z_{95\%} \qquad (1)$$

Similarly an ATIS buffer can also be calculated to represent the variability in travel predictions during the training period. But, in calculating the ATIS variability, the ω factor that adjusts the ATIS estimated travel time by the average prediction error in the training period, is applied to the ATIS predicted travel time (equation 2). The ATIS service recommends departure at the first 5-minute departure time where either the arrival time is within the arrival buffer B_a or waiting five more minutes would mean a late arrival assuming the travel time remained the same. Therefore, B_a (equation 3), is now used as the new variable arrival window buffer in place of the fixed 10-minute value.

$$\sigma_A = \frac{1}{n-1} \sum_{i=1}^{n} (t_i - t_i^p \cdot \omega)^2 \quad (2)$$

$$B_A = \sigma_A \cdot z_{95\%} \qquad (3)$$

where

$n =$ number of training days
$t_i =$ travel time on day i
$t_i^p =$ ATIS predicted travel time on day i
$\omega =$ trip time adjustment factor for savvy ATIS user

2.2 Departure Buffer, ATIS Target Arrival Buffer, and ATIS Adjustment Factor Calculations

As stated in Section 1.2, during training, the habitual commuter adds a buffer time to his average trip time to aim for a specific level of on-time reliability. The ATIS user adopts a target arrival buffer time during training. In addition, the ATIS user incorporates the ATIS adjustment factor, ω, to adjust for a bias in the ATIS prediction. The ATIS adjustment factor, ATIS target arrival buffer, and habitual trip buffer in previous versions of HOWLATE were calculated for a departure time that is based on the average travel time over the habitual path. In reality, these buffers and the ATIS adjustment factor are exercised at an earlier departure time, based on both

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the average travel time and the buffer time. Therefore, the buffers and ω should be based on the actual habitual departure time (for example 7:14am) and not the departure time based only on average travel time. This is illustrated in Figure 2.1.
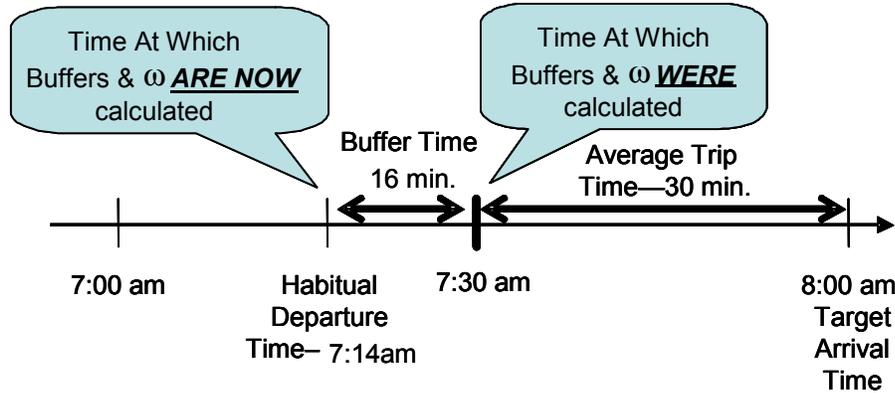
Figure 2-1   Calculation of Buffer Factors and ATIS Adjustment Factor

To resolve this inconsistency, iterative estimates of the three variables (ATIS adjustment factor, ATIS buffer, and habitual buffer) are calculated until the departure decisions of the paired commuters are essentially the same, and yields consistent buffers and ATIS adjustment factor from one iteration to the next. On average, 2 iterations were required to derive these estimates.

2.3   Method for Incorporating Partial ATIS Coverage

In order to test partial ATIS coverage strategies, we first needed to define the ATIS service and user processes associated with partial-trip information. For commuters processing ATIS information that covers only a portion of their trip, we hypothesize that the commuter will use their memory to fill in data gaps to arrive at a full trip travel-time estimate. Conversely, the ATIS service may need to use historic time-variant travel times where no surveillance information exists to derive an entire-trip travel time. To this end during the evaluation period, for each link having ATIS surveillance the ATIS uses will use real-time ATIS travel time estimates. Unmonitored links are assumed to have the average travel time by time of day that occurred during the training period. The ATIS service aggregates links with and without information and reports a total trip time to users. Note that in the case of trips containing links with no surveillance, the average travel time during training is used in notifying users when to depart. Detailed implementation of this heuristic is presented in Appendix A1 of this report.

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2.4 Key Parameters Representing Simulated Commuters

In conducting simulated paired driver trials the ATIS user and non-user both aim for an on-time arrival rate of 95% in all analyses conducted and described in this report. The ATIS non-user is a commuter that is familiar with the network with respect to identifying the best route and departure time, on average. This commuter in previous studies (Jung et al, 2) was called the "F95" commuter. The ATIS user counterpart, called "A95" is also familiar with the network, and furthermore, is aware of the relative inaccuracies of the ATIS. Therefore, the ATIS user will adjust the ATIS report to reflect this awareness (as described in Section 1.2)

Two key parameters related to the F95 and A95 commuters are held constant in all the experiments performed: route diversion threshold, and potential departure window for ATIS users. Another parameter, ATIS error band, is also held constant in the experiment related to ATIS coverage. Following are the specifications for these parameters.

As in Wunderlich (1) an indifference threshold for route switching is set to three minutes, based on the work of (Srinivasan and Mahmassani, 22). The window in which the ATIS service looks to notify the ATIS user of a change in trip departure time or route is centered about the habitual time of trip start. For this study, we assume that the service begins scanning 30 minutes before the trip start time to see if early departure time notification is warranted – and up to 30 minutes after the trip start time for late departure time notification. The link travel time error bands used to generate the Monte Carlo realizations of actual travel times in HOWLATE remain unchanged from Wunderlich (1) as applied to Section 4. Table 2-1 lists these error bands that were determined by conducting a number of travel time runs on I-66 and Route 50 in the Washington metropolitan area (Hardy et al., 7).

Table 2-1   Link Travel Time Error Bands

Facility	Congested Regime		Uncongested Regime	
	Bias	Coefficient of Variation	Bias	Coefficient of Variation
freeway	0%	10%	-10%	25%
arterial	-10%	20%	-5%	5%

2.5 Key Performance Measures

As in Volume I and II (Wunderlich, 1; Jung, 2), we define four core measures of effectiveness: on-time reliability, just-in-time reliability, schedule delay, and travel expenditure, and travel budget. These are a direct measurement of trip outcomes and are defined in the following paragraphs:

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. Just-in-time reliability is defined as the proportion of simulated yoked trials wherein a traveler arrives at the destination node both on-time and no more than 10 minutes early. Schedule delay is defined as the difference between the actual arrival at the destination and the target time of arrival. If schedule delay is negative, it is called early schedule delay. If it is positive it is termed late schedule delay.

Travel expenditure is defined as the time between trip start and the target arrival time, as well as any late schedule delay. Travel expenditure is the same measure defined in Wunderlich (1) as travel budget. We reserve the term travel budget in this study to refer only to the amount of time between trip start and target arrival time.

Disutility, a measure incorporating trip duration, and schedule delay proposed in Volume II is also applied in this document. Dollar-valued disutility provides 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. (6). The disutility of in-vehicle travel time is set at $3.38/hour based on their research. The cost of early arrival is a quadratic function of the magnitude of early arrival. The cost of a late arrival is a linear function of the magnitude of late arrival plus a one-step penalty for arriving late. Note that the cost of late or early arrival is not sensitive to the duration of the trip, however. That is, 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 functionally as:

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

        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 are:

α: $0.0564/min. (linear cost of in-vehicle travel time)
β_{SDE}: $-0.023/min (linear component of quadratic early cost)
β_{SDL}: $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)

Figure 2-2 illustrates the shape of the dollar-valued disutility function for both 30 and 60 minute duration trips.
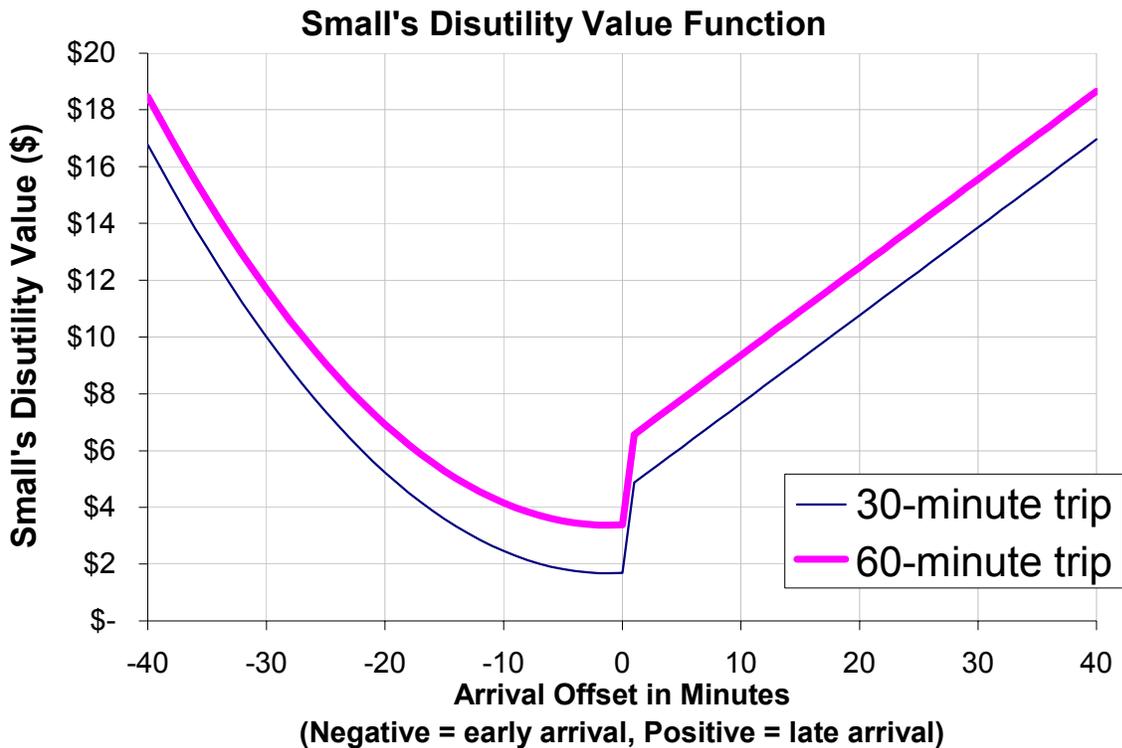
Figure 2-2   **Dollar-Valued Disutility Function based on Small et al.**

2.6   Notification ATIS Services and Current ATIS Services

It is important to note that the ATIS benefit assessment conducted here is not an evaluation of the current SmarTraveler system in Washington DC or in St. Paul/Minneapolis, nor the PEMS system in Los Angeles. What is modeled in HOWLATE is a prospective notification-based

service based on the same basic data collected and disseminated by the two service providers. Users of the two service providers access the service through the Internet and must construct their own estimates of travel time on multi-link routes. Seen this way, the notification service we prospectively model here manipulates the travel time data to suggest changes in trip timing and route choice in manner that is possible but time-consuming for the current ATIS user. Further, the accuracy of the data is based on comparisons of SmarTraveler reported travel time and experienced travel time in instrumented probe vehicles on only two facilities in the Washington area. Findings from other more comprehensive studies of ATIS accuracy indicate that the error bands used herein may be somewhat optimistic. The overall result is that the benefit estimates made in this report are likely to be somewhat higher than would be realized by a user of the SmarTraveler system in either of the two metropolitan areas studied.

3 IMPACT OF ATIS ACCURACY ON USER BENEFITS

An important consideration when evaluating the benefit of ATIS is the accuracy of the information provided to the user. Intuition suggests the more accurate the information the more likely a user is to realize benefit from using the service. In this section, accuracy will be examined with respect to point-to-point travel time estimation.

No ATIS service is perfectly accurate. Traffic advisory services may be out of date or omit important events. Services relying on direct measurement of traffic conditions depend on reliable and accurate sensors. With the exception of automatic vehicle identification (AVI) systems, providing users with point-to-point travel times involves some sort of estimation procedure, most often from spot speeds measured with loop detectors. AVI systems are not free from error either. These systems read electronic tags on individual vehicles at successive detection stations to directly measure travel times of equipped vehicles. However, each detection station must have precisely synchronized clocks to accurately measure travel time, and a high enough proportion of vehicles must be equipped with tags in order for travel time estimates on a segment to be updated often enough. Even if detection was perfect, however, rapidly changing conditions can cause advisory information to the public to be inaccurate by the time it is received. Furthermore, traffic measurements are necessarily averages over a number of vehicles passing a point or traversing a segment. By preference, individual drivers may travel faster or slower than the average flow of traffic so that even if average conditions are measured without error, there will still be some inaccuracy in an individual's travel time or speed estimates.

ATIS accuracy can be improved in a number of ways. One way is by increasing the density of sensors already deployed (e.g., one per ½-mile from one per mile). Another is by improving sensor maintenance. Loop detectors have finite life spans so the quality of the information from a regional ATIS is likely related to the percentage of loops in service at any given time. Some systems also require periodic calibration. Single loops may be used to measure speeds only if an average vehicle length is known. However, this involves tracking the proportion of truck traffic, which varies by location and time of day, another source of inaccuracy. (Rice & Van Zwet, 23)Finally, accuracy may be improved through moving to a more advanced technology. A properly deployed and well-maintained AVI system with adequate market penetration is likely to

provide better estimates of point-to-point travel times than a system based on loop detectors because it measures travel time directly.

Clearly though, improving the accuracy of an ATIS comes with a cost. Perfect accuracy is the ideal, but in the real world such a goal is not realistic. In reality there is a continuum of accuracy that ranges from excellent to good, to good enough, to not good enough. Moving up this continuum costs money, that otherwise could be used for other projects. Decision makers need to first know if their ATIS deployments are accurate enough to provide benefit to their users. Secondly, they need to know whether moving up the accuracy continuum is cost effective relative to other available spending options.

In summary, the purpose of this study is to identify the acceptable level of estimation error in point-to-point travel times reported by a regional ATIS to maintain consistent benefits to users based on performance measures pertaining to on-time reliability. Furthermore, we want to measure the sensitivity of benefit to that error, i.e., the expected result of improving the accuracy of a deployment by one percent. Finally, we want to determine the value of travel time prediction. The goal of this evaluation is to take a step toward a larger decision framework that will help ITS decision makers wisely deploy regional ATIS services based on their true costs and benefits.

This section is organized as follows: Section 3.2 reviews the relevant literature and provides the methodology for this study; Section 3.3 describes the experimental design; Sections 3.4 and 3.5 show the findings regarding the critical point of ATIS error and the value of prediction, respectively; and Section 3.6 gives conclusions and future work. Findings and conclusions are based on the use of data from three cities: Los Angeles, CA; Washington, D.C.; and Minneapolis/St. Paul, MN (hereafter referred to as the Twin Cities).

3.1 Literature Review

The literature pertaining to accuracy and ATIS benefit can be partitioned into two types of studies. The first deals with the measured accuracy of existing ATIS deployments and current sensor technology. The second uses simulation to try and measure the effect of inaccuracy on user benefit.

A pair of studies measured the accuracy of ATIS deployments. In a loop detector-based deployment in San Antonio, Texas, the algorithm converting loop detector speeds produced link travel times that differed from probe vehicle travel times with a coefficient of variation of 17% in the AM peak and 2.7% in the off peak (Quiroga, 24). This is prediction error since it is a comparison between the predicted link traversal time at link entry and experienced travel time. Another study measured the accuracy of AVI in Houston, Texas, against probe vehicles (Eisele & Rilett, 25). They found that for the corridor studied, the AVI-measured travel times for individual probe vehicles matched their true travel times to within 1-2%. However, for an ATIS application, reported travel times depend on sufficient market penetration to keep estimates up to date and to smooth variations between drivers.

An extensive evaluation of different sensor types was conducted on a test bed on Route 6 in College Station, Texas (Middleton et al., 26). Sensors of all types were evaluated based on several criteria such as presence measurement accuracy, speed measurement accuracy, installation and maintenance costs, etc. A microwave detector was found to consistently measure speeds to within 10%. An acoustic sensor was found to have an 8% coefficient of variation about the true speed. Finally, a video image detector (VID) was found to have a coefficient of variation of 12% about the true speed. These are measurement accuracies and do not include possible errors from extrapolating spot speeds to link speeds, the frequency with which estimates are updated, or sensor reliability.

A travel time study in the Washington, D.C., metropolitan area, was designed to test the accuracy of the SmarTraveler internet-based travel time estimation service. (Hardy et al., 7) SmarTraveler manually estimates travel times based on qualitative incident reports, weather, and phone calls from regular commuters. For this study, a probe vehicle equipped with a GPS-Based Odograph Prototype traversed a freeway (I-66) and parallel arterial route (U.S. 50) into Washington, D.C., from suburban Virginia. These trips were made over a period of several days and during a variety of times throughout the day. Data was collected on link travel times. This data was then compared to the corresponding SmarTraveler reported time. It was determined that the SmarTraveler service overestimated travel times on the freeway by 13% and 21% on average in congested and uncongested traffic, respectively. On the arterial, the service underestimated travel times by 18% in congested traffic and overestimated travel times by 14% in uncongested traffic.

Travel time coefficient of variation on the freeway was found to be 17% and 9% in congested and uncongested traffic, respectively. On the arterial, those values were 26% and 6%.

A second study of SmarTraveler, this time in the Twin Cities metropolitan area, had similar findings (Toppen et al., 9). The ATIS travel time error was based on archived data from the SmarTraveler web site and probe vehicle runs undertaken as part of an unrelated ramp metering evaluation study (Cambridge Systematics, 8). The error was found to be lower during uncongested conditions. However, even then the service overestimated travel times, on average, by 16%. The error covariance was 24%. During congested conditions, defined as times when the reported travel time was more than 30% higher than the free flow travel time, the service overestimated travel times by 32%, on average, and the error covariance was 33%.

Several other previous studies have sought to identify the effect of information accuracy on ATIS benefits (Glassco, et. al., 27; Oh & Jayakrishnan, 28). The objective of these studies was to find the market penetration required for route guidance systems to be beneficial. However, they also tracked information accuracy, though this inaccuracy was due to the redistribution of traffic on the network in response to the information rather than inaccuracy in the primary measurement and estimation of travel times. In the first of these studies, information given to vehicles equipped with route guidance systems was assumed to be perfect. The second of these studies used a dynamic traffic assignment model. Due to driver response to the route guidance, the information was not necessarily 100% accurate because the decisions made by drivers of other equipped vehicles may alter the forecasted travel time made by the route guidance system. Route travel time estimation error was at a minimum at 10-20% market penetration of probe vehicles. When estimates were updated every 30 seconds, route travel time estimation error was stable even as market penetration went to 100%. At update intervals of 5 minutes, however, route travel time estimation error increased as market penetration increased beyond 10%. The authors explain that when a high proportion of traffic is responding to route guidance, "over-shifting" may occur. When update intervals are long, the route guidance system is unable to correct itself quickly enough. In terms of travel time savings, which was the key measure of effectiveness of the route guidance system, users of the route guidance ATIS saw a 13% travel time savings over non-users at market penetrations below 20%. At this point, the route travel time estimation error was approximately 13%.

In summary, there are few published studies of sensor and ATIS deployment accuracy, though it appears that AVI is the most accurate technology provided there is adequate market penetration and the system is properly calibrated. Point sensors tend to measure speeds with approximately 10% error, and based on the study in San Antonio, this can result in an error of approximately 17% in point-to-point travel time estimation from point speeds. Since the majority of ATIS deployments employ point speed sensors, this figure may be the best benchmark for the state of the current technology. Many studies of ATIS benefits focus on the sensitivity of benefit to market penetration rather than the accuracy of the ATIS information. They do show that when market penetration is high, the effect of user response to travel time estimates may detrimentally affect the accuracy of those estimates. However, given that market penetration for ATIS services of this type is far from the point where this has an impact, the accuracy of travel time estimates coming from sensors should be given primary consideration.

3.2   Experimental Design

We use the HOWLATE methodology (as described in Section 2) to identify ATIS user benefits under varying levels of ATIS accuracy. In conducting this experiment, we first make a distinction between measurement and prediction error as they pertain to ATIS accuracy (Section 3.3.1). We then define specific study objectives and hypotheses in Section 3.3.2. Based on these objectives, we define the dependent and independent variables of the experiment in Section 3.3.3. Section 3.3.4 describes how travelers behave in the presence or absence of information while Section 3.3.5 lists the sources and content of the data. Finally, in Section 3.3.6, we outline the key limitations of the selected method of experiment.

3.2.1   Types of Error

Based on the model of pre-trip, travel time-based ATIS used in this study, ATIS users receive an estimate of their travel time on a recommended fastest route, and then depart on their trip with the goal of arriving just in time. The accuracy of the service, from their perspective, is how closely the travel time reported by the ATIS matches their actual travel time. The percent difference will be defined, for purposes of this paper, as prediction error, because it has a predictive element; in order to be accurate, it has to factor how conditions will change over the

course of the trip. What we will define as perfect prediction, accurately predicts the ATIS user's travel time and thus, the exact time he will arrive at his destination.

In reality, however, the future is unknown. Any number of weather, accident, or other type of events could occur on a traveler's route between when the travel time estimate is made by the ATIS and when he arrives at his destination. What may have been an accurate estimate of traffic conditions when it was made could turn out to be very inaccurate by the time the trip is completed. Travel time estimation based only on currently known information, i.e., current measurements from sensors, will be defined for purposes of this paper, as measurement. The percent difference between the measurement estimate and the actual travel time based on prevailing conditions is measurement error. Perfect measurement reflects perfectly performing sensors, and if the measurement is point speeds (e.g., loop detectors), perfect translation from point measurements to travel time over a segment. However, it does not necessarily mean a perfect estimate of travel time for an ATIS user.

Errors in a travel time estimate can be divided into two components: bias (systematic) error and noise error. Bias is the tendency to over or under estimate, on average. For instance, if speeds measured from single loop detectors are based on an assumption of average vehicle length that is too low, speed estimates will be systematically high. Given a well-calibrated system, this could potentially be eliminated. Moreover, regular users of ATIS are likely to adjust ATIS travel time estimates to account for bias error. Therefore, we will only consider noise error in this study.

When there is no bias, the remaining error is noise, where the estimate is equally likely to fall above or below the true value. The lower the noise error, the higher the probability the estimate will be close to the true value. Figure 3-1 (top) illustrates the nature of this noise component through a series of random draws. This figure shows, for the same trip at the same time on the same day, 100 hypothetical scenarios of what the estimate could have been, given two levels of accuracy. This is prediction error – error relative to the actual travel time.

Figure 3-1 (bottom) shows the distinction between prediction error and measurement error. Both consist of the noise error component only (no bias). The difference is what the error is relative to. Measurement error is noise relative to perfect measurement. However, if conditions change over the course of the trip, even perfect measurement is inaccurate relative to the actual travel time.

