SHRP 2 Project L03

Analytical Procedures for Determining the Impacts of Reliability Mitigation Strategies

final

report

prepared for

Strategic Highway Research Program 2

prepared by

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Executive Summary

PROJECT BACKGROUND

The fundamental objective of SHRP 2 Project L03 is to develop predictive relationships between highway improvements and travel-time reliability. In other words, how can we predict what effect an improvement will have on reliability? Alternately, how can we characterize reliability as a function of highway, traffic, and operating conditions? A variety of challenging issues have been confronted in addressing this objective.

Travel-time reliability is a significant aspect of transportation system performance. Reliability is important to travelers and transportation practitioners for a variety of reasons:

- From an economic perspective, reliability is highly important because travelers must either build in extra time to their trips to avoid arriving late or suffer the consequences of being late. This extra time has value beyond the average travel time used in traditional economic analyses. Recent work has documented the fact that reliability has value to travelers and that their behavior is influenced by it (*1*, *2*).
- Because of the extra time required in planning trips – and the uncertainty about what travel times will actually be for a trip – reliability influences decisions about where, when, and how travel is made.
- Due to the extra economic cost of unreliable travel on users, transportation planners and operators need to include these costs in the project planning, programming, and selection processes. This is particularly true of strategies that deal directly with roadway events (e.g., incidents). In the past, most assessments of these types of strategies have missed this important aspect of travel.

Travel-time reliability is a new concept to which much of the transportation profession has had only limited exposure. Use of travel-time-based performance measures in planning and operations applications has taken on greater significance in the last few years. Congestion has been growing nationwide and planners increasingly have become involved in short-term activities such as performance monitoring as well as operations and management strategies. These activities have been elevated in importance by transportation agencies in order to be responsive to the demands of the public and state legislatures. Both anecdotal and technical studies indicate that average congestion levels have, and are continuing, to grow in our cities.

However, talking about typical or average conditions in a transportation system that experiences wide fluctuations in performance tells only one part of the story. The notion of *travel-time reliability* – how consistent (or variable) travel conditions are from day-to-day – has taken on increasing importance. The variation in travel times now is understood as a separate component of the public's and business sector's frustration with congestion problems. Reliability is a major part of system performance and of travelers' perceptions of performance. It has not been widely used to describe performance, but increasingly agencies are recognizing its value in assessing their own performance and in communicating performance to the public.

How should travel-time reliability be defined? In terms of highway travel, the F-SHRP Reliability Research Program defined reliability this way (*3*):

… from a practical standpoint, *travel-time reliability can be defined in terms of how travel times vary over time* (e.g., hour-to-hour, day-to-day). This concept of variability can be extended to any other travel-time-based metrics such as average speeds and delay. For the purpose of this study, travel time variability and reliability are used interchangeably.

A slightly different view of reliability is based on the notion of a *probability or the occurrence of failure* often used to characterize industrial processes. With this view, it is necessary to define what "failure" is in terms of travel times; in other words, a threshold must be established. Then, one can count the number of times the threshold is not achieved or exceeded. These types of measures are synonymous with "on-time performance" since performance is measured relative to a pre-established threshold. The only difference is that failure is defined in terms of how many times the travel-time threshold is exceeded while on-time performance measures how many times the threshold is not exceeded.

In recent years, some non-U.S. reliability research has focused on another aspect of reliability – the *probability* of "failure," where failure currently is defined in terms of traffic flow breakdown. A corollary is the concept of "vulnerability" which could be applied at the link or network level: this is a measure of how vulnerable the network is to breakdown conditions.

To understand travel-time reliability, it is essential to understand the factors that cause travel times to be unreliable. Previous work indicates that reliability is determined by the variability in conditions that travelers encounter from day-to-day. Therefore, reliability metrics tell you that variability exists in the system; they do not tell you what is causing it. The original F-SHRP Reliability Research Plan identified the "Seven Sources of Congestion" as the factors that cause travel times to be unreliable and contribute to total congestion: incidents, inclement weather, work zones, special events, traffic control device timing, demand fluctuations, and inadequate base capacity. These categories were developed to move away from the recurring/nonrecurring nomenclature that has been in wide use but is not detailed enough for the purpose of SHRP 2 research.