This difference can be referred to as the effect of aging – the information becoming out of date. Therefore, measurement error has one component of error relative to perfect measurement (noise), but two components relative to the actual travel time (noise and aging). Figure 3-1 (bottom) shows these two components of error relative to the actual travel time.
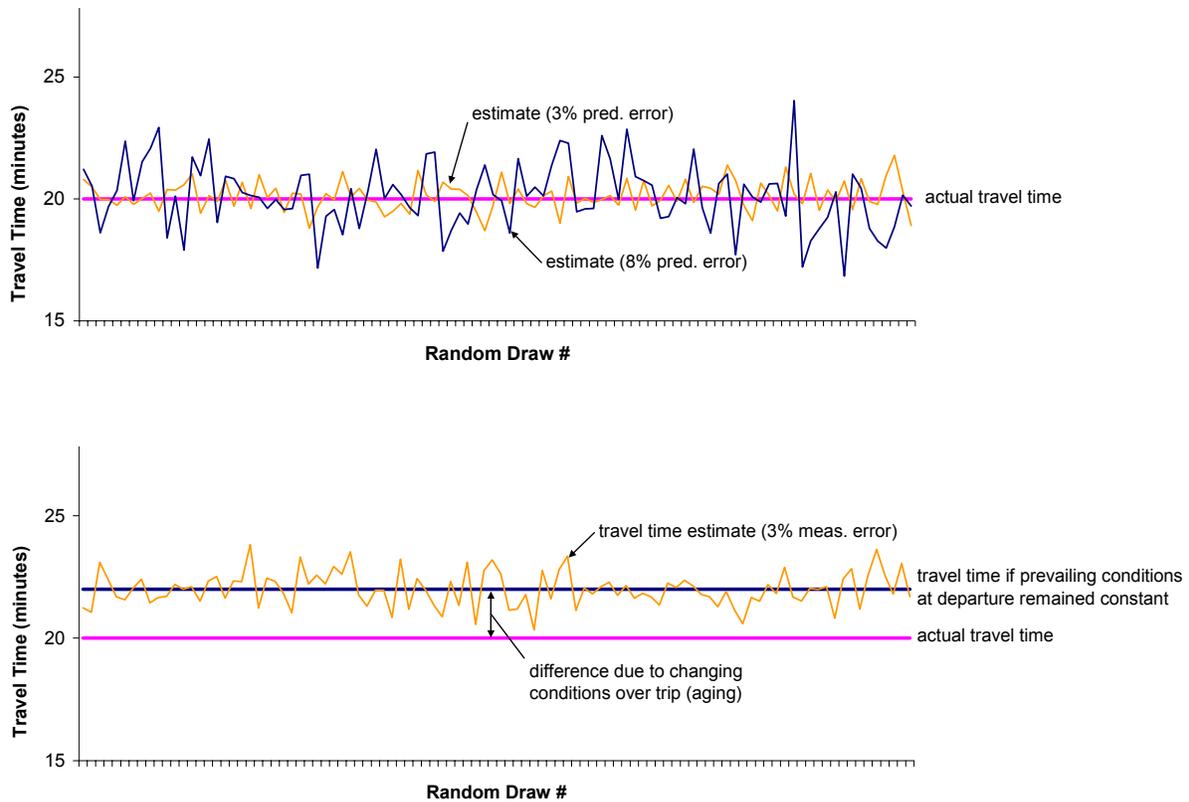
Figure 3-1. **Graphical Depiction of Prediction Error (top) and Measurement Error (bottom)**

Figure 3-2 shows this in a different way. It can be seen in Figure 3-2 (top) that regardless of factors such as average trip length and system variability, the travel time prediction error is equal to the noise error. For travel time measurement, however, error relative to the actual travel time increases with factors such as system variability and average trip length because these affect the aging component. The effect of aging is depicted in Figure 3-2 (bottom). As aging error increases, the user realizes less benefit. This reduction in benefit is the value of prediction. The

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relationship between system variability and trip length and aging is merely hypothesized at this point, but is included here to help clarify the definitions used in this study.
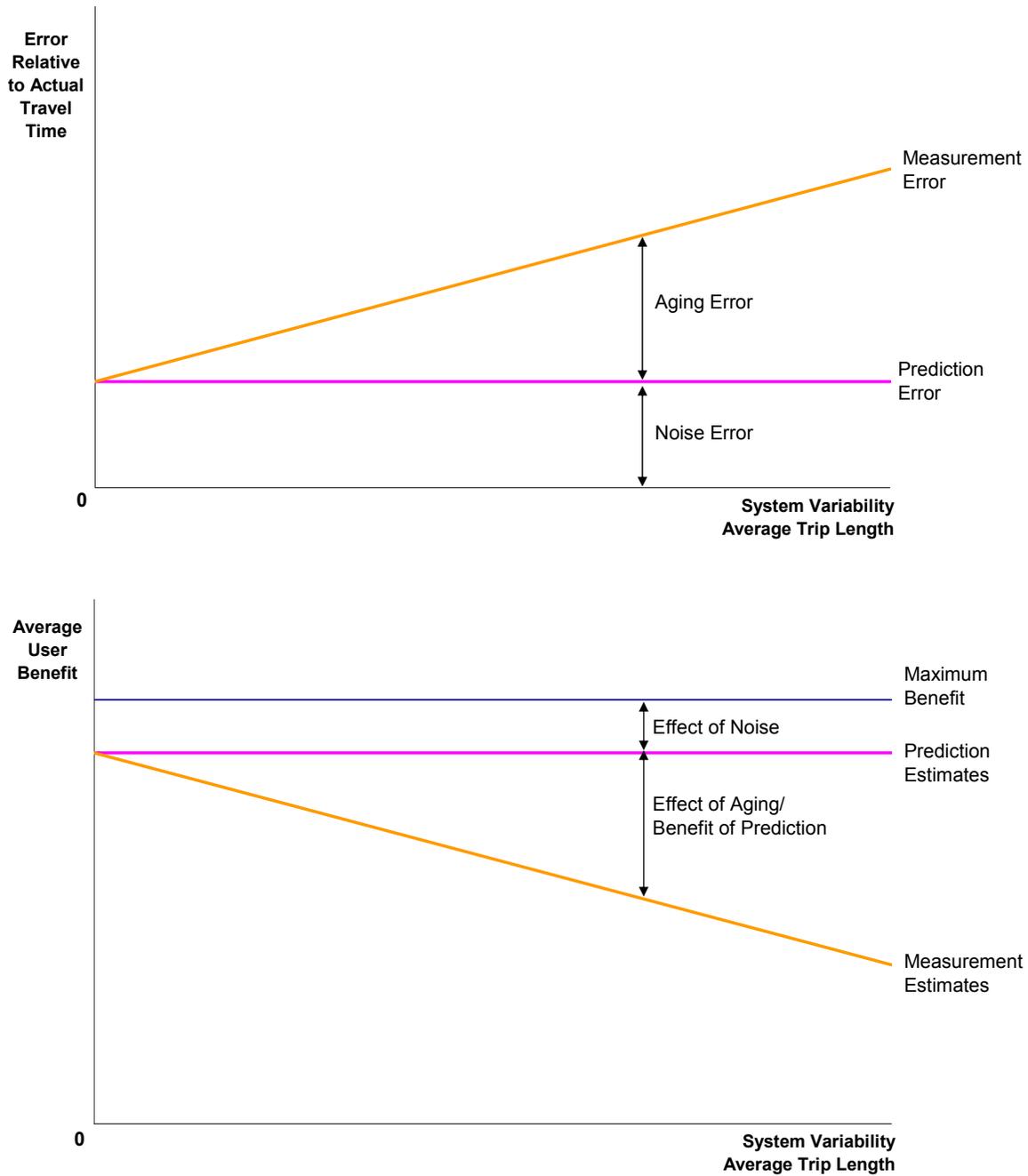
Figure 3-2. **Graphical Depiction of Error Components (top) and Hypothesized Effect on User Benefit (bottom)**

3.2.2   Study Objectives and Hypotheses

There are three primary objectives to this study. The first is to identify the point of error at which ATIS becomes useful, also called the "crossover" point of error, e*. By definition, when error is less than e*, the information is accurate enough for regular use of ATIS to provide benefit for the average aggregate trip. When error is greater than e*, it is more advantageous to not use ATIS, but rather to maintain a habitual route and departure time irrespective of day-to-day fluctuations. It is expected that when day-to-day travel time variability is high, e* will be greater and as a result, users will still benefit at higher levels of ATIS error. When variability is low, it is harder for ATIS to improve upon habitual behavior because travel times are more predictable. As a result, it is expected that the service must be more accurate to provide benefit when there is less variability.

The second objective is to determine the marginal benefit at any point of ATIS error. It is expected that as error approaches zero (100% accurate), each percentage of accuracy gained will result in less and less benefit and at higher levels of error (lower accuracy) each percentage point of accuracy gained will provide a greater benefit improvement.

The third objective is to determine the value of travel time prediction. For this experiment, benefits will be evaluated with an ATIS where travel time estimates are based on measurement. The independent variable is the same as previously: ATIS noise error. However, as described previously, when travel time estimates are based on measurement, the noise error is relative to measurement. Therefore, relative to a user's actual travel time, the estimate will include additional error from aging. By comparing user benefits with the same amount of noise error, we can determine the effect of the aging component of measurement error. This will determine the value of eliminating or reducing this aging component, which in turn, is the value of prediction. We hypothesize that travel time prediction will have some value relative to measurement and that that value will depend on system variability and trip length. However, the majority of ATIS benefit will be achievable from measurement alone.

3.2.3   The Dependent and Independent Variables

To test the effect of ATIS error on user benefit, multiple benefit analyses are conducted, each with a different level of noise error. Noise error is assumed to be normally distributed with

coefficient of variation, e. The first set of experiments considers error to be prediction error. The travel time estimate Test(t), calculated for a trip, is therefore:

$$T_{est}(t) = T(t) + T(t) \cdot e \cdot r \tag{1}$$

where T(t) is the actual travel time given a departure time of t, e is the error, and r is a standard normal random variate. A single random number, r, is drawn for each trip and applied to the actual travel time, T(t), at every decision point, t, until departure. The error, e, is therefore the coefficient of variation of a normal distribution of travel time centered on T(t). Because error is introduced on the trip level, no portion of the network is assumed to be more accurate than any other. A trip is defined as having a unique origin, destination, and target time of arrival on a given day.

A second set of experiments is designed to determine the value of prediction. These experiments, consider error to be measurement error. In these cases, error is introduced the same way with the exception that T(t) in Equation 1 is the travel time based on prevailing speeds. The specified level of error is therefore the amount of noise relative to perfect measurement as described in Section 3.3.1.

The dependent variable is the average utility improvement from ATIS across all possible recurring trips across the network. For each trip a utility (or disutility since travel is a cost) can be calculated based on the utility function (Small et al., 6) described in Section 2. Utility was chosen as the primary trip performance measure because it does the best job of incorporating in a single value three aspects of a trip's cost: in-vehicle travel time and earliness or lateness of arrival. Improvement in utility is the disutility reduction that comes from using ATIS, the difference between the disutility of the ATIS user and the non-user for the same trip.

3.2.4   Traveler behavior profiles

The traveler profiles used in this study were F95, the habitual traveler, and A95, the ATIS user. Descriptions of these traveler profiles summarized in Section 2.4 and are presented in greater detail in Jung et al, (2). All information is received pre-trip and is in the form of an estimate of the travel time of the intended trip and a recommended fastest route. ATIS users (A95) allow themselves an arrival buffer proportional in size to the mean squared difference between the

ATIS reported trip travel time and the true travel time during the training period. Clearly, when travel time estimation error is high, the ATIS user will be conditioned to this error and will therefore leave a larger arrival buffer. The result is that when error is high, ATIS users maintain their target on time reliability (95%) but tend to arrive very early.

3.2.5   Data Sources and Content

The methodology and experimental design of this study are applied to data from Los Angeles, CA; Washington, D.C.; and Minneapolis/St. Paul, MN. The data for Los Angeles comes from PeMS, the California Freeway Performance Measurement System, which estimates segment travel times at 5-minute intervals in Los Angeles and Ventura Counties. PeMS estimates travel times from speeds measured by loop detectors. These data are posted to the PeMS website (http://pems.eecs.berkeley.edu, 29) in real-time and stored in a historical archive. The data used in this study were retrieved directly from the archive. The data for Washington and the Twin Cities come from SmarTraveler (http://www.smartraveler.com, 30), which estimates travel times using human judgment in response to weather, incidents, construction, and time of day averages. Travel times were collected from the SmarTraveler website at 5-minute intervals and stored in an archive. Because these travel times are crude estimates of the true conditions, randomization is applied to simulate what the true conditions may have been based on the SmarTraveler estimates (Wunderlich, 1). No randomization is applied to the PeMS ATIS data, however, as they are assumed to be good estimates of the actual travel times.

The training period for Los Angeles is comprised of 42 days from September 20, 2001 through December 19, 2001. The evaluation period is comprised of 100 days from January 10, 2002 through July 1, 2002. In the Twin Cities, the training period is comprised of 39 days and in Washington, 33 days from March through May 2000. The evaluation period is comprised of 176 days in the Twin Cities and 179 days in Washington from June 1, 2000 to May 31, 2001. The difference in number of days in the two cities is due to gaps in the data archiving process.

In Los Angeles, the start time for the analysis is 5:30 A.M. and the ending time is 9:00 P.M. The peak periods were determined from a clustering analysis based on average network speed by time of day, which is the average segment speed, weighted by segment length. They are 6:30 A.M. to 9:00 A.M. and 2:30 P.M. to 6:45 P.M.

In the Twin Cities and Washington, the start time for the analysis is 6:30 A.M. and the ending time is 6:30 P.M., the period of the day for which SmarTraveler consistently provides travel time estimates. The peak periods, calculated in the same way as for Los Angeles, are 7:00 A.M. to 9:00 A.M. and 4:00 P.M. to 6:30 P.M. in the Twin Cities, and 7:00 A.M. to 9:30 A.M. and 4:15 P.M. to 6:30 P.M. in Washington, D.C.

3.2.6 Known Limitations

Three known limitations to this study are a lack of consideration to demand patterns, disparities in data quality, and general difficulty of accurately modeling driver behaviors.

The results of this study do not incorporate regional demand patterns. All possible trips are evaluated, which includes every possible origin, destination and target time of arrival across the geographic region and throughout the day. All trips are then weighted equally irrespective of demand. Two examples show how this is problematic. During the morning peak both inbound and outbound trips are weighted equally even though in reality, demand is greater for inbound trips than for outbound trips (the reverse is true in the afternoon). Secondly, when considering all trips (as opposed to grouping by peak), trips made during off-peak hours are treated with the same importance as peak period trips even though fewer trips are made in the off-peak than during the peaks. The consequence of these two examples is likely to be an understatement of ATIS benefits since it gives undue weight to trips where there is less demand and therefore, less congestion, and these are the trips for which ATIS does not benefit the user as much.

The SmarTraveler data (Washington, Twin Cities) is generally less accurate than the PeMS data (Los Angeles). SmarTraveler's method of estimating travel times from incident and construction reports is less reliable than PeMS's method of direct measurement of traffic from roadway sensors. Furthermore, the SmarTraveler may understate day-to-day variability, a key determinant of ATIS user benefits. This makes comparisons between the cities more difficult.

As with any modeling effort, describing human behavior is a difficult task. The traveler behaviors used in this study, including the ATIS user and the habitual traveler, are meant to be plausible representations of how people actually make travel decisions. However, it is not possible to capture the diversity of response to traveler information that exists across the driving population. Furthermore, the human thought process is complex and often irrational. We were

therefore forced to simplify the route selection and departure time decision processes for modeling purposes.

3.3   Results

3.3.1   The Critical Points of ATIS Prediction Error

Utility improvement from ATIS as a function of ATIS prediction error is shown in Figures 3-3, 3-4, and 3-5 for AM peak trips, PM peak trips, off peak trips and all trips, for Los Angeles, Washington, and the Twin Cities, respectively. The crossover points e* are given in Table 3-1 for each time of day. Error in this case, is relative to perfect prediction.
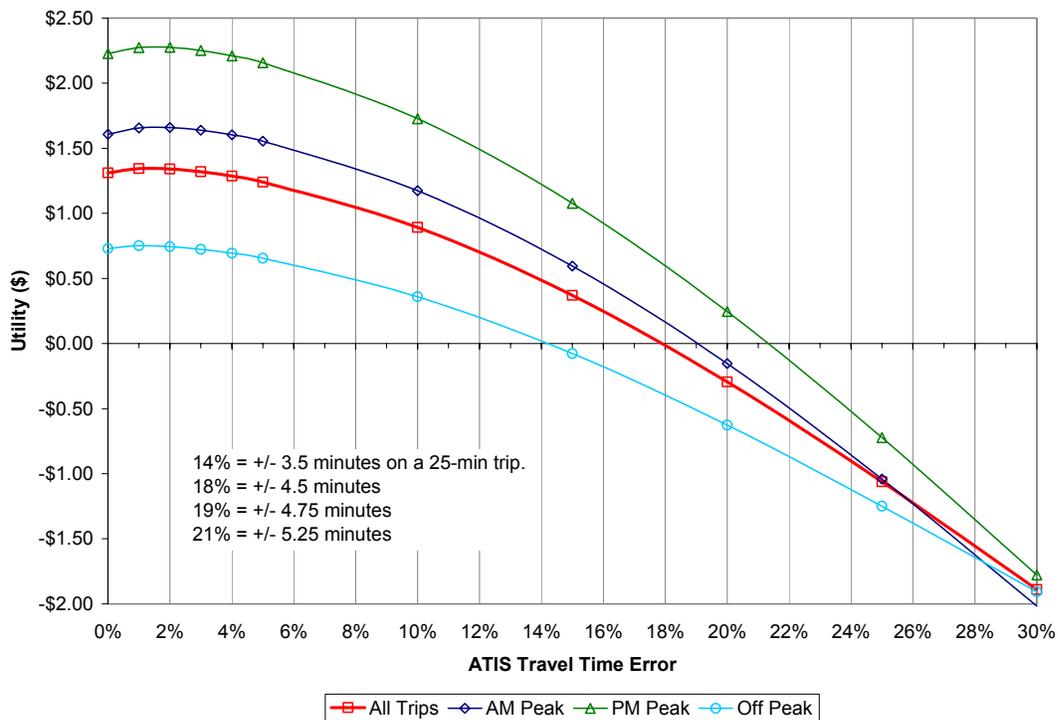
Figure 3-3.   Improvement in Utility as a Function of ATIS Prediction Error – Los Angeles
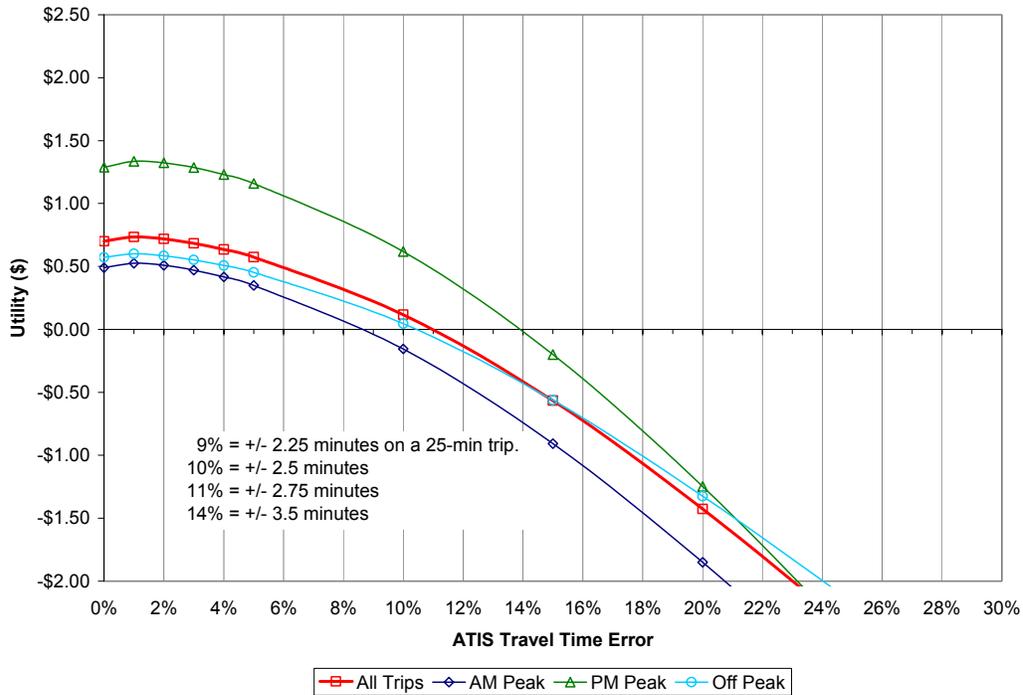
Figure 3-4. **Improvement in Utility as a Function of ATIS Prediction Error – Washington**
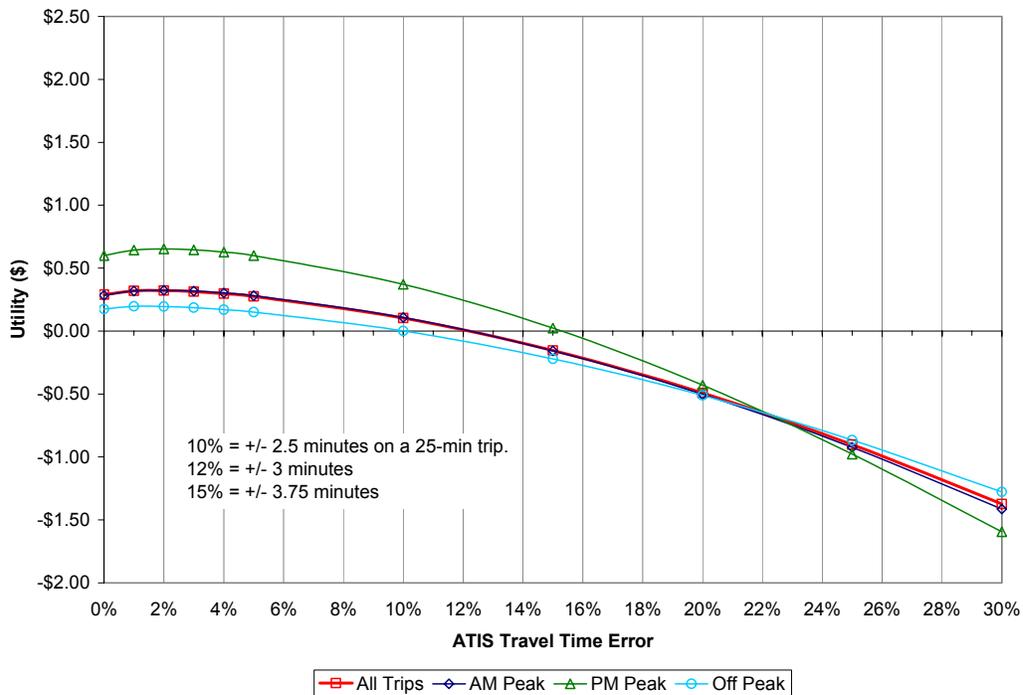
Figure 3-5. **Improvement in Utility as a Function of ATIS Prediction Error – Twin Cities**