Both operational strategies and capacity expansion projects were expected to affect reliability and were to be studied in the research. Many operational strategies are aimed specifically at the factors that cause unreliable travel (e.g., incident management, work zone management). Note, however, that one of the "Seven Sources" affecting reliability is inadequate base capacity. The effect of physical capacity on congestion is well established and has been the focus of analytic procedures for the past several decades (e.g., the *Highway Capacity Manual (*HCM)). Physical capacity also affects the reliability since it interacts with all the other sources. For example, consider an incident that blocks one lane of traffic. Its effect is much greater if there are only two lanes available than if three or more were available. So, adding physical capacity definitely will have an effect on reliability.

Travel-time measurements are critical to any definition of reliability and reliability metrics. Travel time is the starting point for sound congestion measurement because it reflects the actual experience of system users. When measured directly, it also is independent of theoretical capacity concerns – such as what happens in oversaturated conditions. Further, once travel time is obtained, a whole family of additional measures can be created using other basic information about the system (e.g., volume, free-flow speed). Delay is one example of the metrics that naturally flow from travel-time measurements.

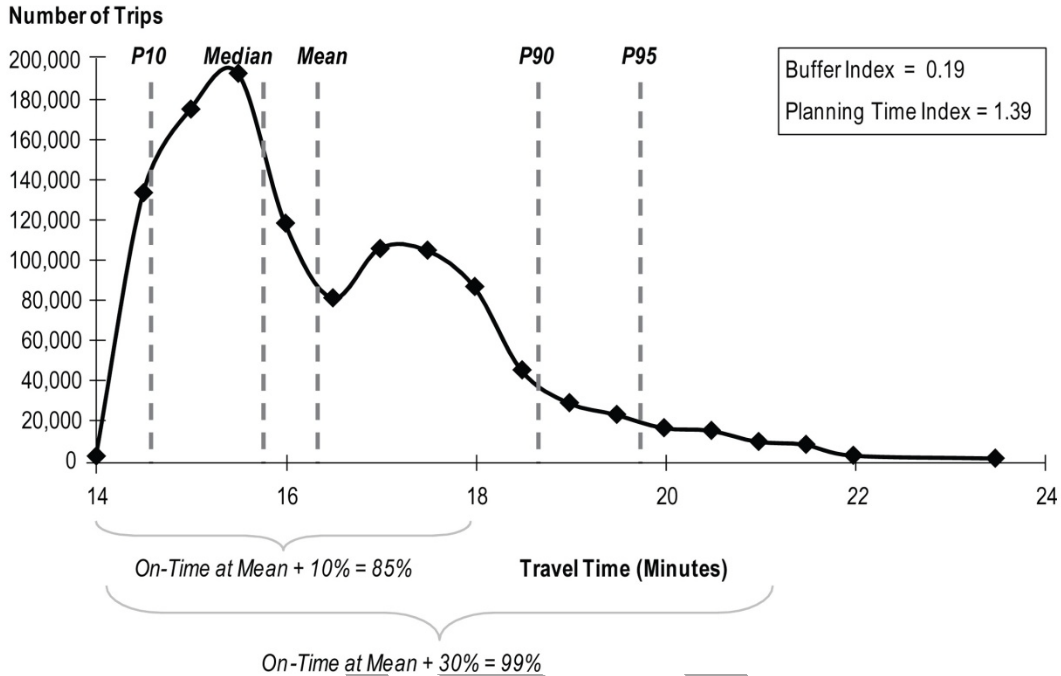
PROJECT APPROACH

Data Collection

The research team decided at the time of preparing the original Work Plan that an empirical approach should be undertaken. The team, which was familiar with the data used to characterize congestion and reliability, felt that data of sufficient quality and amount now existed to allow an empirical approach. However, because reliability is defined by a long history – at least a year – of travel times (a distribution), use of automated equipment is the only feasible method of data collection. Further, to purchase and deploy automated equipment capable of making continuous measurements on multiple highway sections would be cost prohibitive. Therefore, the team relied on data already being collected by transportation agencies, primarily in support of operations programs.