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Table 3-1. **Crossover Points of ATIS Measurement Error – All Cities based on On-Time Reliability**

	Los Angeles	Washington	Twin Cities
All Trips	17%	10%	11%
AM Peak	19%	10%	11%
Off Peak	13%	6%	9%
PM Peak	21%	13%	15%

In Los Angeles, the crossover point e*, ranges from 14% to 22%. In Washington and the Twin Cities, it is lower (9-14% and 10-15% respectively). Reasons for this difference can be found in the primary data - link speeds. Average network speed and speed variability by time of day are shown in 3- 6 and 3-7, respectively.
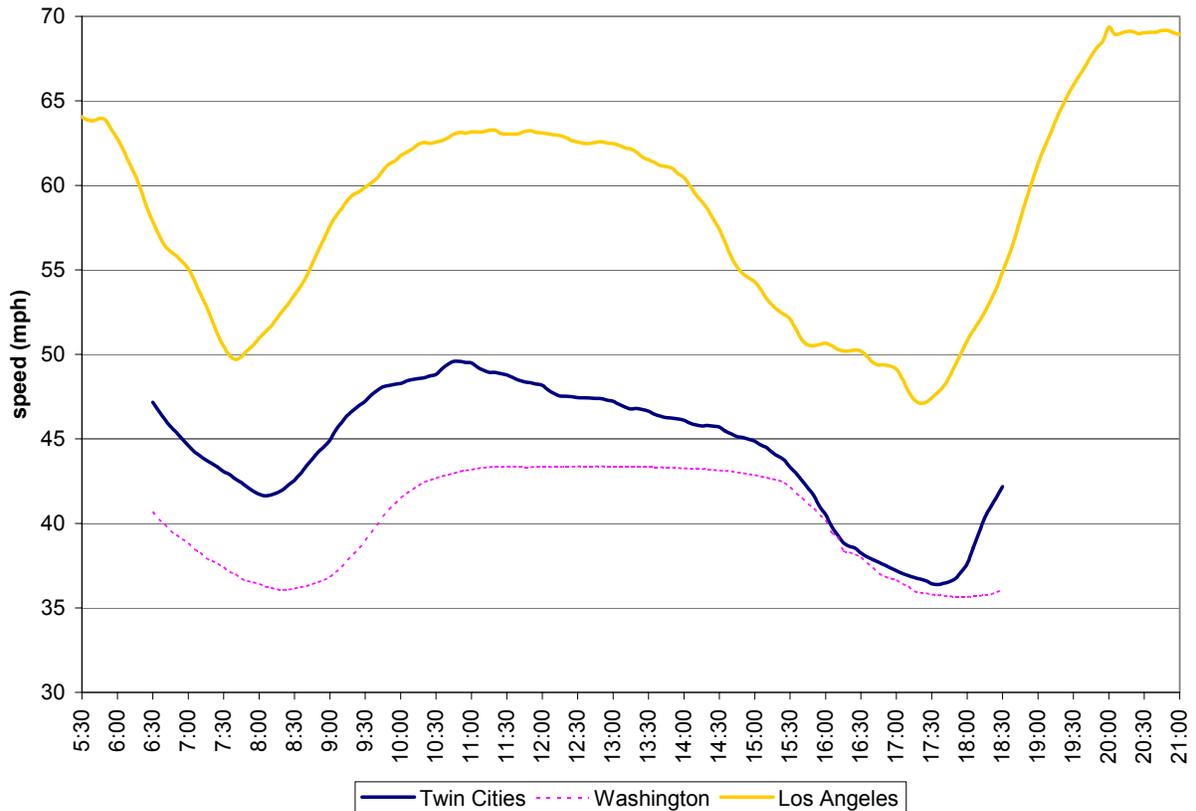
Figure 3-6. **Network Average Speed by Time of Day– All Cities**

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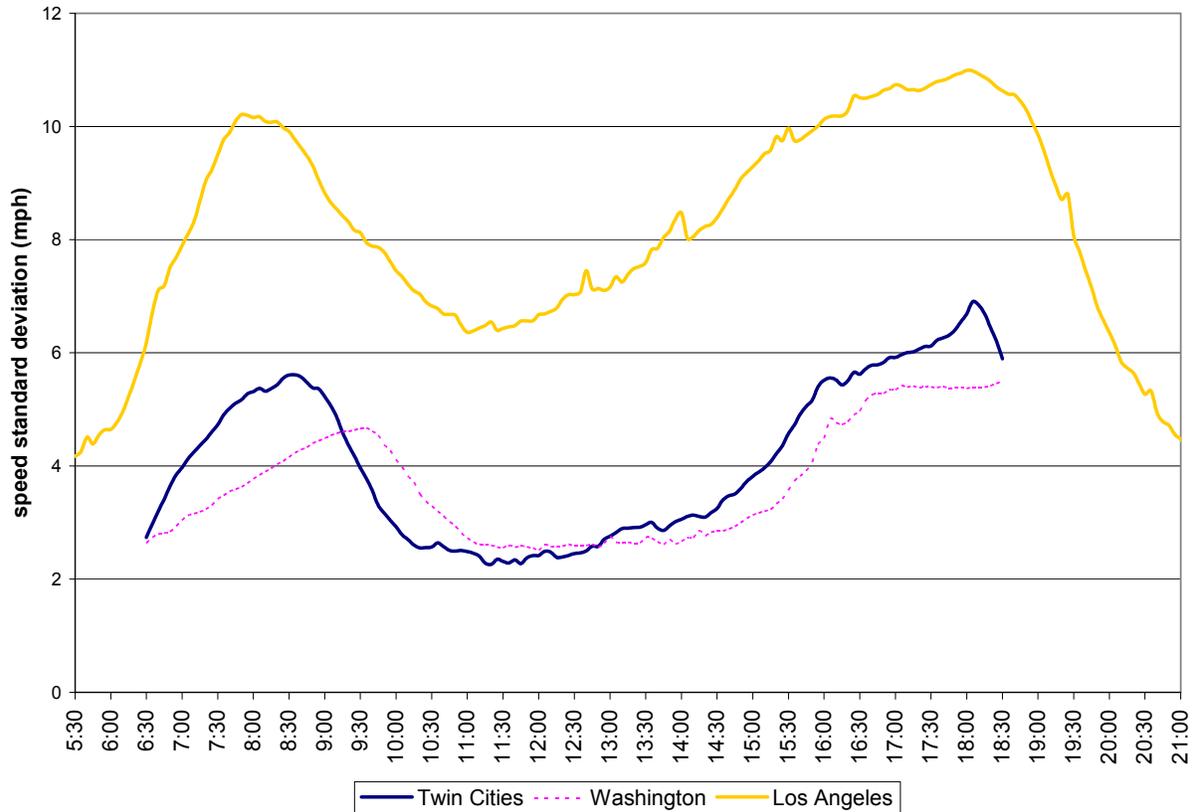
Figure 3-7.   Network Speed Variability by Time of Day – All Cities

For each city, average speed and speed variability are highly correlated. During the peaks average speed decreases and speed variability increases. The crossover point of error also increases during the peaks as shown in Figure 3-8. Above the line, ATIS is beneficial to users in that city, while below the line, it is not accurate enough to provide overall benefit. For any given city, this crossover point may be correlated to average speed, speed variability or both. However, by comparing different cities it becomes clear that it is more highly correlated with speed variability than average speed. Los Angeles, which has the highest variability, also has the highest e* across the day despite having the highest average speed of all the cities. Washington has the lowest network speeds because it includes more arterials than the other cities. This shows that it is not the magnitude of congestion but the variability that is the important factor in determining how accurate an ATIS needs to be.

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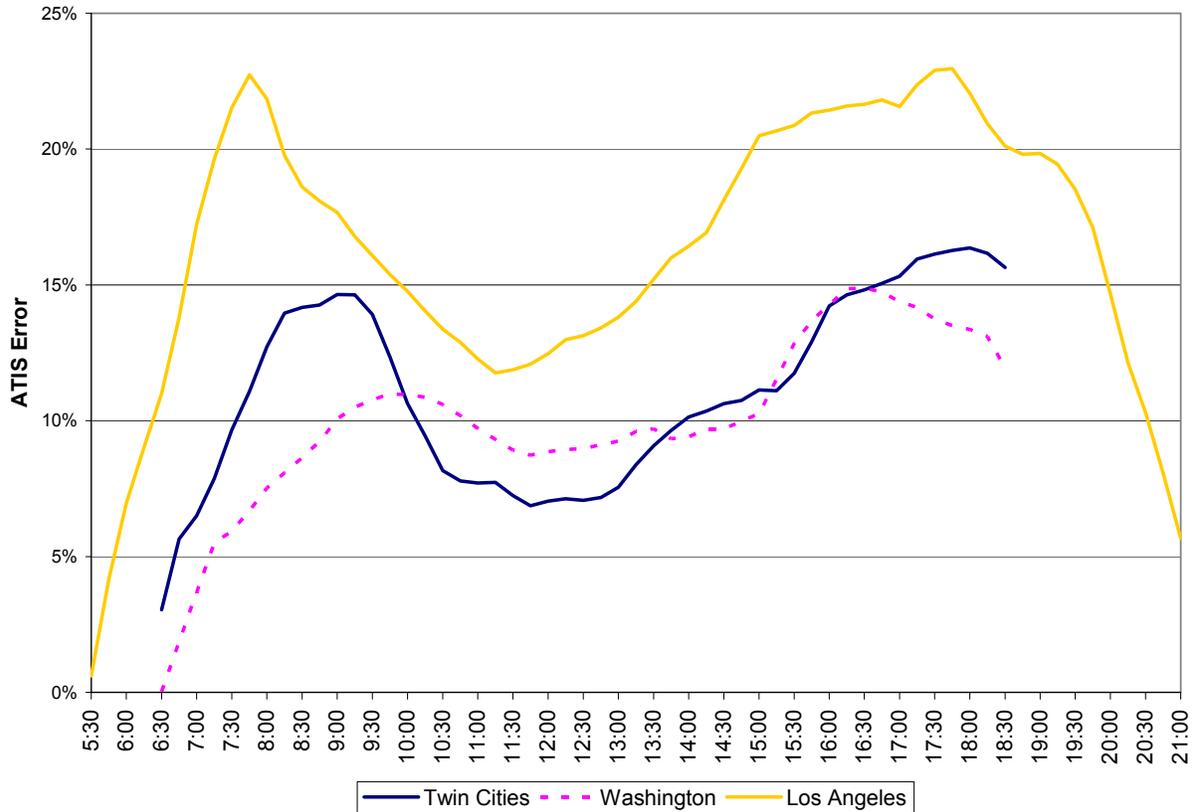
Figure 3-8.   Crossover Point by Time of Day – All Cities

While results for more than three cities are needed to make firm conclusions, the correlation between e* and variability suggests it may be possible to predict the necessary accuracy of a planned ATIS prior to deployment. The greater the speed variability, the greater is the tolerance for error.

Another item to note is the benefit when error is low. This gives a sense of how much benefit is possible under the most accurate deployment. According to Figures 3-3, 3-4, and 3-5, the maximum benefit is not achieved when accuracy is perfect, but rather when error is 1% to 2%. As is often the case, models tend to break down at the boundary conditions. This particular result comes from the constraint that the ATIS user may only depart on a multiple of five minutes past the hour. Thus, at every decision point, if he chooses to delay his departure, the soonest he can leave is in five minutes. When his information is very accurate, he learns this in the training period and as a result, leaves himself little extra time to account for error in the estimate. When this is the case, a small unexpected increase in travel time over that five minutes results in him

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arriving late. When the estimate is less accurate, he leaves himself a buffer proportional to the average error in the training period, which allows him to be less affected by such circumstances.

The maximum benefit achievable from ATIS is $2.23 in Los Angeles, $1.29 in Washington, and $0.60 in the Twin Cities. This is a function of average trip length and day-to-day trip time variability. The average trip length, a function of the coverage area of the data source and the makeup of the network (i.e., the network connectivity and the number of short links), is 23.7 miles, 21.2 miles and 14.1 miles in Los Angeles, Washington, and the Twin Cities, respectively. This translates to 9.4¢, 6.1¢, and 4.3¢ per mile, respectively. The greater per-mile benefit in Los Angeles could be attributed to greater variability, but a disparity exists between Washington and the Twin Cities despite little difference in variability between these two cities. If regional demand patterns were accounted for, average trip length would be a function of actual trip demand and not a function of the coverage area and network type. This would better isolate the role of travel time variability in trip utility.

3.3.2 Marginal Benefit

At any point along the error continuum, the slope of the benefit curve gives the marginal benefit, which is the slope of the benefit curve. Marginal benefit is the benefit that would result from improving accuracy 1%. For all trips in Los Angeles, this is shown in Figure 3-9. Though not shown, plots for other cities and other times of day depict the same trend: as error increases, the slope becomes more negative indicating a higher impact of accuracy improvement (or degradation) at higher levels of error.

For a hypothetical ATIS deployment, the higher the current level of error the greater is the benefit achievable by improving accuracy. Cleary if the deployment has error greater than e*, it is very important to improve accuracy because overall, the system is not beneficial. Beyond that point, the return diminishes as accuracy improves. If the deployment is already very accurate, the benefit may not justify the cost of accuracy improvements. In Los Angeles, it makes little sense to reduce error to below 5% since at that point nearly all of the potential benefit is already realized. Of course, cost is an important element in such a decision. There are plans to extend this study to incorporate cost estimates and ATIS market penetration.
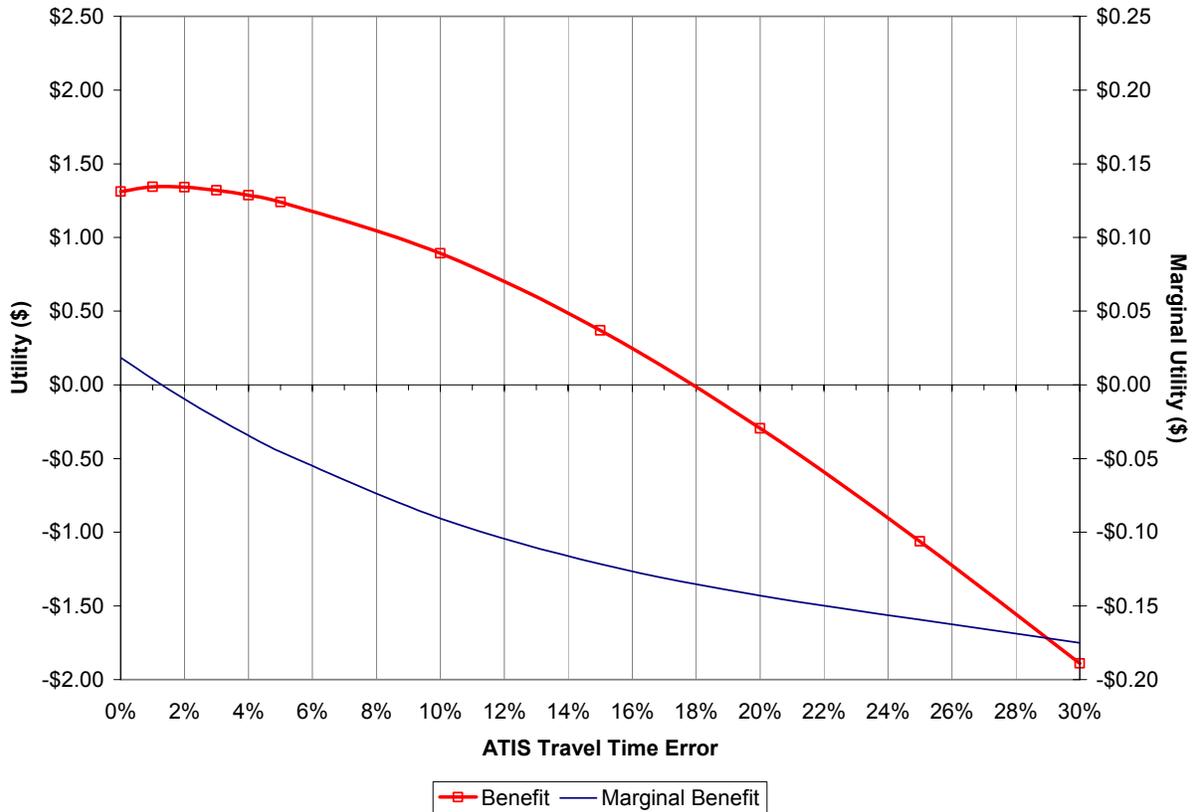
Figure 3-9.   Marginal Benefit as a Function of ATIS Error – Los Angeles, All Trips

3.3.3   The Critical Points of ATIS Error by Other Performance Measures

To this point, the dependent variable has been average improvement in utility. However, there are other performance measures worth considering as well. This section examines how other performance measures are affected by ATIS error.

Table 3-2 shows the crossover point of ATIS error based on just-in-time reliability (JITR). Just-in-time reliability is defined as the percentage of trips the traveler arrives on time and not more than ten minutes early. While OTR does not change with ATIS error, JITR also reflects that when error is higher, the frequency of early arrivals increases. The crossover points based on JITR are nearly identical to when utility is the performance measure of interest.

Table 3-3 shows the crossover point of ATIS error based on travel expenditure. Travel expenditure is defined as the time between trip start and the target arrival time, as well as any late schedule delay. Previous studies have found that the true value of ATIS comes less from

saving in-vehicle travel time but rather from improved time management (Wunderlich, 1; Jung, 2). A traveler who needs to leave very early in order to not be late will waste a good deal of time by arriving early. While this time may be put to use, it is usually better spent prior to departure. These values are nearly the same as when utility or just-in-time reliability is the performance measure of interest.

Table 3-2.   e* by Just-in-Time Reliability

	Los Angeles	Washington	Twin Cities
All Trips	16%	10%	11%
AM Peak	19%	8%	11%
Off Peak	13%	9%	9%
PM Peak	24%	14%	15%

Table 3-3.   e* by Travel Expenditure

	Los Angeles	Washington	Twin Cities
All Trips	17%	9%	9%
AM Peak	19%	7%	11%
Off Peak	12%	7%	7%
PM Peak	23%	14%	13%

Based on these results, e* does not depend heavily on the trip performance measure used. The results are nearly the same regardless of whether JITR or travel expenditure are used as the basis. This gives some credibility and robustness to the results so far.

3.3.4   The Value of Prediction

3.3.4.1   Comparing critical points of ATIS accuracy

The results of the previous section treat error as prediction error – error relative to a perfect travel time prediction. This is the definition most closely tied to traveler experience. Given an

estimate of travel time, the user's perception of its error is the difference between when he expects to arrive, based on this estimate, and when he actually does arrive. Perfect prediction may not be the best benchmark, however. Typically the best estimate of the travel time for a trip is measurement of current conditions, which is travel time based on prevailing speeds, coupled with historic time-of-day averages.

This section explores the value of predictive information over information based on measurement of current conditions. There are important implications to this topic. Short term forecasting of traffic conditions, i.e., predicting how incident and weather-induced congestion may propagate over time and space, is a difficult task. Clearly, accidents that haven't happened yet are impossible to predict. Newer applications, such as dynamic traffic assignment, attempt to predict and control the propagation of congestion in the short term, but for ATIS applications, the value of these forecasts, even if perfectly accurate, has yet to be studied. Since currently, ATIS market penetration is low enough that the influence of user response to the information may be disregarded, the key factor is how quickly pre-trip traffic information becomes outdated.

To this end, we designed an experiment by which we compare the outcome of an ATIS non-user, the control subject, and two users of pre-trip ATIS, the experimental subjects. The first ATIS user is given an estimate of his travel time based on prevailing speeds. Even if perfectly reflective of current conditions, this estimate will ultimately be inaccurate depending on how quickly conditions change over the course of his trip. The second ATIS user is given an estimate that anticipates how conditions will change over the course of his trip. By comparing the outcomes of these two travelers to each other and to the ATIS non-user we can determine (1) the value of knowing current conditions over no real-time information and (2) the value of predictive information over knowledge of current conditions only.

The results of the ATIS user with measurement-based estimates are shown in Figures 3-10, 3-11, and 3-12 and Table 3-4. As we would expect, benefit under measurement error is always less than under prediction error (Figures 3-3, 3-4, 3-5 and Table 3-1). Interestingly, in terms of e*, the difference between measurement and prediction is small. There is little difference between the levels of measurement accuracy and prediction accuracy required to achieve benefit. Clearly, at these levels of accuracy, the effect of the noise component of error dwarfs the effect of aging.
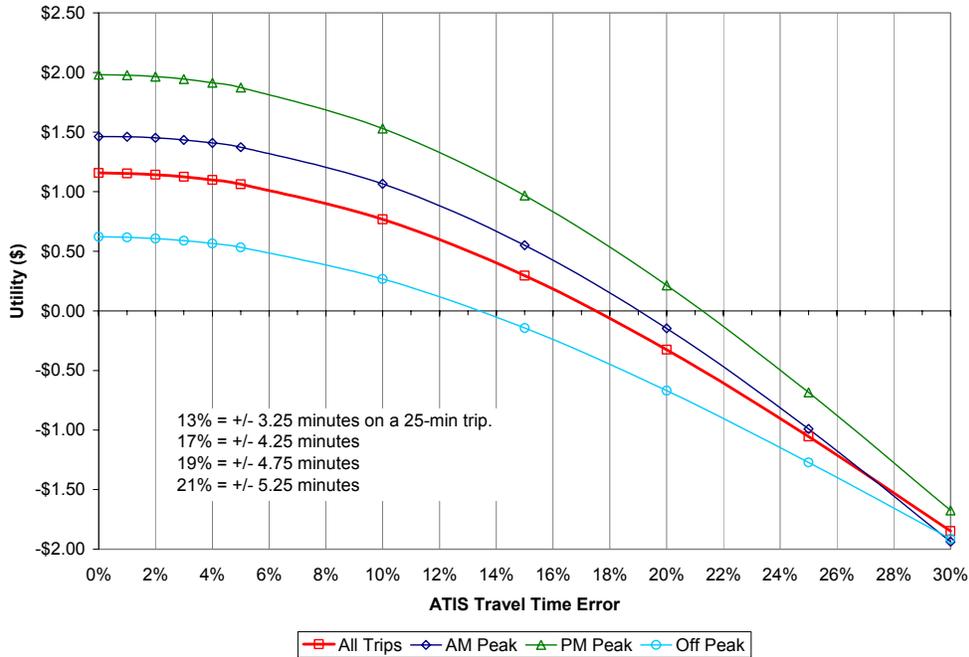
Figure 3-10.   Improvement in Utility as a Function of ATIS Measurement Error – Los Angeles
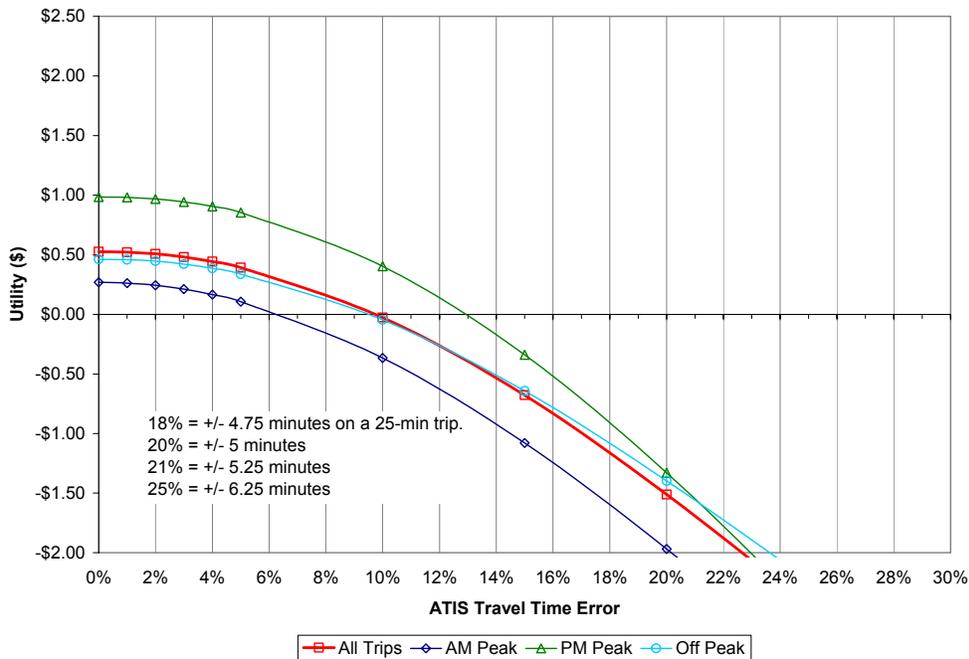
Figure 3-11.   Improvement in Utility as a Function of ATIS Measurement Error – Washington
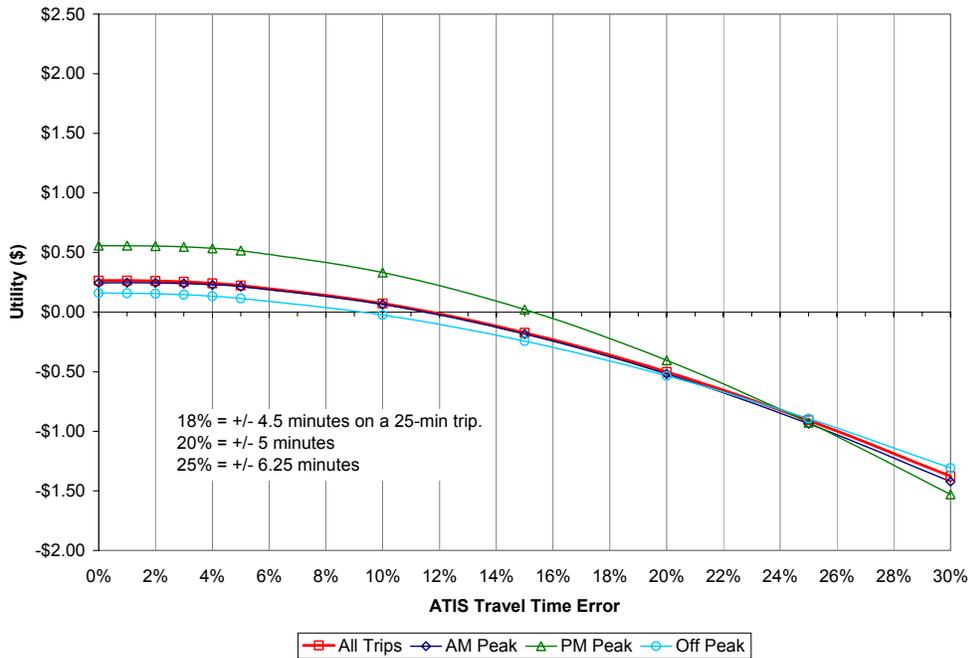
Figure 3-12.   Improvement in Utility as a Function of ATIS Measurement Error – Twin Cities

Table 3-4.   Crossover Points of ATIS Prediction Error – All Cities

	Los Angeles	Washington	Twin Cities
All Trips	**18%**	**11%**	**12%**
AM Peak	**19%**	**9%**	**12%**
Off Peak	**14%**	**10%**	**10%**
PM Peak	**21%**	**14%**	**15%**

This begs the question: When, if at all, does information aging have a significant effect on the benefit of the ATIS user? Based on what has been presented so far, it seems to have a small effect when noise error is near e*. However, at very high levels of accuracy (i.e., when noise error is low), aging may figure more prominently. When this is the case, prediction has greater value.

3.3.4.2   Relative Costs of Noise and Aging

We can measure the relative contribution of noise and aging error by determining how much cost each imposes on the ATIS user. The maximum ATIS benefit is realized when noise error is low (not necessarily 0% as was explained in Section 3.5.1, but rather 1% to 2%). As noise error increases, ATIS benefit declines until at some point, it is preferable to rely on habitual behaviors based on experience than to use ATIS (zero or negative benefit). Along this continuum, a percentage of the maximum benefit is achieved, the difference from the maximum benefit being a measure of the cost of error. Predictive ATIS consists only of noise error; the difference between this and the maximum achievable benefit is therefore the cost of noise error. Measurement-based ATIS consists of a noise component and an aging component. The difference between this and the maximum achievable benefit therefore reveals the sum of these two error components. The difference is the cost of aging, which reveals the value of prediction. This is shown in Figures 3-13, 3-14, and 3-15 for Los Angeles, Washington, and the Twin Cities, respectively.
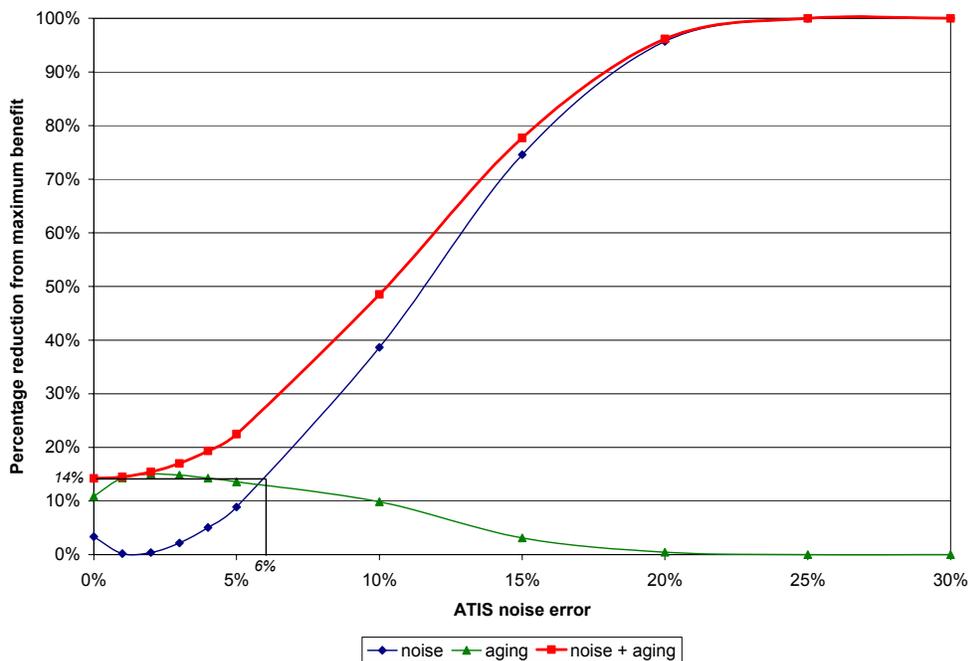
Figure 3-13.   Cost of Noise and Aging Error Components Expressed as the Percentage of Reduction from Maximum Benefit – Los Angeles
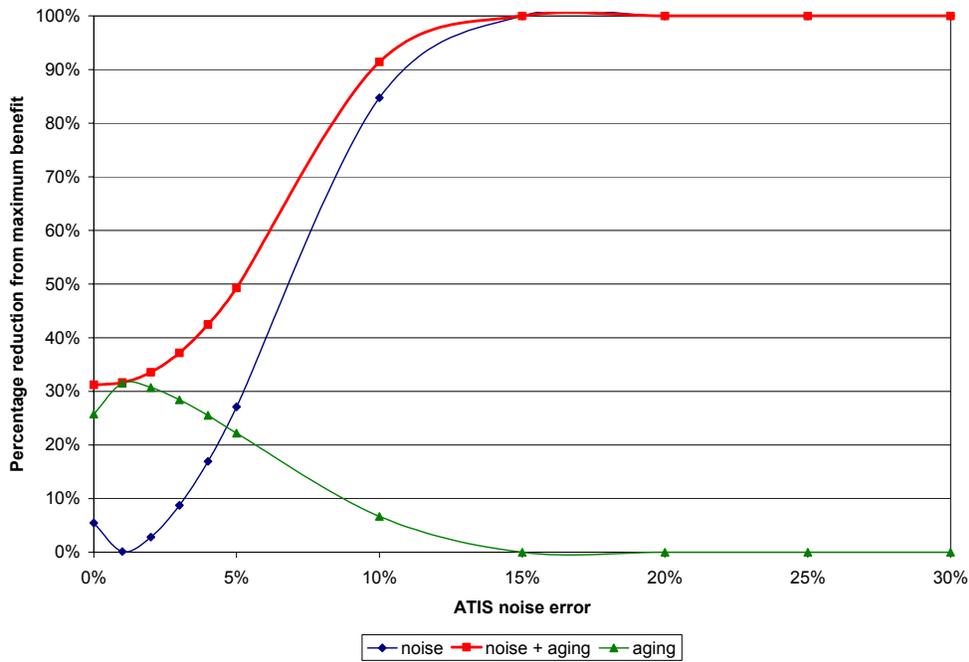
Figure 3-14. **Cost of Noise and Aging Error Components Expressed as the Percentage of Reduction from Maximum Benefit – Washington**
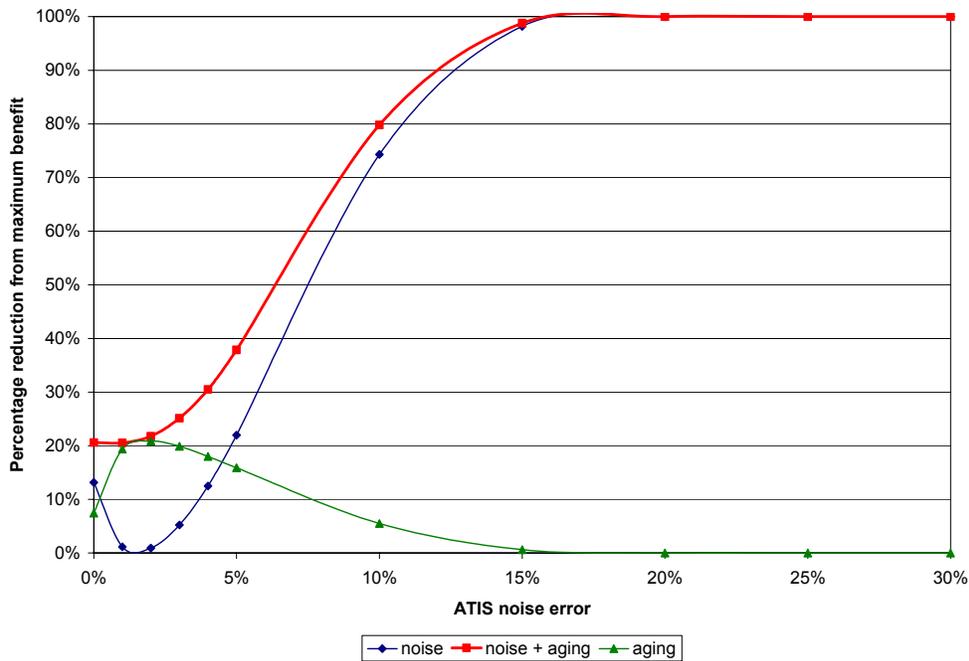
Figure 3-15. **Cost of Noise and Aging Error Components Expressed as the Percentage of Reduction from Maximum Benefit – Twin Cities**

The first item to note from Figures 3-13, 3-14, and 3-15 is that the impact of aging is a function of the amount of noise error. As would be expected, when noise error is high, the impact of aging diminishes to zero. This is because the impact of noise error is so great it overshadows the effect of aging. When noise error is low, aging has a higher relative impact and prediction is more valuable. In Los Angeles, when noise error is greater than 10%, noise error accounts for more than 90% of the total error-related cost to the user. In Washington, and the Twin Cities, this value is 7% and 8%, respectively. When noise error is less than 6%, 5% and 5% for Los Angeles, Washington, and the Twin cities, respectively, aging has a greater impact than noise. Therefore, for deployments in cities with similar characteristics to these, the value of prediction is limited when noise error is greater than this. Since ATIS benefit is measured by utility, which is primarily a function of on-time reliability, the most important characteristic is likely to be day-to-day travel time variability.

As shown in the previous paragraph, the vertical distance between "noise" curve and the "noise + aging" curve is the cost of aging, which is the value of prediction. The horizontal distance is the amount of error aging imposes on the measurement-based travel time estimate. In the case of perfect measurement, this is 6%, 5% and 5% in Los Angeles, Washington, and the Twin Cities, respectively. Clearly, aging does not impose a large error on the estimate.

3.4   Conclusions and Future Work

In conclusion, the maximum level of error an ATIS deployment may tolerate if the average user is to realize benefit is between 10% and 22%. For ATIS deployments with more error, benefit may only be realized by certain portions of the driving population, such as those with long or highly variable trips.

The crossover point of error increases with regional speed variability. It is lower for Washington and the Twin Cities where day-to-day variability is lower and higher in Los Angeles where variability is higher. It does not, however, increase with average travel speed, based on the data for these three cities. Washington, which had the lowest average speeds because of the number of arterial links covered by the ATIS, had a lower crossover point than Los Angeles, which had the highest average speeds.

In addition, marginal benefit decreases as accuracy improves. This result is consistent for the three cities. Because of this, at high levels of accuracy, there is less benefit to improving accuracy. Furthermore, the cost of improving an already accurate system is likely to be high. This suggests that the most cost effective deployment has some error, perhaps in the range of 5% to 15% in Los Angeles or 5% to 10% in Washington and the Twin Cities. In future work, cost data will be incorporated in a more detailed cost benefit analysis. One item to consider is the effect of improved accuracy on usage. As accuracy is improved, market penetration may increase meaning a smaller per trip benefit may not necessarily mean a smaller total-user benefit.

Travel time prediction for ATIS applications has little value based on this study, though when noise error is low, it has some value. In Los Angeles, when error is greater than 10%, prediction has little value relative to measurement as the noise component of error overshadows the effect of information aging. It appears that for ATIS applications, travel time prediction has some value, though the first priority for any deployment is accurate measurement. Short-term prediction depends on accurate measurement and the question of whether or not it should be pursued depends on the cost of developing, testing and calibrating prediction algorithms.

This work will be extended to include cost data for further cost benefit analysis. Trip demand data will also be incorporated in order to better represent the potential benefit of ATIS on a per user basis. Finally, additional metropolitan areas can be studied to further explore how much the results vary based on regional characteristics such as speed variability and population.

4   IMPACTS OF ROADWAY ATIS COVERAGE ON USER BENEFITS

In developing a plan to deploy ATIS, decisions regarding the coverage, content, real-time nature, and accuracy of the system all depend upon the underlying traffic monitoring system –be it loop detectors, toll tag readers, or some other technology. Conversely in the deployment of traffic monitoring systems, decision makers need to consider a variety of travel management tasks, one of which is ATIS.

Moreover, given limited funding, decision makers often cannot fund and deploy a region-wide traffic monitoring system in a single year. Instead, these systems evolve over many years through a series of incremental deployments. In developing incremental deployment plans, as well as in selecting the initial deployment, user benefits such as on-time reliability were not likely to be addressed or addressed only from a qualitative nature. This is explainable given that tools or techniques for evaluating and quantifying user benefits were not available, and that the focus was on traffic management.

New technologies are changing the way traffic monitoring systems are designed and deployed. High-end traffic monitoring systems that support traffic management functions (eg. incident management and ramp metering) are expensive but not required everywhere in a metropolitan area. However, supporting traffic monitoring for ATIS provision can be less expensive and potentially cost-effective over a wider area. Therefore, decision makers have a new challenge and opportunity to develop cost-effective traffic monitoring programs that feature ATIS as the primary generator of user benefit.

In order to provide decision-makers with insight and guidance on the deployment of traffic monitoring to support ATIS, we extend the HOWLATE methodology to evaluate the user benefits of ATIS based on varying levels of geographic coverage of the traffic monitoring systems. We develop three strategies for the incremental deployment of traffic monitoring systems: rank ordered deployment based on travel time variability, randomly selected deployment, and rank ordered deployment based on effect. We assess user benefits from a prospective ATIS service that incorporates real-time data where monitoring systems are deployed and incorporates historic data where no real-time monitoring systems exist. User

benefit is measured by using the disutility function based on Small et al. (6) as presented in Section 2. The disutility function translates the minutes of in-vehicle travel time as well as minutes of arrival offset, be it early or late, into a single monetary value.

The strategies for deployment are applied to case studies of three cities: Washington DC, Los Angeles, and St. Paul/Minneapolis (hereafter referred to as the Twin Cities). Based on the analysis results from the three incremental deployment strategies, we make inferences on smart strategies for making deployment plans, and on how such a plan may vary based on regional roadway system characteristics such as the form (radial versus grid) of the regional network.

Section 4.1 presents the hypotheses and limitations of this study while Section 4.2 explains the three incremental deployment strategies that are tested. Section 4.3 describes the three case study cities and why they were chosen for use in this analysis. Section 4.4 presents the outcomes of the three deployment schemes and Section 4.5 discusses the implications of these outcomes and directions for future study.

4.1   Study Hypotheses

The first hypothesis of this study is that more ATIS coverage always implies more benefit. That is, the marginal benefit from increased ATIS coverage will always be greater than zero. We will test this hypothesis by increasing the network coverage percentage and comparing the benefit for each level of coverage.

The second hypothesis we examine is that the marginal benefit from increasing coverage will vary by urban network from. The three case studies are insufficient to conclusively test this; however, they can provide a first level comparison between grid and radial networks.

Our third hypothesis is that incremental deployment plans based on observed roadway travel time variability are relatively efficient in garnering user benefits. One way of developing incremental deployment plans for ATIS is to consider observable current roadway segment characteristics such as annual average daily traffic (AADT), link speeds, or travel time variability. The first of the three deployment strategies evaluated is that of incremental deployment based on observed roadway travel time variability. This plan is most representative

of data that system designers are more likely to have at hand for the planning of ATIS incremental deployments.

As a benchmark, we also consider a random deployment plan. This strategy is expected to be a relatively poor heuristic as ATIS instrumentation is applied randomly throughout the region. This is a simplistic plan that provides insight as to the outcome of strategies in the absence of any information beyond consideration of major roadways and roadway length.

Identifying the optimal, or best, deployment plan is difficult given the enormous number of possible incremental deployments and limitations in the time to test a large array of options. For example, a simple 10-link network where in an incremental deployment of 5 links is desired, results in 252 distinct deployment combinations. As the number of links increases, the number of possible incremental deployments increases exponentially. The number of possible options for only the first 10% of network deployment for the cities of Los Angeles, Washington, DC, and Minneapolis/St. Paul ranges in the millions.

In lieu of an optimal deployment plan, we instead identify a near-optimal benchmark for comparison. This strategy, named most-effective link ranked, is based on the evaluation of ATIS effectiveness in an experiment where each roadway segment is instrumented in isolation from the rest of the network. Based on this experiment, roadway links are rank-ordered for deployment from most to least effective. This plan, however, is not one that decision-makers could actually follow since it employs data that can only be generated from an existing ATIS.

It is important to note that assessments in this study only consider a single trip from each origin to each destination for each time period. We do not weight these trips based on the actual regional demand pattern. As such, outcomes may be somewhat skewed compared to the actual sum of potential benefit to travelers in a region. The following section details the three incremental deployment strategies.

4.2   Modeling Incremental Deployment Strategies

Modeling ATIS provision under an incremental deployment plan is accomplished by classifying links into two disjoint groups. Links in the first group are covered by ATIS service (instrumented) and links in the other group not covered (uninstrumented). We apply the standard

HOWLATE methodology for both groups with the exception that for the uninstrumented group of links we use historic time-variant travel time data in the absence of real-time data. As such, in the case of zero network instrumentation, ATIS users have the same travel time information as ATIS non-users and their trip decisions (and therefore, their outcomes) are the same.

To test ATIS coverage effects, we used three major incremental deployment strategies: (1) Travel Time Variability Ranked deployment, (2) Randomly Ranked deployment (RR), and (3) Most-Effective Link Ranked deployment (MELR). We consider network coverage levels ranging from 0% to 100% in increments of 10% for all incremental deployment strategies. Therefore, 11 network coverage levels are analyzed for each deployment plan. The 10% increments are based on the percentage of regional roadway miles. Thus, each 10th percentile may have different numbers of links, but will have approximately the same number of roadway miles of coverage.

4.2.1 Travel Time Variability Ranked Deployment

This is the plan that most represents a likely analytical process by which regional planners might design deployments. In reality, other metrics such as link volume also play into deployment decisions; however only the link travel time and length metrics were available for use in this initial research.

Link travel time variability is considered in three ways in this study: variability within a day, variability from day to day at a specific time, and variability across all days and times-of-day. In ranking links from highest to lowest variability, we use each of the three forms of variability. The ranked list of links associated with each form of variability is then apportioned into 10 bins with the first bin having links with greatest variability and constituting approximately 10% of regional network miles. The last bin will have links with lowest variability and the sum of miles of links in the bin will also constitute approximately 10% of regional network miles. Table 4-1 lists the top ten links in Washington DC based on each of the three forms of variability.

We generate incremental deployments starting with none of the bins of links instrumented for real-time travel time estimation (no real-time ATIS data), followed by the first bin of links being instrumented. Subsequent bins of links are then instrumented until all 10 bins, or 100% of the network is covered with sensors that report real-time travel times. No process for maintaining network connectivity within bins or from bin to bin is instituted.