Figure ES.1 shows the distribution of travel times along a section of highway. This distribution – and the statistics that describe it – is the basis for research. In Figure ES.1, several statistics are superimposed on the distribution that represents the reliability metrics used in the research. P10, P90, and P95 are the 10^{th}, $90^{th,}$ and 95^{th} percentiles of the distribution. The remaining metrics are defined elsewhere in this report.

Figure ES.1 Reliability is Defined by How Travel Times Vary



A very large dataset was assembled using a variety of sources (Figure ES.2). Most of the data covered urban freeways; the data source was traffic management centers (TMC; Tables ES.1 through ES.3). A separate dataset of urban freeways was compiled for the Seattle area for the congestion-by-source analysis; this dataset is documented at the end of this section.

Figure ES.2 The Analysis Data Set Fused Data from a Variety of Sources

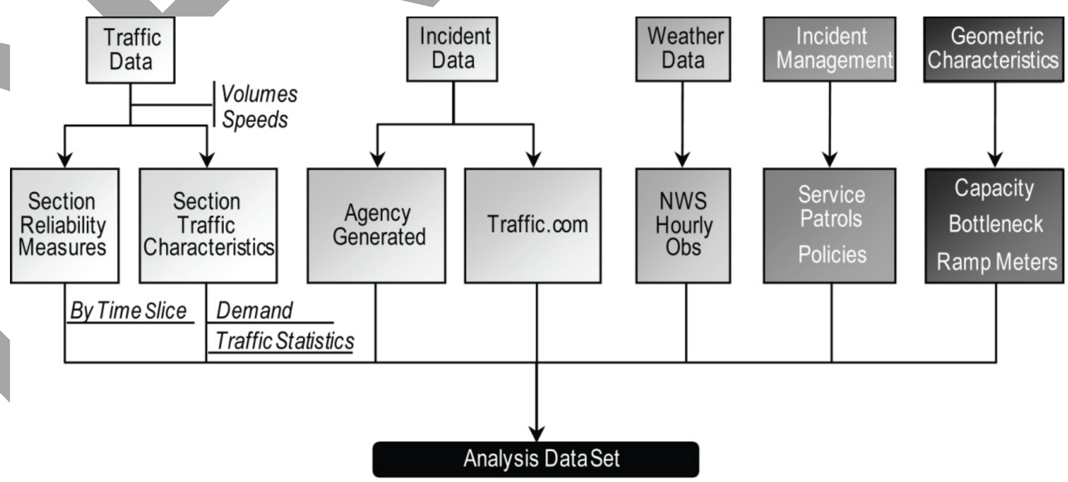


Table ES.1 Urban Freeway Study Section Summary

City	Number Directional Study Sections	Total Directional Mileage
Houston	13	58.80
Minneapolis	16	62.63
Los Angeles	3	50.27
San Francisco Bay Area	4	19.98
San Diego	6	28.04
Atlanta	10	54.66
Jacksonville	8	17.71
Total	60	292.09

Data on the basic characteristics of incidents were available from three sources and were used to varying degrees, depending on the team's assessment of data sources for each city's situation. First, incident data were available from a private vendor, Traffic.com, for the research. The incident and event data were provided to the project team by Traffic.com at no cost from their Traveler Information Management System (TIMS). The TIMS data provided a standardized source of information for traffic incidents, events, scheduled and unscheduled construction, and other events that could affect traffic conditions (such as severe weather or transit delays). The sources of incident data used in the urban freeway analysis are as follows:

- **Atlanta –** TMC data is primary source (includes work zones and special events), checked against both Traffic.com and GDOT crash data.
- **Houston –** Traffic.com data was found to match TMC (Transtar) incident data very well, and since it contains work zones and special events, is the source of incident information.
- **Minneapolis –** Traffic.com data.
- **San Diego, Los Angeles, and San Francisco (Bay Area) –** Traffic.com data.
- **Seattle –** Special data set, a fusion of TMC and police CAD data.
- **Jacksonville –** TMC data.

The weather data for SHRP 2 L03 project were obtained from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). NCDC is the world's largest active archive of weather data. NCDC produces climate publications and responds to data requests from all over the world. The data consisted of hourly weather observations (e.g., precipitation, temperature, wind, fog) at multiple points within the urban areas.