Table 4-1   Ranking of Top Ten Links Based on the Three Forms of Variability for Washington DC

Top Ten Links Ranked By Different Measures of Variability for Washington DC		
Variability Within A Day	Variability from Day to Day	Variability Across All Days and Times of Day
1. Connecticut Ave between DC Line and DC Mall/Garage	1. I-95 in VA between Dale City and Fairfax County Pkwy	1. Connecticut Ave between DC Line and DC Mall/Garage
2. Rt. 214 between DC Mall/Garage and DC Line	2. Rt. 1 in VA between 14th Street Bridge and North Kings Hwy.	2. Rt. 214 between DC Line and DC Mall/Garage
3. Georgia Ave between DC Line and DC Mall/Garage	3. I-270N between I-495 and Gaithersburg	3. Georgia Ave between DC Line and DC Mall/Garage
4. New Hampshire Ave between DC Mall/Garage and DC Line	4. Rt. 214 between DC Mall/Garage and DC Line	4. New Hampshire Ave between DC Mall/Garage and DC Line
5. I-95 in VA between Dale City and Fairfax County Pkwy	5. New Hampshire Ave between DC Line and DC Mall/Garage	5. New York Ave between DC Line and DC Mall/Garage
6. I-270S between Gairsburg and I-495	6. I-95 in MD between Laurel and I-495	6. Rt. 1 between DC Mall/Garage and DC Line
7. Rt. 1 in VA between North Kings Hwy. and 14th Sreet Bridge	7. Connecticut Ave between DC Line and DC Mall/Garage	7. Pennsilvania Ave between DC Line and DC Mall/Garage
8. I-95 in MD between Laurel and I-495	8. Georgia Ave between DC Mall/Garage and DC Line	8. I-95 in VA between Fairfax County Pkwy (Rt. 7100) and Dale
9. Rt. 7100/Fairfax County Pkwy between Springfield and Rt. 620	9. Suitland Pkwy between DC Line and I-495	9. I-270S between Gairsburg and I-495
10. Rt. 50 in VA between DC Line and I-495	10. I-495W in VA between Rt. 1 and I-95	10. Independence/Connecticut between DC Mall/Garage and DC

4.2.2   Randomly Ranked Deployment

In this strategy, we assume no information about the road network of the region beyond link length is available in the region where ATIS is to be instrumented. We generate a random number for each link and sort links by the random number order. We then bin links according to random order ensuring that the sum of miles of links in each bin is 10% of the total regional network miles. We generate incremental deployments starting with none of the bins of links instrumented for real-time travel time estimation (no real-time ATIS data), followed by the first bin of links being instrumented. Subsequent bins of links are then instrumented until all 10 bins, or 100% of the network is covered with sensors that report real-time travel times. To avoid bias by the random selection process, we generate 10 sets of random numbers and conduct binning and incremental deployment strategies with each set of random numbers. There is only one network scenario for 0% and 100% of network coverage. Therefore, 92 cases are analyzed for each city under randomly ranked incremental deployment strategy. As with the previous strategy, no process for maintaining network connectivity within bins or from bin to bin is instituted.

4.2.3   Most-Effective Link Ranked Deployment

The three cities upon which we base the case studies are currently implemented with ATIS; thus, we can calculate the impact of real-time data transmission for each link in each city using HOWLATE. We do this by assigning that link to have ATIS instrumentation while all other are not instrumented. Then, for each link we can calculate the average dollar-valued disutility for the network assuming that only that one link is instrumented to deliver real-time data. The link having the least network dollar-valued disutility is the most effective in generating ATIS benefit, while the link with greatest network dollar-valued disutility is the least effective in generating ATIS benefit. We rank order links from least to greatest disutility, and as with the previous two strategies, bin the links so that the total miles of links in each bin are equivalent. We generate incremental deployments starting with none of the bins of links instrumented for real-time travel time estimation (no real-time ATIS data), followed by the first bin of links being instrumented. Subsequent bins of links are then instrumented until all 10 bins, or 100% of the network is covered with sensors that report real-time travel times.

This incremental deployment strategy is not the optimal deployment plan, but we expect it to be the most effective incremental deployment plan among the three modeled. The disadvantage of this strategy is that it is an exercise in reverse engineering and such a methodology could not be performed without already having ATIS deployment. Therefore this strategy cannot be used by decision-makers during the planning stages of ATIS deployment.

In addition, we develop two variants to this strategy to evaluate the impact of network connectivity: single link connectivity and bin group connectivity. These strategies are described in the following two subsections. They differ in that the first is a coverage extending from a starting link whereas the second is a coverage extending from multiple groups and joining in later bins.

4.2.3.1 Single Link Connectivity

In this strategy we rank the link with lowest disutility first. The link with lowest disutility among all links connected to the first-ranked link is ranked second. The link with lowest disutility among all links connected to either the first or second ranked link is ranked third. The link with lowest disutility among all links connected to either the first, second, or third ranked link is

ranked fourth. The ranking process continues until all links are ranked. Then the links are assigned to 10 bins according to ranking and maintaining equal link-miles across the ten bins. We generate incremental deployments starting with none of the bins of links instrumented for real-time travel time estimation (no real-time ATIS data), followed by the first bin of links being instrumented. Subsequent bins of links are then instrumented until all 10 bins, or 100% of the network is covered with sensors that report real-time travel times.

4.2.3.2 Bin Group Connectivity

In this strategy we preserve the 10 bins from the Most Effective Link Ranked Strategy but remove all disconnected links from the first bin into the second bin. We replenish the first bin by drawing links from the second bin with lowest disutility and connectivity to any of the links in the first bin. In the event that the second bin is not sufficient in replenishing the first bin, links from the third bin will be selected. The links replenishing the first bin should have lengths that sum approximately to the links expelled from the first bin. We then move to the second bin and perform the same process with removals and replenishments drawn from the lower bin or bins.

4.3   Case Studies

The three cities selected for conducting case studies include: Washington DC, Twin Cities, and Los Angeles. These cities were chosen because of the availability of travel time data by link, time of day, and across many days. Both the Washington DC and the Twin Cities data are based on publicly available internet-based posting from SmarTraveler.com. The Los Angeles, CA data is based on loop detector data from PeMS website (http://pems.eecs.berkeley.edu).

The Washington DC network consists of 33 unique roadway sections (18 freeways and 15 major arterials), with a total of 711.8 directed miles. As shown in Figure 4-1, the Washington DC roadway network is comprised of a beltway and freeway connected radially. Roadway sections are subdivided into 75 links that are on average 4.6 miles long. These links are connected by 55 nodes. The average trip time across all trips simulated on this network is 32 minutes.

 The Twin Cities network consists of 31 unique roadway sections (24 freeways and 7 major arterials). The coverage area encompasses 510 directional miles. Figure 4-2 shows the grid shaped roadway network of Twin Cities. Roadway sections are subdivided into 138 links that are

on average 3.7 miles long. These links are connected by 42 nodes. The average trip time across all trips simulated on this network is 32 minutes.

Figure 4-1   Map of Washington DC and conversion to Network

Figure 4-2   Map of Twin Cities and Conversion to Network

The roadway network of Los Angeles (Figure 4-3) is also grid shaped like Twin Cities, but consists of all freeways. The coverage area encompasses 734 directed miles. Roadway sections are subdivided into 61 links that are on average 11.9 miles long. These links are connected by 40 nodes. The average trip time across all trips simulated on this network is 27 minutes.
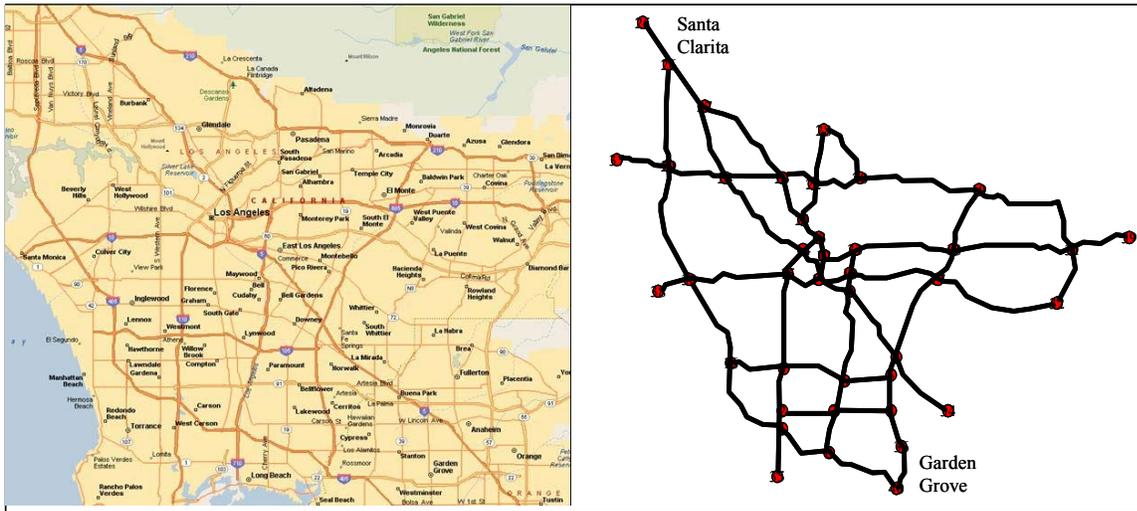
Figure 4-3   **Map of Los Angeles ATIS Network**

The training period for Los Angeles is comprised of 42 days from September 20, 2001 through December 19, 2001. The evaluation period is comprised of 100 days from January 10, 2002 through July 1, 2002. For Twin Cities and Washington DC, the training period is comprised of 39 and 33 days, respectively, while the evaluation period is comprised of 176 and 179 days, respectively. Training periods in both cities span from March through May 2000 while evaluation periods in both cities span from June 1, 2000 to May 31, 2001.

4.4   Experimental Results

A total of 2992 simulated ATIS deployment schemes were tested across the various deployment strategies. Table 4-2 presents the disutility value of ATIS users based on 0% and 100% ATIS deployment levels for the three cities. To note, 100% ATIS deployment in each city implies that all of the previously illustrated networks are instrumented with real-time ATIS, not that all roads in the region have ATIS instrumentation. The potential for ATIS user benefit is greatest in Los Angeles followed by Washington DC and then Twin Cities. The following three sections demonstrate how the incremental deployment strategies affect the share of total potential ATIS

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user benefit achievable at each level of deployment. Section 4.4 compares the three strategies and explores the relative importance of freeways versus arterials in deployment benefits.

Table 4-2   ATIS Users' Average Trip Disutility based on 0% and 100% ATIS Network Coverage

Coverage Level	Washington DC	Twin Cities	Los Angeles
Zero Coverage	$2.67	$1.47	$2.84
100% Coverage	$2.19	$1.24	$1.82

4.4.1   Travel Time Variability Ranked Strategy Outcome

The results of incremental ATIS deployments based on the travel time variability ranked strategy are represented in Figures 4-4, 4-5, and 4-6 for the cities of Washington DC, Twin Cities, and Los Angeles, respectively. Each figure presents the results of ranking based on each of the three forms of variability: variability within a day, variability from day to day at a specific time, and variability across all days and times-of-day. ATIS users' average trip disutility is represented in each figure by a bar that is associated with the left side y-axis. The percentage of benefit accrued by ATIS users at each level of incremental deployment compared to that of full deployment is represented by lines in each figure, and is associated with the right side y-axis.

The percentage of benefit accrued by ATIS users at each level of incremental deployment compared to that of full deployment does vary based on the type of variability used to rank links. Yet, no one ranking based on a specific type of variability is consistently better than the others across all stages of incremental deployments. Across the three cities, rankings based on variability across all days and times of day proved slightly better compared to rankings based on the other two methods of variability.

In Washington DC, 80% network deployment of ATIS produces 85% of the total benefit associated with 100% deployment. In Twin Cities 80% network deployment of ATIS produces 96% of the total benefit associated with 100% deployment. And, in Los Angeles, 80% network deployment of ATIS produces 87% of the potential total benefit associated with 100% deployment. In general, the relationship between deployment percent and the percent of benefit compared with full deployment is relatively linear using the Travel Time Variability Ranked strategy.

	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Across whole period	$2.67	$2.67	$2.50	$2.47	$2.46	$2.43	$2.39	$2.36	$2.31	$2.22	$2.19
From day to day	$2.67	$2.64	$2.61	$2.46	$2.43	$2.42	$2.41	$2.39	$2.26	$2.20	$2.19
Within a Day	$2.67	$2.65	$2.64	$2.63	$2.47	$2.42	$2.42	$2.40	$2.35	$2.22	$2.19
Effect(across whole period)	0.0%	0.0%	35.6%	41.6%	43.3%	49.8%	57.5%	65.0%	74.9%	94.4%	100.0%
Effect(from day to day)	0.0%	5.6%	11.7%	43.9%	50.4%	52.2%	54.5%	58.4%	84.7%	98.5%	100.0%
Effect(within a day)	0.0%	3.4%	7.0%	9.1%	41.0%	51.5%	52.9%	55.5%	67.4%	94.9%	100.0%

Percentage of Network with ATIS Instrumentation

Figure 4-4   Outcome of Incremental Deployment Strategy based on Travel Time Variability Ranked: Washington DC

	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Across whole period	$1.47	$1.43	$1.40	$1.38	$1.36	$1.33	$1.29	$1.26	$1.25	$1.24	$1.24
From day to day	$1.47	$1.43	$1.40	$1.38	$1.37	$1.34	$1.31	$1.29	$1.26	$1.24	$1.24
Within a Day	$1.47	$1.44	$1.39	$1.38	$1.36	$1.34	$1.33	$1.31	$1.26	$1.26	$1.24
Effect(across whole period)	0.0%	17.8%	30.8%	39.5%	47.9%	61.6%	77.1%	90.2%	95.6%	98.0%	100.0%
Effect(from day to day)	0.0%	17.4%	28.8%	37.5%	48.2%	55.3%	61.4%	69.5%	92.2%	98.0%	100.0%
Effect(within a day)	0.0%	12.4%	32.4%	38.8%	48.2%	55.3%	61.4%	69.5%	91.3%	91.7%	100.0%

Percentage of Network with ATIS Instrumentation

Figure 4-5   Outcome of Incremental Deployment Strategy based on Travel Time Variability Ranked: Twin Cities, MN

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The chart shows "ATIS Users' Average Trip Disutility" on the left y-axis (from $1.80 to $3.00) and "ATIS Users' Benefit As a Percent of Benefit Accrued at 100% Deployment" on the right y-axis (0% to 100%). The x-axis is "Percent of Network with ATIS Instrumentation."

	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Across whole period	$2.84	$2.79	$2.66	$2.56	$2.43	$2.33	$2.17	$2.06	$1.97	$1.85	$1.83
From day to day	$2.84	$2.74	$2.67	$2.61	$2.51	$2.32	$2.25	$2.05	$1.96	$1.89	$1.83
Within a Day	$2.84	$2.70	$2.64	$2.55	$2.45	$2.36	$2.32	$2.16	$2.06	$1.90	$1.83
Effect(across whole period)	0.0%	4.7%	18.1%	27.9%	40.2%	50.4%	65.8%	76.8%	85.3%	97.1%	100.0%
Effect(from day to day)	0.0%	10.4%	17.2%	22.8%	32.4%	51.8%	58.7%	78.1%	87.2%	93.3%	100.0%
Effect(within a day)	0.0%	13.8%	19.4%	28.6%	38.2%	47.5%	51.7%	67.3%	77.2%	92.8%	100.0%

Figure 4-6   Outcome of Incremental Deployment Strategy based on Travel Time Variability Ranked: Los Angeles, CA

4.4.2   Randomly Ranked Deployment Strategy (RR)

Figure 4-7, 4-8, and 4-9 present the average trip disutility of the ATIS users for various levels of incremental ATIS deployments based on the random deployment strategy in the cities of Washington DC, Twin Cities, and Los Angeles, respectively. At each level of coverage (with the exception of 0% and 100% coverage levels where there is only one possible scenario), there are ten points corresponding to the ten randomly ranked incremental deployment plans. The number in gray circle represents the worst strategy at each level of coverage and the number in white circle represents the best strategy. Graphs also show lines connecting subsequent points which are most frequently the best and the worst at each coverage level.

No single randomly ranked incremental deployment in any city proved to be consistently best or worst for all levels of incremental deployment. Also, the spread of benefit across random trials is significant at all levels of deployment in each of the three cities. Each randomly ranked deployment proves to be at times very good and at times very poor compared to the other nine random deployments at equivalent levels of ATIS deployment.

The general shape of benefits across incremental levels of ATIS deployment shows large disutility drops in Washington DC. The common links for the large disutility drops in Washington are parts of I-495, the Capital Beltway, the connector freeway for most of the regional trips. In comparison, Los Angeles and Twin Cities have a relatively linear relationship between deployment level and ATIS user benefits as a percent of benefit at 100% deployment. In contrast to our hypothesis, the best random strategies perform as well as or better than the travel time variability ranked deployment strategies.

In Washington DC, 70% of total benefit is garnered by 30% of deployment across the 10 random trials; whereas in the travel time variability ranked deployments, only 44% of total benefit is garnered by 30% of deployment. In Twin cities, the values of benefit at the 30% deployment level are 45% and 40% for the average randomly ranked and travel time variability ranked strategies, respectively. Similar values of benefit at the 30% deployment level in Los Angeles are 44% and 40% for the average randomly ranked and travel time variability ranked strategies, respectively.

Figure 4-7   Outcome of Incremental Deployment Strategy based on Randomly Ranked: Washington DC

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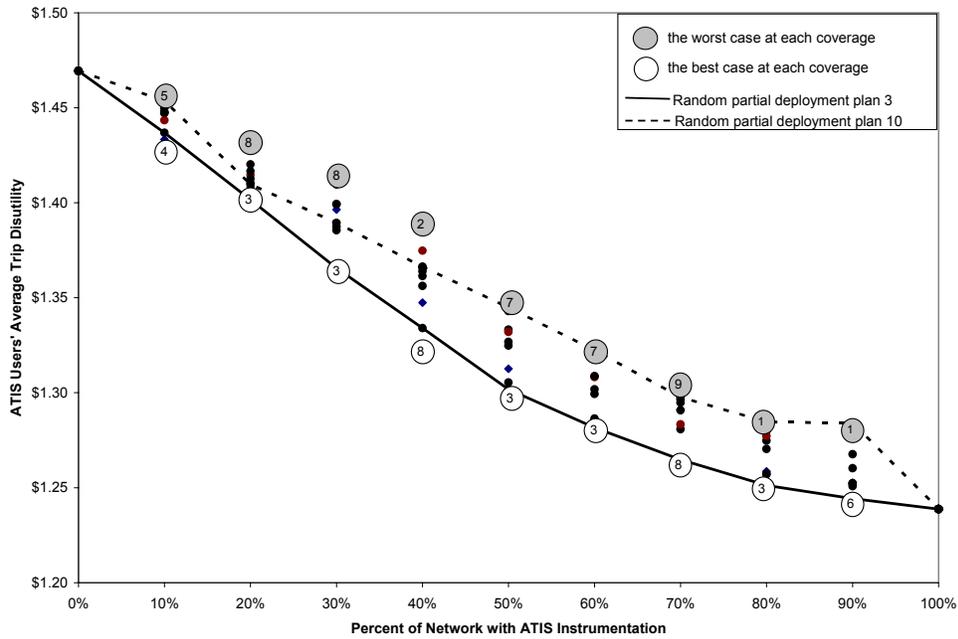
Figure 4-8   Outcome of Incremental Deployment Strategy based on Randomly Ranked: Twin Cities, MN

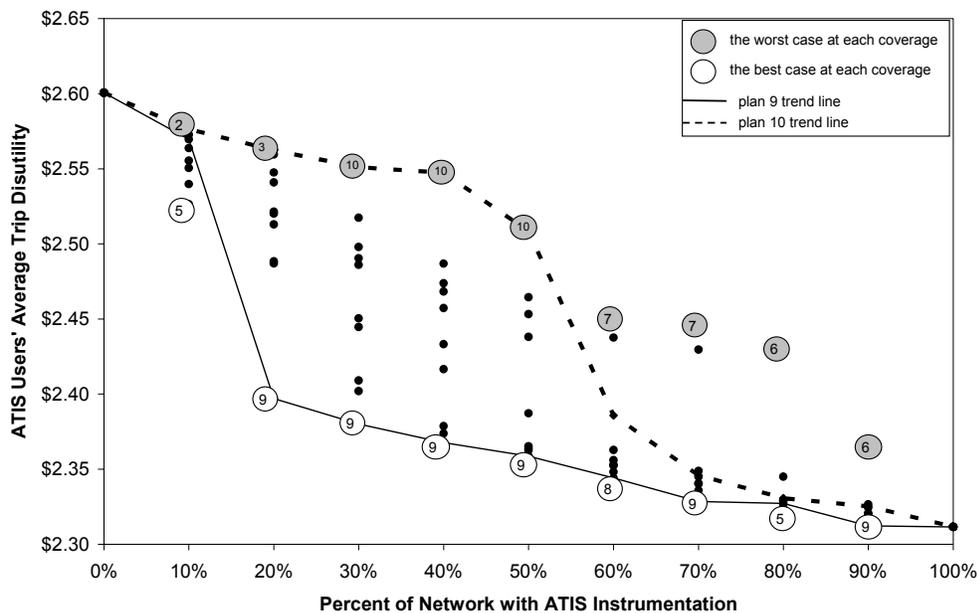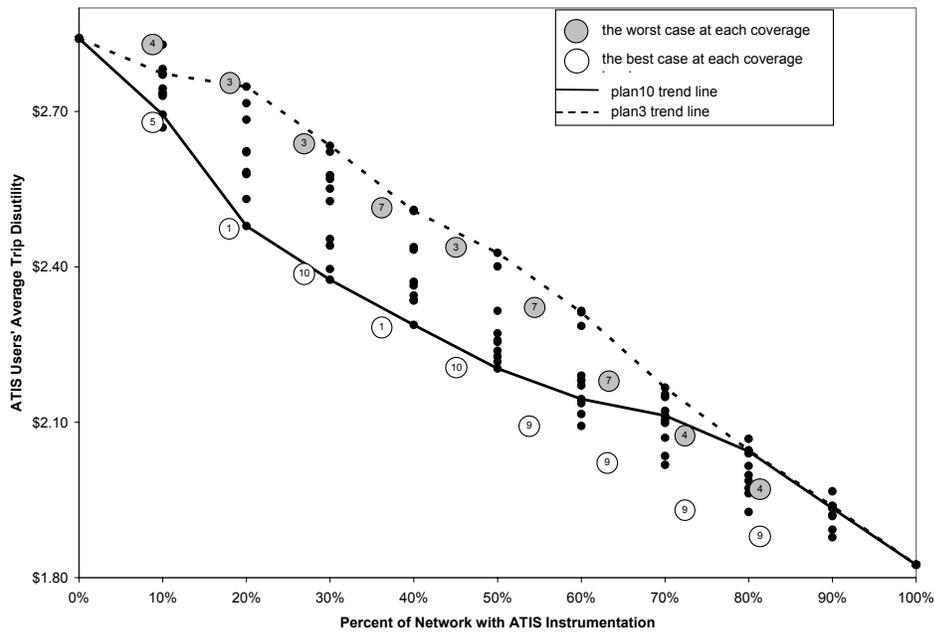**Figure 4-9   Outcome of Incremental Deployment Strategy based on Randomly Ranked: Los Angeles, CA**

4.4.3   Most Effective Link Ranked Strategy (MELR)

In this strategy, we rank each link based on the average disutility of ATIS users' trips associated with ATIS instrumentation only on that particular link. We generate incremental deployments starting with the link with lowest disutility first. Because some links are longer than others we graph link length by network disutility in Figure 4-10 to assess whether ranking is biased by longer links. If in fact disutility is significantly influenced by link length, then the graph would show some linear or other relationship. However, the absence of any meaningful trends leads us to conclude that longer links do not overwhelm the ranking of links by effectiveness in reducing network level disutility.

Figure 4-10   Average Disutility of ATIS Users' Trips Based on Single Link Instrumentation Compared to Link Length

The results of incremental ATIS deployments based on the most effective link ranked strategy are represented in Figures 4-11, 4-12, and 4-13 for the cities of Washington DC, Twin Cities, and Los Angeles, respectively. Each figure presents the results of ranking based on the basic most effective link ranked strategy and the two variants to this strategy –single link connectivity and bin group connectivity. The average trip disutility of ATIS users is represented in each figure by a bar that is associated with the left side y-axis. The percentage of ATIS users' benefit accrued at

each level of incremental deployment compared to that of full deployment is represented by lines in each figure, and is associated with the right side y-axis.

Generally the original most effective link ranked strategy is slightly better than the two variants to this strategy, suggesting that connectivity may not be as important a factor in garnering user benefit compared to the link's effectiveness in reducing ATIS users' trip disutility. Of course, link connectivity would be an important factor in the marketing of the service to commuters.

The overall shape of the relationship between ATIS deployment level and the ATIS users' benefit as a percent of total achievable benefit at 100% deployment is not linear in any of the three cities. Based on the most effective link ranked benchmark, 93% of total benefit is garnered by 30% of deployment. In Twin Cities and Los Angeles the values of ATIS user benefit at the 30% deployment level are 80% and 50%. In Washington DC and Twin Cities, links instrumented with ATIS after 70% of the most effective links in the network are instrumented contribute minimally to reducing disutility.

	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Original	$2.67	$2.32	$2.25	$2.22	$2.21	$2.20	$2.20	$2.19	$2.19	$2.19	$2.19
Single Link Con.	$2.67	$2.34	$2.26	$2.22	$2.21	$2.20	$2.20	$2.19	$2.19	$2.19	$2.19
Bin Group Con.	$2.67	$2.34	$2.26	$2.23	$2.22	$2.20	$2.20	$2.19	$2.19	$2.19	$2.19
Effect(original)	0.0%	73.3%	87.0%	93.0%	95.7%	97.5%	98.9%	99.6%	100.0%	100.0%	100.0%
Effect(single link con.)	0.0%	67.9%	85.7%	93.5%	95.7%	97.5%	98.9%	99.6%	100.0%	100.0%	100.0%
Effect(bin group con.)	0.0%	67.9%	85.7%	92.6%	94.9%	97.5%	98.9%	99.6%	100.0%	100.0%	100.0%

Percent of Network with ATIS Instrumentation

Figure 4-11   Outcome of Incremental Deployment Strategy based on Most Effective Link Ranked: Washington DC
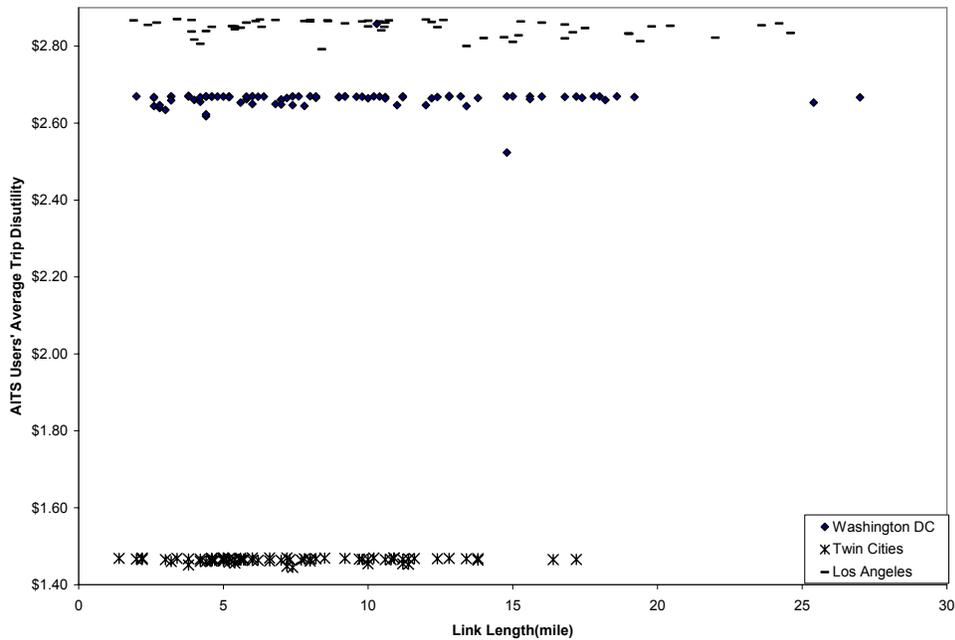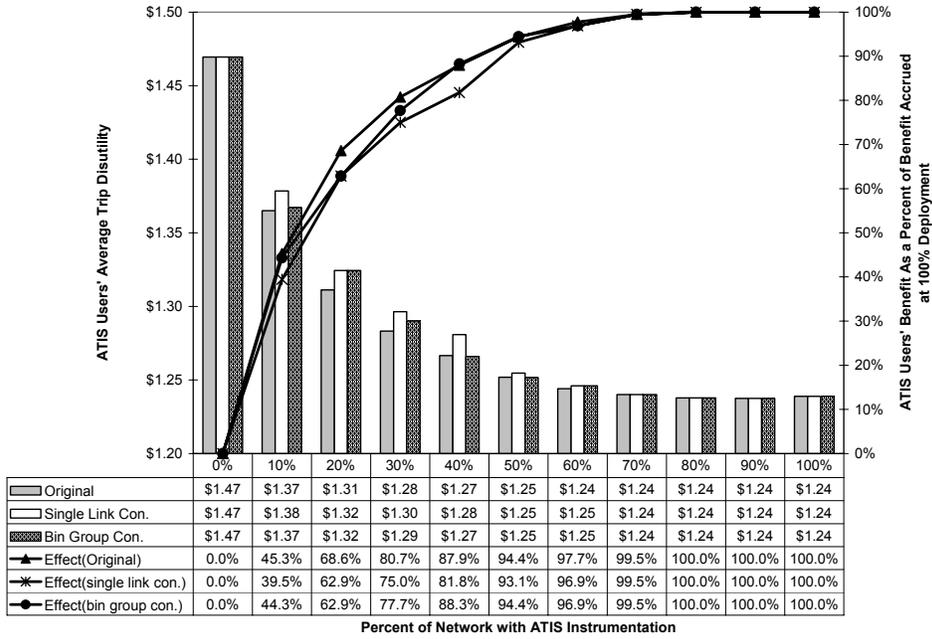
Figure 4-12   Outcome of Incremental Deployment Strategy based on Most Effective Link Ranked: Twin Cities, MN
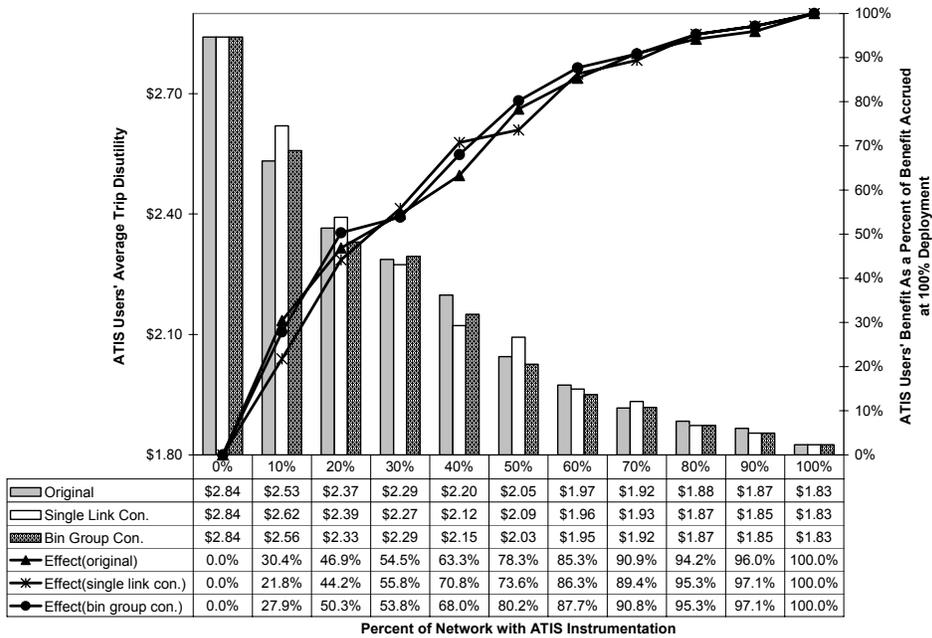
Figure 4-13   Outcome of Incremental Deployment Strategy based on Most Effective Link Ranked: Los Angeles, CA

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4.4.4 Comparison of Strategies

In this section we compare the travel time variability ranked strategy to the randomly and most effective link ranked deployment strategies using the metric of ATIS users' benefit as a percent of benefit associated with 100% ATIS deployment. The travel time variability ranked strategy represents an analytical process by which regional planners might design a deployment, while the most effective link ranked strategy is our benchmark for near-optimal deployment. The randomly ranked strategy represents the worst case scenario for regional planners where no information is available in making incremental deployment decisions. We also explore the importance of freeways compared to arterials in generating ATIS user benefit, and how network form may play a role in how much benefit can potentially be garnered by early increments of ATIS deployment.

Figures 4-14, 4-15, and 4-16 present the travel time variability strategy, the average of the 10 randomly ranked strategies, and the original most effective link ranked strategy for each of the three cities, respectively. The ATIS users' benefit accrued at each level of incremental deployment as a percent of benefit associated with full deployment is represented by the y-axis, while the level of ATIS deployment is represented by the x-axis in each of the three figures.
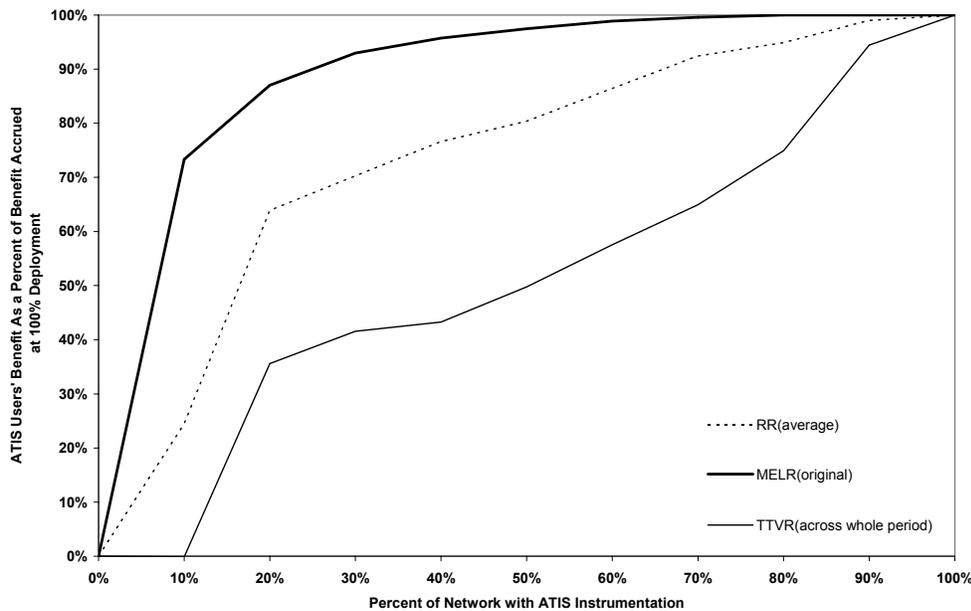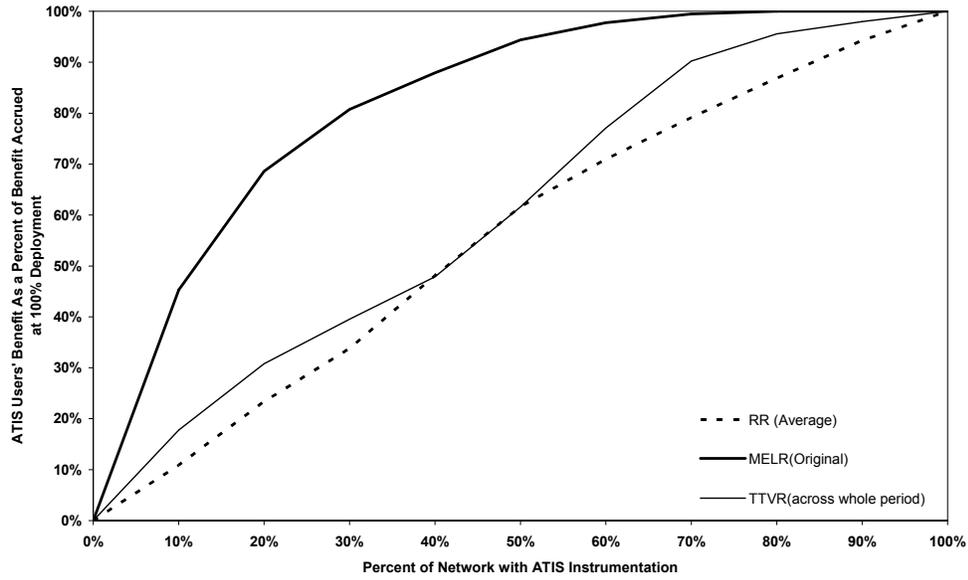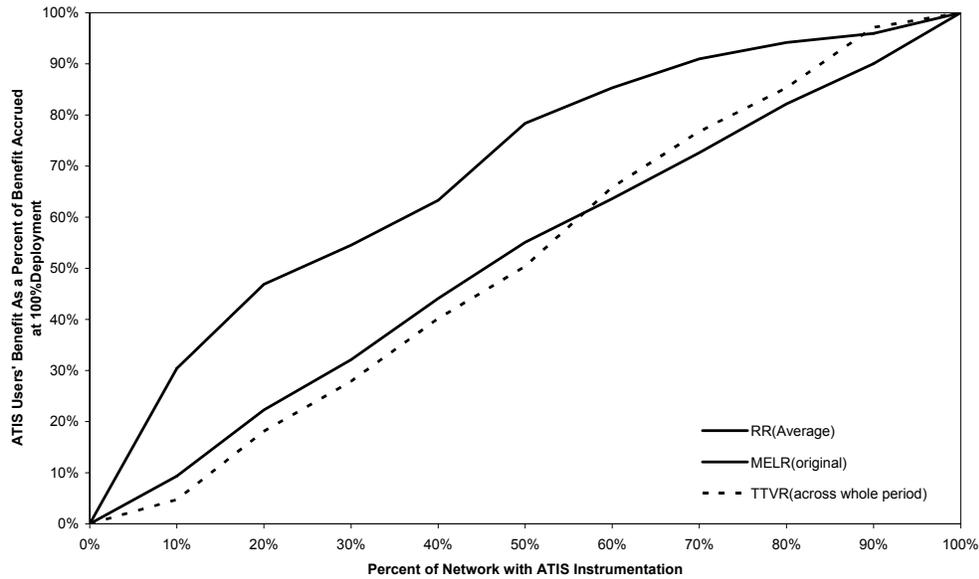

Figure 4-14   Outcomes of All Three Deployment Strategies in Washington DC

Figure 4-15   Outcomes of All Three Deployment Strategies in Twin Cities, MN

Figure 4-16   Outcomes of All Three Deployment Strategies in Los Angeles, CA

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Most surprisingly, in Washington DC the travel time variability ranked strategy proves significantly worse than the randomly ranked strategy. Upon further investigation we find that the strategy based solely on link travel time variability ranks and deploys arterial facilities above freeways and consequently garners minimal benefit during the earlier increments of ATIS deployment. This is because although arterial have greater variability, freeways are used by far more trips in the Washington DC network. Figure 4-17 presents the 10%, 20%, and 30% deployments of ATIS for the three strategies.

The near-optimal strategy in Washington DC deploys the Capital beltway (I-495) first, followed by other major freeway facilities. The beltway accounts for 18% of the regional network, yet instrumentation of this 18% garners 80% of benefit associated with 100% regional ATIS instrumentation. In comparison, a 20% deployment level based on the average random strategy and the travel time variability strategy garner only 65% and 36% of benefit associated with 100% regional ATIS instrumentation, respectively. To note, in Washington DC, instrumentation only on freeways yields 95% of benefit compared with full deployment while freeways account for 67% of network miles. In contrast, instrumentation only on the arterials in Washington DC, comprising 33% of network miles, generates only 2% of benefit compared with full deployment.

In Twin Cities, a 20% deployment based on the near-optimal strategy garners 69% of benefit associated with 100% regional ATIS instrumentation. In comparison, a 20% deployment level based on the average random strategy and the travel time variability strategy in Twin Cities garners only 31% and 24% of benefit associated with 100% regional ATIS instrumentation, respectively.

As with Washington DC, the near-optimal deployment in Twin Cities focuses first on the major freeways followed by arterial deployment. And, as with Washington DC, the travel time variability ranked strategy results in arterial deployment before freeways. But in the case of Twin Cities, the travel time variability ranked strategy performs about at par with the randomly ranked strategy. This is likely because the Twin Cities network is grid shaped and has fewer arterial roadways. Consequently ATIS instrumentation on a random few freeways does not get the same effect as in Washington DC where I-495 pushed the randomly ranked strategy above the travel time variability ranked strategy.
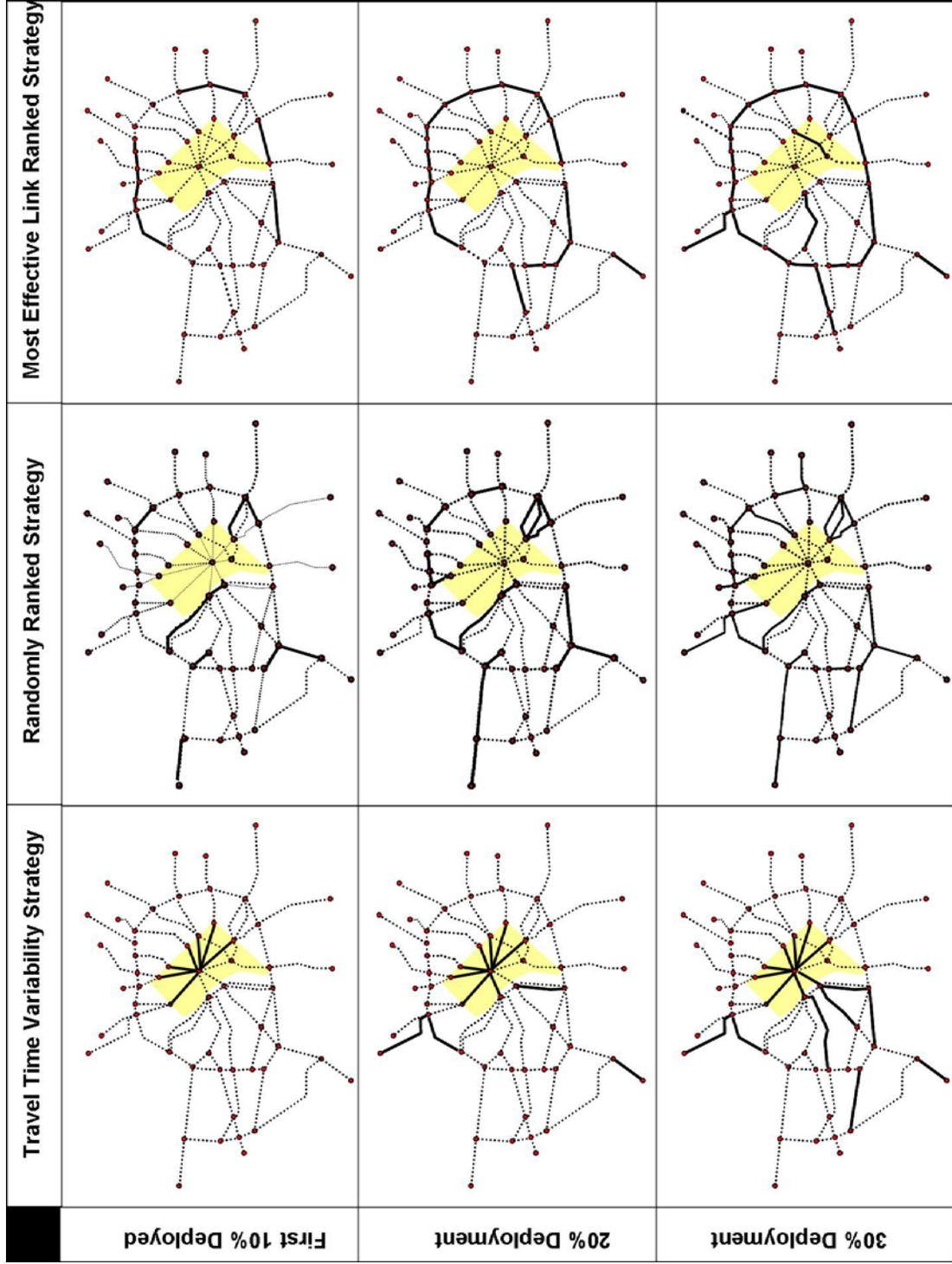
Figure 4-17   Initial ATIS Deployment Maps of All Three Deployment Strategies for Washington, DC

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Unlike Washington DC and Twin Cities, the Los Angeles near-optimal deployment is less dramatically curved. A 20% deployment based on the near-optimal strategy garners 30% of benefit associated with 100% regional ATIS instrumentation. In comparison, a 20% deployment level based on the average random strategy and the travel time variability strategy in Los Angeles garners only 18% and 15% of benefit associated with 100% regional ATIS instrumentation, respectively. Because the Los Angeles network is all freeways, and is grid-shaped, links here have relatively similar importance compared to the other two cities.

4.5 Key Findings and Conclusions

This study analyzes how trip disutility is reduced for users of ATIS at various levels of ATIS deployment under three different incremental deployment strategies. We used case studies of three metropolitan areas: Washington DC, Los Angeles, and Twin Cities. In this section, we summarize the key findings from this study with respect to our initial hypotheses.

The hypothesis that more coverage always implies more benefit was not found to be true in Washington DC and Twin Cities. Links added after a near-optimal ATIS instrumentation on 70% of the network proved no benefit to ATIS users. This is likely due to the fact that variability on those links is less than the error inherent with the ATIS information. Therefore, instrumentation on such links does not benefit ATIS users traversing such links. However, the hypothesis of more coverage yielding more benefit was found to be true based on the randomly and travel time variability ranked strategies.