Geometric data were obtained from satellite imagery (lane configurations) and the 2007 Highway Performance Monitoring data. Operating and improvement data were obtained directly from the state DOTs. The most important data in this category are those elements related to calculating capacity for each individual link.

Table ES.2 Signalized Arterial Study Sections

City	Arterial	From	To	Length (Miles)	Travel-Time Data: Data Technology	Travel-Time Data: Period
Orlando	Sect 1: SR 50 Eastbound	Florida Turnpike	SR 408 West	6.85	Tag-Based Probe	March 2008+
	Sect 2: SR 50 Westbound	SR 408 West	Florida Turnpike	6.85	Tag-Based Probe	March 2008+
	Sect 3: U.S. 441 Northbound	SR 417	SR 408	10.67	Tag-Based Probe	March 2008+
	Sect 4: U.S. 441 Southbound	SR 408	SR 417	10.67	Tag-Based Probe	March 2008+
	Sect 5: U.S. 441 Northbound	SR 408	N. John Young Parkway	4.35	Tag-Based Probe	March 2008+
	Sect 6: U.S. 441 Southbound	N. John Young Parkway	SR 408	4.35	Tag-Based Probe	March 2008+
Los Angeles	Santa Monica Boulevard	I-405	N. Gardner Street	6.9	GPS Probe (Inrix)	2006/2007
Phoenix	E. Camelback Road	44th Street	Highway 51	4.2	GPS Probe (Inrix)	2006/2007
Minneapolis	Washington Avenue	County Highway 153	U.S. 65	3.4	GPS Probe (Inrix)	2006/2007
Miami	U.S. 1	17th Avenue	Le Jeune Road	3.8	GPS Probe (Inrix)	2006/2007
Houston	Westheimer Road	W. Sam Houston	I-610	6.9	GPS Probe (Inrix)	2006/2007

Note: Probe tag technology provide direct estimates of travel time over the segment.
Inrix-provided data are supplied as speed estimates by link (approximately one-half- to one-mile long). Only the Orlando sections were used in the analysis because of sample size limitations on the other sections.

Table ES.3 Rural Freeway Study Sections

State	Route	From	To	Length	Travel-Time Data: Data Technology	Travel-Time Data: Period
Texas	I-45	Exit 213, Navarro County	Exit 267, Ellis County	54.1	GPS Probe (Inrix)	2006/2007
South Carolina	I-95	South Carolina/Georgia Border	SR 68, Hampton County	38.2	GPS Probe (Inrix)	2006/2007