The hypothesis that the urban network form impacts the magnitude of benefit generated at lower levels of ATIS deployment proved accurate. Washington DC a radial network proved under the near-optimal strategy to garner 80% of the benefit associated with 100% ATIS deployment with only approximately 20% of the network deployed. In contrast, the cities of Los Angeles and Twin Cities, under the near-optimal deployment strategy, at a 20% ATIS deployment level garner only 69% and 30% of the benefit associated with 100% ATIS deployment, respectively.

The travel time variability ranked strategy proved far less effective than the average randomly ranked strategy in Washington DC, and only as effective as the average randomly ranked strategy in Twin Cities and Los Angeles. The key shortcoming of this strategy may be related to

the fact that arterials generally have greater variability than freeways, while freeways are used for many more trips than arterials. Based on the cities of Washington DC and Twin Cities, we observed that ATIS instrumentation on freeway facilities provides generally higher ATIS user benefit compared to instrumentation on arterial facilities.

In summary, the shape of the deployment-benefit relationship depends foremost on the ambient congestion level in network, followed by the form of the urban network (radial vs. grid), and finally the level of roadway variability in comparison to the accuracy of the ATIS.

4.6 Future Work

Thus far, we evaluated three incremental deployment strategies: travel time variability ranked, randomly ranked, and most effective link ranked. Of these, the most effective link ranked strategy serves as a benchmark for near-optimal deployment, while the randomly ranked strategy serves as the scenario of incremental deployment based on little a priori information about the network. The travel time variability ranked strategy most represented a likely analytical process by which regional planners might design deployments. In the future, we will focus on the development and evaluation of more savvy deployment strategies based on observable data that a planner could use. Some metrics we plan to consider in developing deployment strategies include speed, incident rates, and annual average daily traffic. In continuing further, we also plan to look at weighing trip outcomes based on observable regional demand patterns.

5   KEY FINDING AND FUTURE WORK

In this section, we revisit the hypotheses of the study first presented in Section 1.3. In Section 5.1 we provide a summary of key findings from across the three areas of research exploring ATIS user benefits: ATIS accuracy, ATIS incremental deployment, and limited data sets.

5.1   Hypotheses and Key Findings

Hypotheses Regarding ATIS Accuracy: There exists a unique value level of error, called the crossover point of error, where ATIS provides positive travel reliability benefits on aggregate for a region. The crossover point of error is higher for cities with higher day-to-day variability, and similarly is higher during peak periods for a city given that day-to-day variability is greater during periods of greater congestion. Further, it is likely that cities currently providing ATIS are at or above their crossover points of error.

Findings: Crossover points of error were found in the three cities examined in this study: St. Paul/Minneapolis, MN; Washington, DC; and Los Angeles, CA. ***Crossover point values range from 10% to 21% based on city and time of day. For ATIS services beyond these levels of accuracy, only certain subsets of the driving populations such as those with relatively long or highly variable trips may realize benefit.*** Conversely, the marginal benefit from ATIS improvements decreases at higher levels of ATIS accuracy. Figure 5-1 illustrates the relationship of utility from improved trip reliability versus travel time error for the Los Angeles region. In Los Angeles, the crossover point of error ranges from 14% to 21%. ***Once regional ATIS services reaches a level of accuracy in the range of 5%, benefits from improvements to ATIS accuracy may outweigh costs associated with such efforts.*** The curves for the cities of Washington, DC and St. Paul/Minneapolis have the same shape as that of Los Angeles.

Figure 5-2 presents a graph of crossover error point by variability in link speeds, disaggregated by city and congestion period. St. Paul/Minneapolis and Washington DC, the cities with lower day-to-day speed variability have a significantly lower crossover points compared to Los Angeles, a city with greater speed variability. Thus, ATIS in the cities of Washington DC and St. Paul/Minneapolis need to be more accurate than in Los Angeles to achieve a net positive ATIS

user benefit across their regions. Also, the PM peak period for all cities tends to have greatest speed variability, and consequently highest thresholds for ATIS error.

To note, the relationship between the crossover point of error and system-level travel speed variability can be shown to be linear with a R-square value of 0.92 and a slope of 1.55%. This suggests that *as regional trip variability decreases by 1 minute, the system needs to increase accurate by 1.55% to maintain the same level of potential user travel time savings.*

With respect to the current level of accuracy of ATIS providers, we identified a limited number of corridor studies of ATIS accuracy for the cities of Washington DC, and St. Paul/Minneapolis. In Washington DC the error of ATIS excluding bias ranged from 9% to 17% for freeways and 6% to 26% for arterials (Hardy et al., 7) compared to the crossover point of error ranges identified in this report between 9% and 14%. In St. Paul/Minneapolis the error of ATIS excluding bias ranged from 24% to 33% depending or peak versus off-peak periods (Cambridge Systematics, 8; Toppen et al., 9). This report identifies the crossover point of error to range between 10% and 15%. These ranges of current accuracy are illustrated in Figure 5-2. Based on these limited efforts measuring ATIS accuracy, clearly the St. Paul/Minneapolis ATIS is beyond the point at which the net user trip reliability impact of ATIS would be positive. For Washington, the ranges of ATIS error and crossover point overlap, leaving the status of regional benefit from ATIS use ambiguous.
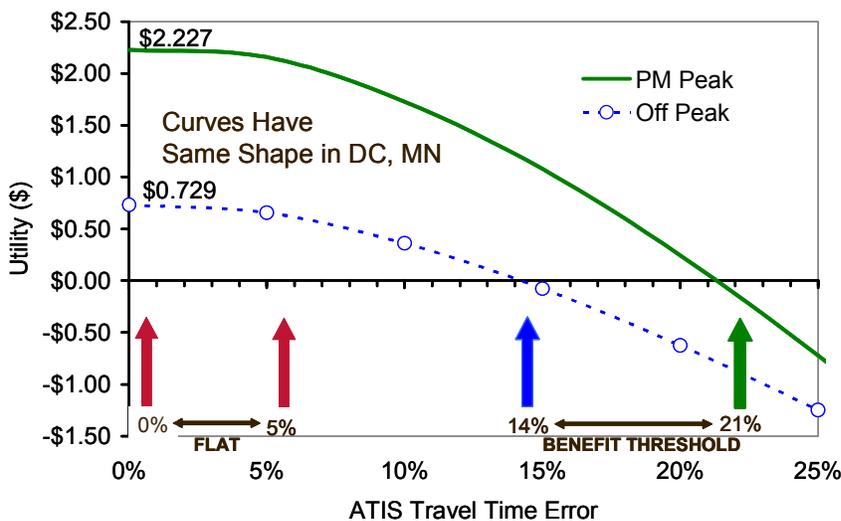

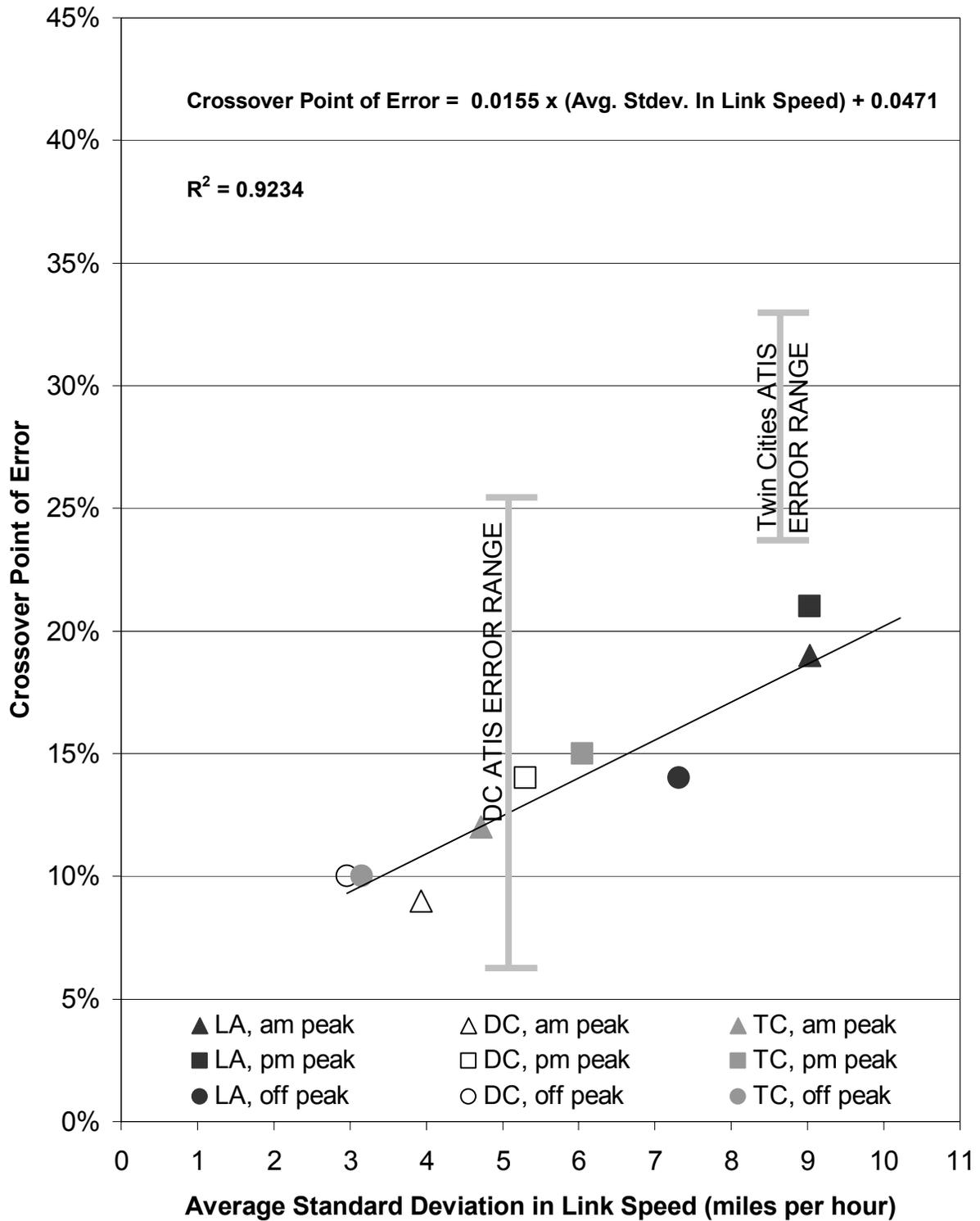**Figure 5-1   Los Angeles Network Utility Curve by ATIS Error Level**

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Figure 5-2   Error Crossover Point by Average Network Link Speed Variability

Studies on the accuracy of travel measurement devices indicate accuracy levels ranging from 8% to 17%. These are the base levels of error generally associated with point estimates of speed. Error in ATIS provision is further introduced going from point speeds to link speed or link travel-time, and further from data ageing between measurement and information dissemination. Based on these factors and the range of crossover error points calculated between 9% and 21% ***we expect that cities are likely at or above the level where ATIS proves a net benefit to users in the region aiming for improved on-time reliability.***

Hypotheses Regarding Incremental Geographic Deployment: For near-optimal incremental deployment strategies of ATIS, an overwhelming percentage of the benefit associated with full deployment can be achieved through efficient deployment of travel time surveillance over a relatively limited set of a few key roadway segments. Incremental deployment strategies based on the observable roadway condition, link travel time variability, will be relatively closer to near-optimal efficiency compared to a random deployment strategy. The geometric form of the regional roadway network will affect the magnitude of benefit achieved by the first few levels in an incremental deployment strategy. More deployment always implies more benefit.

Findings: ***The most effective link ranked strategy, offered as a benchmark for near-optimal incremental deployment, generate deployment plans wherein 30% of network miles deployed account for as much as 93%, 80%, and 56% of the benefit in terms of trip disutility reductions in the cities of Washington DC, St. Paul/Minneapolis, and Los Angeles, respectively.*** However implementing this strategy would require an experiment in which each portion of the network is instrumented individually and the efficiency of the network is evaluated based on that individual instrumentation. The findings from these individual instrumentations and network evaluations form the basis upon which to rank links in the most effective link ranked strategy.

Figure 5-3 presents the percent of total benefit garnered by percent of roadway miles covered using the most effective link ranked strategy. As demonstrated from the evaluations, ATIS real-time coverage on key facilities in the region has the potential to generate the majority of ATIS user benefits associated with full deployment.
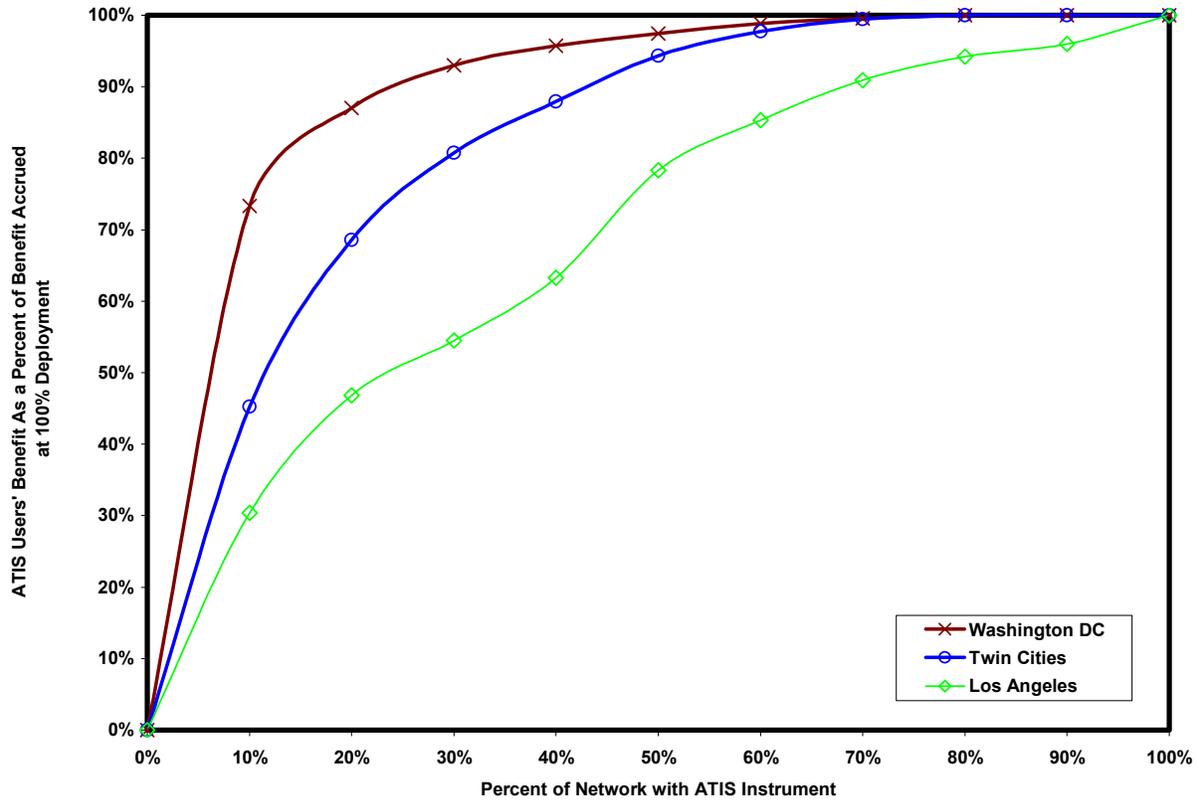
Figure 5-3   Percentage of Full Deployment Benefit by Deployment Levels

We then explored incremental deployment strategies based on observable data. ***Deployments based solely on the criterion of link travel time variability proved no better and sometimes even less efficient the randomly selected link deployment strategy, and in all cases far less efficient than the most effective link ranked strategy.*** Incremental deployments based on the random link selection strategy were on average 68% to 76% as efficient as our near-optimal benchmark across the three cities. In contrast, incremental deployments based on the travel time variability ranked strategy were on average 57% to 75% as efficient as the near-optimal strategy across the three cities. Table 5-1 presents the relative efficiency of the travel time variability strategy and the random strategy compared to the near-optimal strategy of most effective link first.

For Washington DC, this outcome can be explained by the travel time variability strategy choosing arterial deployments before freeway deployments (Table 5-2). This is because arterial links tend to have greater variability compared to freeway links. Yet, freeways far more likely to

be utilized for network-wide travel. It may be that an incremental deployment strategy of instrumenting freeways with high variability first may return patterns more similar to the near-optimal benchmark illustrated in Table 5-2.

Table 5-1 **Efficiency of Random and Travel Time Variability Strategy compared to the Near-Optimal Benchmark**

STRATEGY	Washington, DC	Twin Cities	Los Angeles
Most Effective Link Ranked	Set to 100% Effectiveness		
Travel Time Variability Ranked	57.2%	73.7%	74.8%
Average of 10 Randomly Ranked	68.1%	67.7%	75.6%
Best of 10 Randomly Ranked	85.7%	77.7%	87.7%
Worst of 10 Randomly Ranked	42.7%	57.9%	62.9%

Table 5-2 **Washington Roadway Segments for the 10%, 20%, and 30% Level Deployments based on Most Effective Link and Link Travel Time Variability Strategies**

Coverage Level	Travel Time Variability Ranked Strategy		Most Effective Link Ranked Strategy	
	Mileage	Roadway Name	Mileage	Roadway Name
First 10% Deployment	6.4	Connecticut Ave between DC Line and DC Mall/Garage	16.0	**I-495 in MD between Clara Barandn Hwy. andI-95**
	5.1	Rt. 214 between DC Line and DC Mall/Garage	6.7	**I-495 in VA between Rt. 1 and I-95**
	6.6	Georgia Ave between DC Line and DC Mall/Garage	7.6	**I-495 in MD between Rt. 50 and Rt. 4**
	5.2	New Hampshire Ave between DC Line and DC Mall/Garage	5.5	**I-495 in MD between Rt. 5 and Rt. 210**
	4.1	New York Ave between DC Line and DC Mall/Garage		
	4.0	Rt. 1between DC Line and DC Mall/Garage		
	3.8	Pennsilvania Ave between DC Line and DC Mall/Garage		
	Total Mileage = 35.2 miles		Total Mileage =35.8 miles	
Second 10% Deployed	12.7	**I-95 in VA between Dale City and Fairfax County Pkwy**	6.0	**I-66 between Rt. 50 I-495**
	9.1	**I-270 between Gairsburg and I-495**	7.9	**I-495 in MD between I-95 and Rt. 50**
	3.0	Independence/Connecticut between DC Mall/Garage and DC Line	3.4	**I-495 in MD between Rt. 4 and Rt. 5**
	5.6	Rt. 1 in VA between North Kings Hwy. and 14th Sreet Bridge	12.7	**I-95 in VA between Dale City and Fairfax County Pkwy**
	7.4	**I-495 in MD between Clara Barandn Hwy. and I-270**	6.5	**I-495 in VA between I-95 and Rt. 50**
	Total Mileage = 37.8 miles		Total Mileage =36.5 miles	
Third 10% Deployed	9.3	**Rt. 50 in VA between I-495 and DC Line**	7.0	**I-495 in VA between Rt. 66 and G.W. Pkwy**
	6.9	**Shirley Hwy. (I-395N) between Rt. 236 and 14th St. Bridge**	9.1	**I-270 between I-495 and Gaithersburg**
	2.2	**I-395 between DC Line and DC Mall/Garage**	2.0	**I-495 in MD between Rt. 210 and Rt. 1**
	6.7	**I-495 in VA between I-95 and Rt. 1**	2.9	**I-66 between Fairfax County Pkwy and Rt. 50**
	8.9	VA 620/Braddock Rd. between Fairfax County Pkwy and I-495	7.8	**I-66 between Rt. 267 and Roosevelt Bridge**
			5.3	**Anacostia Fwy. (I-295) between Suitland Pkwy and Rt. 50**
	Total Mileage =34.0 miles		Total Mileage =34.1 miles	
*Roadways in bold are freeway facilites				

In Los Angeles, regional network is that of freeways only. Here, as in DC, our hypothesis about the effectiveness of incremental plans based on link travel time variability is not supported. The incremental deployment based on link travel time variability performs as well as the average of 10 random deployments. The poor performance of this strategy compared to a random

deployment may be attributed to the fact that the demand pattern weights trips from each origin to each destination equally. We expect in reality that the freeway sections with greatest variability will be those most used and that weighting trips by demand will prove that incremental deployments based on travel-time variability will be more efficient than random deployments. We will investigate these and other incremental deployment strategies in future work.

The first 10%, 20%, and 30% levels of incremental deployment based on the near-optimal strategy in Washington DC, a region with radial roadway network of freeways and arterials, garner 73%, 87%, and 93% of benefit, respectively, compared to a full deployment in that region. In Twin Cities, a region with a grid network of freeways and arterials, the first 10%, 20%, and 30% levels garner 69%, 81%, and 88%, respectively. The same levels of deployment in Los Angeles, also a grid network but only of freeway facilities, garner 30%, 47%, and 55% of benefit. ***The outcomes in the three cities support the hypothesis that concentration of ATIS user benefits depends on the network form.***

Finally, as illustrated in Figure 5-3 for the near-optimal strategy, ***deployments beyond the first most effective 7-% of the networks in Washington DC and Twin Cities, generated no benefit. This is because the accuracy of the ATIS was not high enough compared to the variability of links instrumented to make ATIS useful or beneficial. In Los Angeles, however, the hypothesis that more deployment means more benefit holds true.***

5.2   Implications

In making effective tradeoff decisions about how to invest in improved ATIS—be it increasing geographic coverage or increasing accuracy, the findings of this report underscore the importance of understanding what levels of accuracy are required to generate ATIS user benefit based on regional day-to-day roadway variability. Figure 5-4 presents a notional nomograph based on the findings of this report that may assist decision-makers in planning cost effective investments in ATIS deployments. ATIS services with information accuracy and coverage levels landing them in the "don't deploy" area should focus on improving accuracy. Conversely, ATIS services landing in the "add coverage" area have sufficiently accurate information and should focus on increasing ATIS deployment. The ideal for regional ATIS is in the "stand pat" region

where both geographic coverage and accuracy of the ATIS service is at a level where the marginal benefits from improvements do not warrant the cost of such improvements.
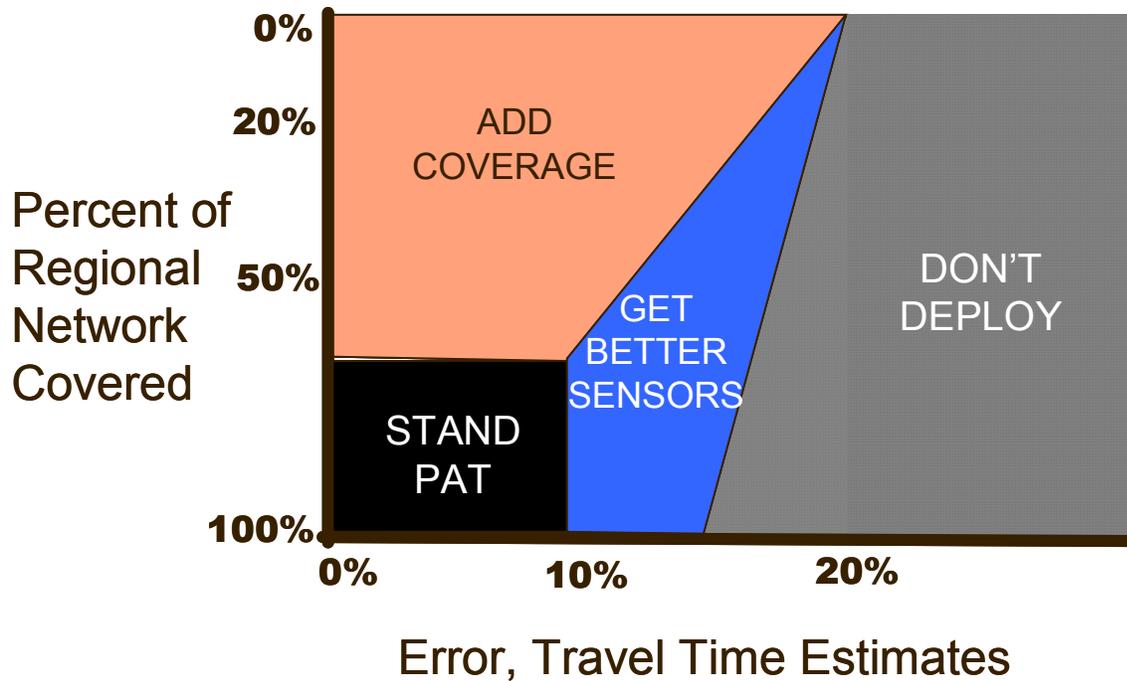
Figure 5-4   Notional Nomograph of Potential Decision Making Regimes

Public sector investment in ATIS is predicated on the expectation of mobility and productivity benefits to both users of ATIS and the transportation system. For aggregate user benefits to be realized, the ATIS service must perform at or above a specific level of accuracy, or conversely, provide information below a certain level of error. Thus, the first step toward efficient ATIS investment decision-making for regions with existing ATIS is to evaluate the accuracy of the current ATIS system.