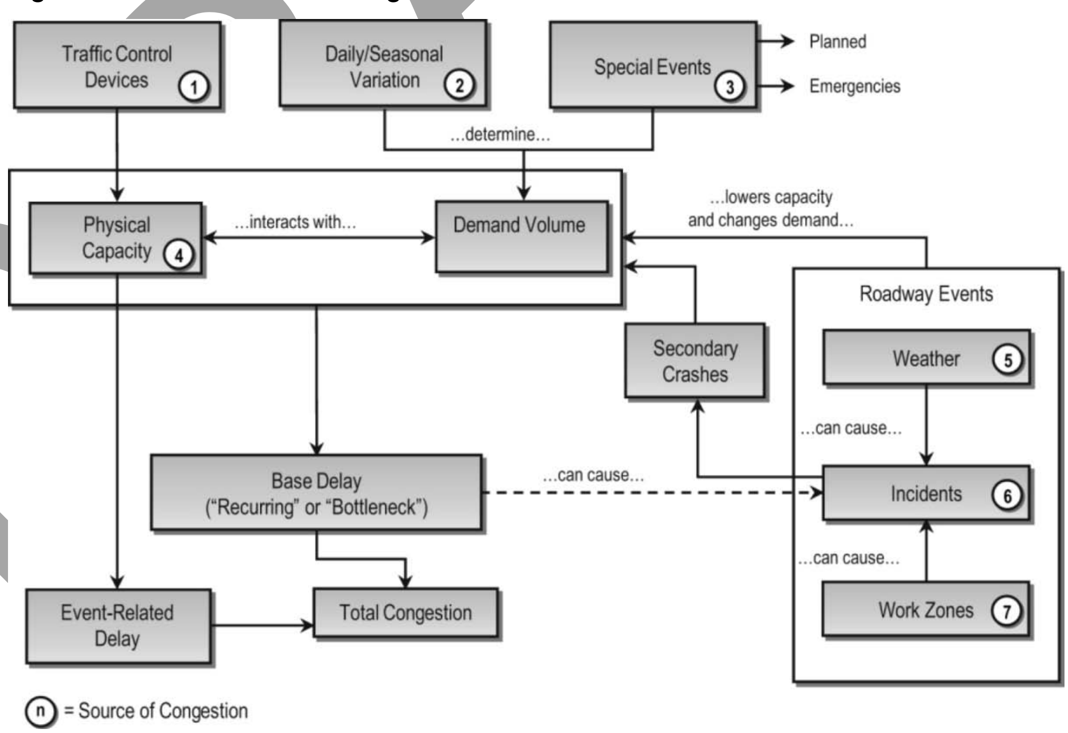
Analysis Approach

The analysis was based on a conceptual model previously developed by members of the research team (Figure ES.3). The model indicates that the sources of congestion interact to produce total congestion. Reliability is an aspect of total congestion and is greatly influenced by the complex interactions of traffic demand, physical capacity, and roadway "events."

The analysis proceeded with four different tracks:

1. Exploratory analysis, which was used to improve our understanding of reliability and establish many of the research parameters.
2. Before/after studies on selected study sections which resulted in empirical measurements of the change in reliability.
3. Cross-sectional statistical modeling, which was used to develop statistically based predictive models of reliability as a function of traffic, operating, and geometrics conditions. The cross-sectional modeling was an extremely important part of the research because it was possible to study all of the possible improvement types in the field using a before/after approach.
4. Congestion-by-Source analysis, which was a microlevel approach to decomposing daily congestion into its component sources.

Figure ES.3 A Model of Congestion and Its Sources



FINDINGS AND PRODUCTS OF THE RESEARCH

Dataset Compilation and Usage

A large and comprehensive dataset was compiled in order to conduct the research. The dataset will be of use for future research and the SHRP 2 data archive being constructed with the L03 dataset as its core. The dataset includes many different levels of aggregation and summarization. The traffic data from urban freeways is the largest portion of the dataset and includes the original measurements from roadway detectors (five-minute intervals by lane), numbering in the hundreds of millions of records. The traffic data also is summarized at several spatial and temporal aggregation levels. The most summarized portion of the dataset is the one used for the cross-sectional statistical analysis: every record is an annual summary of traffic and reliability characteristics, with annual event characteristics and roadway features merged into it. The data processing included new procedures that the Research Team created specifically for the project (see the next section).

The sources of the data were primarily from state DOTs; data included continuous traffic measurements, incidents, work zones, ITS equipment, operating policies, and geometric characteristics. In addition, we purchased a limited amount of private vendor vehicle probe data for rural freeways and signalized arterials; the rural freeway data was adequate to establish reliability but the signalized arterial data did not appear to have enough samples and local signal timing data was not available for the time period of the probe data. Incident data from a second private vendor also was available without fee; these provided the needed lane blockage data in several locations where public agencies did not collect this type of information.

Fusion/integration of the various data proved to be a daunting and time-consuming task. The data sets had different georeferencing which complicated the matching of traffic data, incidents, improvements, and geometric characteristics. A good deal of the matching had to be done manually. A large amount of testing, quality control, and development of new processing procedures had to be conducted.

The utility of the dataset as a research resource was proven several times during the project. Often, the team needed to investigate new areas or compute factors and these were easily accomplished because the data was "analysis already." We expect future researchers to appreciate this feature.

In addition to supporting research, the dataset represents an excellent model for practitioners to use in developing performance monitoring systems for congestion and reliability. Specifically, the different levels of temporal and spatial aggregation can be used to support many local requirements. The fusion of traffic, event, and geometric data provide the basis for not only tracking reliability trends but also includes the data required to explain those trends (e.g., demand and events). The data processing methods which supported the research also should be strongly considered for state and local congestion/ reliability monitoring systems. Data processing for performance monitoring is not trivial and many different methods and assumptions can be used. The L03 research provides a basis for standardizing those procedures.