For regions with existing ATIS as well as for regions in the planning stages of ATIS, decision-makers also need to assess how accurate their ATIS needs to be to generate positive user benefit in their region. The crossover point of error, the value below which ATIS yields a net regional benefit, ranged from 10% to 21% based on the three cities evaluated in this report. More importantly, the crossover point of error proved to be highly linearly related to the day-to-day roadway variability of the region. Thus, ATIS planners can use measured roadway variability to gauge how accurate ATIS in their region needs to be to garner user benefit.

Across the three cities we found that once ATIS error is reduced to a 5% level, benefits from improvements in accuracy are minimal. Having an understanding of the range within which a region's ATIS level of error is acceptable may have significant implications in identifying the types of sensor technologies selected for deployment. For example, in Los Angeles where the crossover point of error ranges from 14% to 21%, detectors using certain technologies with an error range around 12% may be most cost effective. Those same detectors may not be adequate in Washington DC where the crossover point of error ranges from 9% to 14%. The key finding is that if the regional variability is relatively low, the accuracy of ATIS to realize regional user benefit must be relatively high. Conversely, if the regional variability is relatively high, ATIS accuracy to realize aggregate regional user benefits can be relatively lower.

An equally important step toward efficient ATIS investment decision-making for regions is smart geographic deployment of ATIS coverage. We observed that near-optimal geographic deployments of ATIS can garner as much as 50% to 80% of benefits from as little as the first 30% of deployment, yet identifying the near-optimal is not as straightforward as implementation on links with highest variability. Travel demand is expected to play a significant role in the deployment selection process as is facility type (eg. freeway versus arterial).

Across the dozens of existing ATIS services, overwhelmingly, the level of error in the information they provide is poorly known. A review of literature on the accuracy of ATIS or speed/travel time sensor devices proved limited data on ATIS accuracy. Based on these reviews and the notional nomograph (Figure 5-4) presented earlier in this section, we derive a nomograph (Figure 5-5) of the current state of ATIS in the United States and the direction ATIS decision-makers should strive toward. Our findings from this study suggest that the initial focus should be on accuracy, followed by an expansion of geographic deployment.
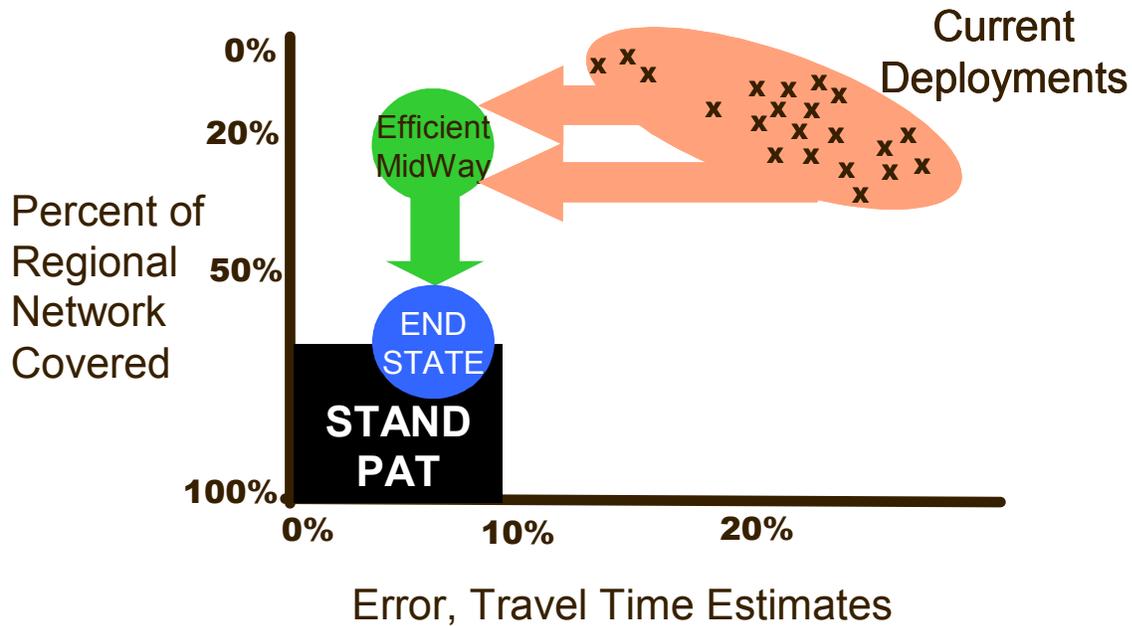
Figure 5-5 Suggested Direction for ATIS Investment

5.3 Conclusions and Next Steps

By extending the HOWLATE methodology, we successfully evaluated how ATIS user benefits of on-time reliability and travel time vary by ATIS accuracy and deployment coverage. The implications for field managers considering ATIS investment strategies, based on the findings from case studies in the cities of Los Angeles, Washington DC, and Minneapolis/St. Paul are noteworthy. Implications for decision makers in regions with existing ATIS are:

- Before considering further ATIS investments, first gain an understanding of the accuracy of your current posted travel time information and of the day-to-day variability of travel on roadways instrumented with ATIS.

- If the accuracy of the existing service is poor in relation to day-to-day travel variability, focus investment into improving accuracy. The variability-accuracy relationship is demonstrated in Figure ES-2.

- Once system accuracy is relatively good in relation to day-to-day travel time variability, then, focus on increasing ATIS coverage(Figure ES-4).

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- Keep in mind that more deployment does not always mean more benefit. There exists an end-state wherein deployment on roadways may not generate additional benefit to users of the ATIS.

For decision makers in regions considering ATIS:

- First identify the day-to-day variability of travel on major regional roadways.

- Select technologies and data processing techniques with a level of accuracy that is appropriate considering the magnitude of variability in your region.

- A good deployment plan can generate significant benefit from minimal investment. Identifying such a plan is difficult if only limited data is available. Deployments of ATIS based on both travel demand and roadway variability data are likely to be a good start in developing an efficient deployment plan.

Case studies in the three cities identified that for ATIS to generate user benefits of on-time reliability, the level of error in information delivered by ATIS needs to meet a minimum range of 10% to 21%. Further, regions with greater day-to-day roadway variability can generate ATIS user benefits at higher levels of error in ATIS information compared to regions with lesser day-to-day roadway variability. We also confirmed that near-optimal, incremental ATIS geographic deployment plans can garner as much 50% to 80% of benefit associated with full deployment with as little as 20% to 30% of the full geographic deployment.

Based on these findings, we have presented notional nomographs aimed at assisting ATIS decision-makers in developing effective investment strategies that provide the highest possible value of service to their constituencies. In future work, we expect to expand on these nomographs to deliver decision-makers more detailed graphs that identify efficient directions for investment based on their specific situation. In expanding the notional nomograph, we also expect to expand on the various accessible metrics upon which to base incremental geographic deployments of ATIS. In this report, we evaluated deployments based solely on travel time variability. In future work we hope to consider other factors such as annual average daily traffic, travel demand, or other metrics readily available to transportation planners.

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APPENDIX A: Revised HOWLATE Algorithmic Statement

HEURISTIC ON-LINE WEB-LINKED ARRIVAL TIME ESTIMATOR (HOWLATE)

Overview

Step 1.   Expectation During 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 ATIS Users in Evaluation Period
                 OPTION 1: Pre-Trip Time Shift with Pre-Trip Route Choice
                 OPTION 2: Pre-Trip Time Shift with En Route Path Choice

A. Forward A-STAR Dynamic Program: D'

B. Reverse Time Dynamic Program: $`D$

C. Forward Path Traversal Under Estimated Travel Times: $T'\left(\cdots,\hat{c}_{\ell}(t)\right)$

D. Forward Path Traversal Under Actual Travel Times: $T'\left(\cdots,\widehat{c}_{\ell}(t)\right)$

E. Evaluating Arc Costs Between Lattice Points

Step 1. Expectation-Setting Under Training Period

Network Structure File:

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

$\ell:(a,b)$ link ℓ defined as unidirectional arc from node a to node b

f_ℓ facility type (currently arterial or freeway)

ξ_ℓ congestion threshold time (seconds)

δ_ℓ distance along link (miles)

Archived Daily Link Travel Time Files, Training Period

For each day $k = 1, 2, 3 \cdots N$ in the training period of N days, one file containing:

For each link $\ell \in L$, and 5-minute time slice day $k : t = 0, 1, 2 \cdots T$;

$\hat{c}_\ell^k(t)$ archived link travel time for link ℓ 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 $\hat{c}_\ell^k(t)$:

   a. compute congestion factor based on ℓ, t:
   $$\kappa = \begin{cases} 1 & \hat{c}_\ell^k(t) > \xi_\ell \\ 0 & \hat{c}_\ell^k(t) \le \xi_\ell \end{cases}$$

   b. compute estimates based on link characteristics, time of arc traversal, and adjustment factors:
   $$\widehat{c}_\ell^k(t) = \mathrm{M}(\ell, t) = \mathrm{NORMAL}\left(\hat{c}_\ell^k(t) - \mu_f^\kappa, \sigma_f^\kappa\right)$$

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

   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 $\widehat{c}_\ell(t)$:

$$\widehat{c}_\ell(t) = \frac{\sum_k \widehat{c}_\ell^k(t)}{N}$$

3. For each destination node d and target arrival-at-destination time τ,
   where $\tau: 1, 2, 3 \cdots T_\tau$, 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:

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

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

   $t' = \tau - \overline{p}_{o,d,\tau}^1$

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 t' using training day k arc costs:

   $\mathrm{T}'\left(\overline{\mathbf{P}}_{o,d,\tau}, t', \widehat{c}_\ell^k(t)\right) \to \overline{p}_{o,d,\tau}^k$, the travel time on the habituated path

   b. from the vector series $\left\{\overline{p}_{o,d,\tau}^k : k = 1, 2, \cdots N\right\}$, compute $\overline{p}_{o,d,\tau}$, the average path travel time and

   $\overline{\sigma}_{o,d,\tau}^{\mathbf{P}}$, the standard deviation of the series of days of travel on the habitual path

   c. compute the habituated time of trip start, $t_{o,d,\tau}^0 \forall o, d, \tau$:

   $t_{o,d,\tau}^0 = \tau - \left(\overline{p}_{o,d,\tau} + Z_\chi \overline{\sigma}_{o,d,\tau}^{\mathbf{P}}\right)$, 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 $\overline{\delta}_{o,d,\tau} = \sum_{\ell \in \overline{P}_{o,d,\tau}} \delta_\ell$.

   e. identify the savvy ATIS user correction factor, $\omega_{o,d,\tau}$ .and the uncertainty associated with the ATIS-
   estimated travel time, $\widehat{\sigma}_{o,d,\tau}^{\mathbf{P}}$.

   traverse $\overline{\mathbf{P}}_{o,d,\tau}$ forward with ATIS-estimated arc costs fixed at time t' :

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

Let $\omega_{o,d,\tau} = \dfrac{\overline{p}_{o,d,\tau}}{\dfrac{1}{N}\sum_{k}\hat{p}^{k}_{o,d,\tau}}$, the ratio of experienced to predicted travel times in the period.

Let $\hat{\sigma}^{\overline{\mathbf{P}}}_{o,d,\tau} = \dfrac{1}{N-1}\sum_{k}\left(\overline{p}^{k}_{o,d,\tau} - \hat{p}^{k}_{o,d,\tau}\cdot\omega_{o,d,\tau}\right)^{2}$, the uncertainty associated with the ATIS-

estimated travel time.

   f. let $t' = t^{0}_{o,d,\tau}$. Repeat steps 4a, 4b and 4e ONCE.

5. Skip forward to Step 2., Optimal Paths in Evaluation Period.

6. UNFAMILIAR TRAINING

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

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

7. For each destination node d and target arrival-at-destination time τ,
    where $\tau: 1, 2, 3 \cdots T_\tau$, 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:

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

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

8. 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 $t^0_{o,d,\tau} = t^0_{o,d,\tau} - REM\left(\dfrac{t^0_{o,d,\tau}}{\Delta}\right)$, where REM() is the

    remainder after integer division.

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

$\hat{c}_\ell^j(t)$ $\qquad$ archived link travel time for link ℓ 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 $\widehat{c}_\ell^j(t)$:
    For each $\ell \in L, t \in T$:

    a. compute congestion factor based on ℓ, t as in Step 1.1.
    b. compute estimates based on link characteristics, time of arc traversal, and adjustment factors:
    $$\widehat{c}_\ell^j(t) = \mathrm{M}(\ell, t) = \mathrm{NORMAL}\!\left(\hat{c}_\ell^j(t) - \mu_f^\kappa, \sigma_f^\kappa\right)$$
    c. enforce consistency in actual travel time profiles, enforcing FIFO for arc costs in time:
    $$\text{if } \widehat{c}_\ell^j(t) - \widehat{c}_\ell^j(t+1) > 300 \text{ then set } \widehat{c}_\ell^j(t+1) = \widehat{c}_\ell^j(t) - 300.$$

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:

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

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

Step 3. Determine Performance of Non-Users in Evaluation Period

<u>NEW INPUT FILES</u>:

None.

<u>PROCEDURE</u>:

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:

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

Step 4. Determine Performance of ATIS Users in Evaluation Period

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

<u>NEW INPUTS:</u>

<u>From Control File:</u>

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

<u>PROCEDURE</u>:

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 $t = t'$;

   $$D'\left(o, d, t', \hat{c}^j_\ell(t')\right) \rightarrow \dot{\mathbf{P}}^j_{o,d,\tau} \text{, a candidate fastest path with predicted travel time } \dot{p}^j_{o,d,\tau}$$

   c. check to see if trip start can be safely postponed five minutes longer

        CHECK#1: $t' + \omega_{o,d,\tau} \dot{p}^j_{o,d,\tau} < \tau - (\Delta + Z_\chi \hat{\sigma}^{\overline{\mathbf{P}}}_{o,d,\tau})$ (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 $\hat{\dot{p}}^j_{o,d,\tau} = \dot{p}^j_{o,d,\tau}$ and GOTO step h.

   e. forward traverse the habitual path, $\overline{\mathbf{P}}_{o,d,\tau}$, using arc costs fixed at $\tilde{t}^j_{o,d,\tau}$;

   $$T'\left(\overline{\mathbf{P}}_{o,d,\tau}, \tilde{t}^j_{o,d,\tau}, \hat{c}^j_\ell\left(\tilde{t}^j_{o,d,\tau}\right)\right) \rightarrow \hat{\dot{p}}^j_{o,d,\tau} \text{, the predicted travel time on the habitual path.}$$

   f. perform check to see if the alternative route is attractive enough to warrant diversion

        CHECK#3: $\hat{\dot{p}}^j_{o,d,\tau} - \dot{p}^j_{o,d,\tau} > \varepsilon$

        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 $\tilde{t}^j_{o,d,t}$:

   $$T'\left(\dot{\mathbf{P}}^j_{o,d,\tau}, \tilde{t}^j_{o,d,\tau}, \hat{c}^j_\ell(t)\right) \rightarrow \tilde{p}^j_{o,d,\tau} \text{, experienced travel time for the ATIS user.}$$

        Set pre-trip switch indicator $x^j_{o,d,\tau} = 1$, and trip distance $\tilde{\delta}^j_{o,d,\tau} = \sum_{\ell \in \dot{\mathbf{P}}^j_{o,d,\tau}} \delta_\ell$.

        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 $\widetilde{t}^{\,j}_{o,d,t}$:

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

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

$\widehat{p}^{\,j}_{o,d,\tau}$ optimal travel time

$\widehat{\delta}^{\,j}_{o,d,\tau}$ travel distance on optimal path

$t^{0}_{o,d,\tau}$ habitual time of trip start

$\widehat{\overline{p}}^{\,j}_{o,d,\tau}$ non-user experienced travel time (leaves at habitual trip start time)

$\overline{\delta}_{o,d,\tau}$ travel distance on habitual path

$\widetilde{t}^{\,j}_{o,d,\tau}$ ATIS user time of trip start

$\widehat{\overline{p}}_{o,d,\tau}$ 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

$\widetilde{p}^{\,j}_{o,d,\tau}$ experienced travel time, ATIS user

$\widetilde{\delta}^{\,j}_{o,d,\tau}$ experienced travel distance, ATIS user

$x^{j}_{o,d,\tau}$ 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, No Time Shift (Late Schedule Delay Minimization)

<u>NEW INPUTS:</u>

<u>From Control File:</u>

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

<u>PROCEDURE</u>:

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

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

   c. check to see if trip start can be safely postponed five minutes longer

   CHECK#1: $t' + \omega_{o,d,\tau}\,\dot{p}_{o,d,\tau}^{j} < \tau - (\Delta + Z_{\chi}\hat{\sigma}_{o,d,\tau}^{\overline{\mathbf{P}}})$ (predicted to be early?)

   CHECK#2: $t' < t_{o,d,\tau}^{0} + e^+$ (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 $\widetilde{t}_{o,d,t}^{j} = t'$.

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

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

f. Switch to the alternative path:

Let $\ell' = I\left(\hat{\mathbf{P}}^j_{i,d,\tau}(\alpha)\right)$ next link to be traversed from alternative path

If $i = o$, then set $x^j_{o,d,\tau} = x^j_{o,d,\tau} + 1$;   increment route switch counter

       Else set $y^j_{o,d,\tau} = y^j_{o,d,\tau} + 1$

Set $\mathbf{P}_{i,d,\tau}(\alpha) = \hat{\mathbf{P}}^j_{i,d,\tau}(\alpha)$,   the alternative path is now the current path

GOTO step h.

g. Stick with the current path:

Let $\ell' = I\left(\mathbf{P}_{i,d,\tau}(\alpha)\right)$ next link to be traversed from current path

h. Set $\widetilde{\mathbf{P}} = \widetilde{\mathbf{P}} + \ell'$,   update list of traversed links

Set $i = B(\ell')$,   update current position

Set $\alpha = \alpha + \hat{c}^j_{\ell'}(\alpha)$,   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 $\widetilde{\delta}^j_{o,d,\tau} = \sum_{\ell \in \widetilde{\mathbf{P}}} \delta_\ell$.

k. Generate performance record (identical to OPTION 1)

A. Forward A-STAR Dynamic Program: D'

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

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

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

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

3.   a. find $n = \min_{n' \in \mathbf{O}} \{F(n')\}$; $\alpha = G(n)$.
        b. if $n = d$, then GOTO Step 5.
        c. for each $n' \in S(n)$:
                   Let $\ell = (n, n')$ and $\alpha' = \alpha + c_\ell(\alpha)$.
                   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 $\bar{N}(n') = n$.
                       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 $G(d) - t^0$.

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B. Reverse-Time Dynamic Program: `D

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

d trip destination

τ target time of arrival at d

$c_\ell(t)$ set of actual arc costs to be used, defined $\forall \ell, t$

Plus, it uses the following array already constructed:

c_ℓ^0 free-flow arc travel times $\forall \ell$

1.   Define the following:

       O   the set of open nodes, set $\mathbf{O} = d$.

       C   the set of closed nodes, set $\mathbf{C} = \varnothing$.

       $G(n)$ 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 $n = \max\limits_{n' \in \mathbf{O}} \{G(n')\}$; set $\alpha = G(n)$.

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

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

       (b*)   if $\alpha'' + c_\ell(\alpha'') \leq \alpha$ then

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

           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: $T'\left(\cdots, \hat{c}_\ell(t)\right)$

$T'\left(\mathbf{P}_{o,d}, t^0, c_\ell\left(t^0\right)\right)$: 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_ℓ set of estimated arc costs fixed at time t^0, defined $\forall\, \ell$

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

D. Forward Path Traversal Under Actual Travel Times: $T'\left(\cdots, \widehat{c}_\ell(t)\right)$

$T'\left(\mathbf{P}_{o,d}, t^0, c_\ell(t)\right)$: 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

$c_\ell(t)$ set of actual arc costs, defined $\forall\, \ell, t$

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

$$\widehat{c}_\ell(t) = \widehat{c}_\ell(\overline{t}) + \left(t - \overline{t}\right)\frac{\left(\widehat{c}_\ell(\overline{\overline{t}}) - \widehat{c}_\ell(\overline{t})\right)}{\left(\overline{\overline{t}} - \overline{t}\right)} \qquad \text{(see Appendix E)}$$

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

3.   If $\ell \equiv (a,b); b \neq d$ 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 $\hat{c}_\ell(t) = c_\ell(\bar{t})$.

2. For traversals and DP applications using actual data, $\widehat{c}_\ell(t)$, use linear interpolation:

$$\widehat{c}_\ell(t) = \widehat{c}_\ell(\bar{t}) + (t - \bar{t})\frac{\left(\widehat{c}_\ell(\vec{t}) - \widehat{c}_\ell(\bar{t})\right)}{\left(\vec{t} - \bar{t}\right)} .$$