Exploratory Analyses

A large variety of exploratory analyses were undertaken prior to the main analyses in order to test assumptions, develop data processing methods, and as an aid in understanding reliability in general. The highlights of these exploratory analyses include:

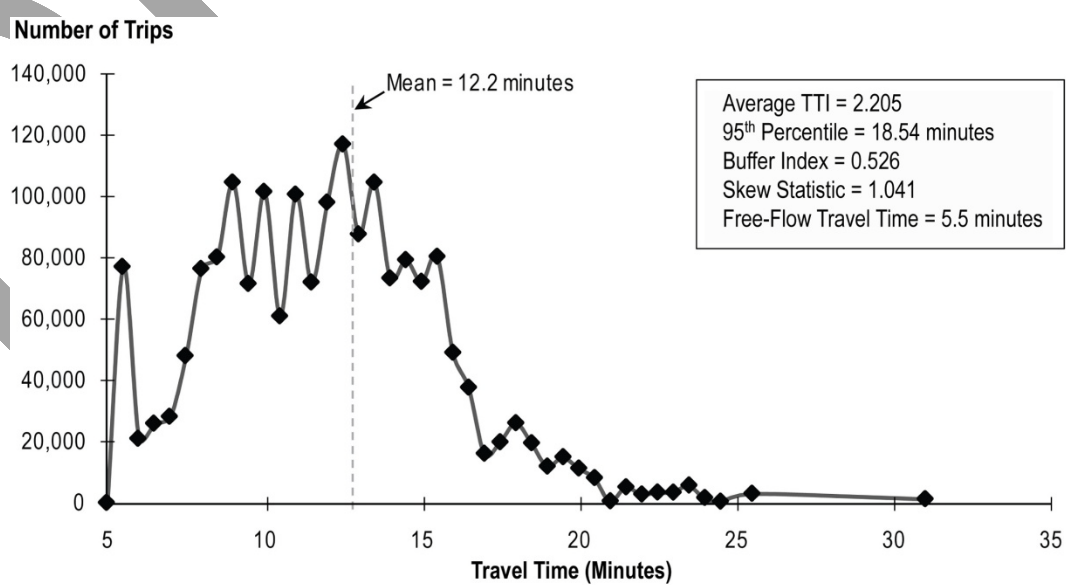
- **Recommended Reliability Metrics.** Based on empirical tests, it was found that the performance metrics defined in the early stages of the research are sensitive to the effects of improvements. However, it was noticed that the 95th percentile travel time or TTI may be too extreme a value to be influenced significantly by operations strategies and that the 80th percentile was more sensitive to these improvements. As a result, the 80th percentile was added to the list of reliability performance metrics for the remainder of the research. The final set of reliability metrics – which also are appropriate for general practice – appear in Table ES.4.

Table ES.4 Recommended Reliability Metrics

Reliability Performance Metric	Definition	Units
Buffer Index (BI)	The difference between the 95th percentile travel time and the average travel time, normalized by the average travel time. The difference between the 95th percentile travel time and the median travel time, normalized by the median travel time.	Percent
Failure/On-Time Measures	Percent of trips with travel times <: • (1.1 * Median Travel Time); and • (1.25 * Median Travel Time). Percent of trips with space mean speed <: • (50 mph, 45 mph, 30 mph).	Percent
Planning Time Index	95th percentile Travel Time Index.	None
80th Percentile Travel Time Index	Self-explanatory.	None
Skew Statistic	The ratio of (90th percentile travel time minus the median) divided by (the median minus the 10th percentile).	None
Misery Index (Modified)	The average of the highest five percent of travel times divided by the free-flow travel time.	None

- **Travel-Time Distributions.** Development of travel-time distributions is the starting point for defining reliability metrics and a convenient way to visualize general congestion and reliability patterns for a highway section or trip. Examination of the distributions from the study section used in this research reveals several characteristics:
  - The shape of the travel-time distribution for congested peak times (weekdays, nonholidays) is much broader than the sharp spike evident in uncongested conditions. The breadth of this broad "shoulder" of travel times decreases as congestion level decreases.
  - Likewise, the tails of the distributions (to the right) appear more exaggerated for the uncongested time slices. However, note that the highest travel times occur during the peaks.
  - Despite the fact that peaks have been defined, there are still a number of trips that occur at close to free-flow; more in the peak period than in the peak hour. This is probably due to the fact the peak times actually shift slightly from day-to-day as traffic demand can be shifted by events. Also, there are probably some days where overall demand is lower than other days.
- **Data Requirements for Establishing Reliability: How Much Data is Enough?** Because reliability is defined by the variability of travel conditions (travel time), it must be measured over a substantial portion of time to allow all of the influences of random events to be exerted. Tests showed that an absolute minimum of six months of data is required to establish reliability within a small error rate, in areas where winter weather is not a major factor (Figure ES.4). A full year of data is preferred.

Figure ES.4 Peak-Hour Travel-Time Distribution, Atlanta, I-75 NB, I-285 to SR 120
2007



- **Trends in Reliability.** A study was undertaken using the Atlanta study sections, tracking performance for 2006, 2007, and 2008. Between 2006 and 2007, average congestion increased and reliability decreased (got worse), where reliability was measured by both the Planning Time Index and the Buffer Index (Table ES.5). However, between 2007 and 2008, average congestion levels fell on all study sections as demand fell due to the reduction in overall economic activity; this corresponded to many anecdotal stories and other analyses about congestion in 2008. However, on most study sections, the Buffer Index showed an increase or a very marginal decrease, which would indicate that reliability worsened in most cases. In contrast, the Planning Time Index decreased on all sections. This raised doubts about the use of the Buffer Index as the primary metric for tracking trends in reliability. The problem comes from way the Buffer Index is calculated: it is the "buffer time" (difference between the 95th percentile and the mean) normalized by the mean. What happened in this experiment is that the 95th percentile decreased less than the mean, resulting in a higher Buffer Index. In other words, the decreased demand affects all points on the travel-time distribution, not just the upper tail. We believe the mechanism for these changes is that reduced demand led to across-the-board decreases in congestion, including days with and without roadway events (disruptions). However, conditions on the worst days, which are primarily a result of severe disruptions, were improved to a lower degree than "typical" or average conditions. We would expect operations strategies to have a more pronounced effect on the times influenced by severe events.

  The end result of this experiment is that the Buffer Index is considered to be too erratic/unstable for use as the primary reliability metric for tracking performance trends or for studying the effects of improvements. However, as a secondary metric, it does provide useful information and should not be discarded but rather should be included in a suite of reliability performance metrics. In the case of Atlanta from 2007 to 2008, it might be said that from the perspective of the user, the new conditions of 2008 are indeed less reliable, if one assumes that the 2008 average congestion is the base level: the worst days (as measured by the 95th percentile are still out there). If, however, one considers the base level of congestion to be 2007, then it is clear that overall, the user's experience has been improved.

- **Defining the Peak Hour and Peak Period.** Most previous studies of reliability and congestion define fixed time periods for the peak hour and peak period. However, for the research, we decided that the most appropriate method would be to define them specifically for each study section. Several methods were tested with the best using a definition based on the most typical start and end times of continuous congestion. The resulting time slices were reviewed against local anecdotal knowledge and required very little adjustment.

Table ES.5 Changes in Reliability on Atlanta Study Sections
2006 to 2008

	Year		
Metrics	2006	2007	2008
Travel Time Index	1.720	1.800	1.585
Average Travel Time	10.033	10.492	9.220
95th Percentile Travel Time	14.266	15.151	13.597
Buffer Index	0.399	0.428	0.451
80th Percentile Travel Time	11.874	12.400	10.989
Skew Statistic	1.186	1.196	1.308
Daily VMT	1,789,122	1,790,030	1,734,742

- **Estimating Demand in Oversaturated Conditions on Freeways.** Because the study took an empirical approach to studying reliability, the team had to deal with the thorny issue of how to measure demand given that measured volumes under congested flow are actually less than capacity on freeways. A method for assigning the demand stored in queues during periods of flow breakdown was developed and used throughout the remainder of the research, particularly in defining the demand-to-capacity ratio for the statistical modeling.
- **Reliability Breakpoints on Freeways.** It was shown that travel-time reliability on a freeway is NOT a function of counted traffic volumes until a "breakpoint volume" is reached. At that breakpoint, the travel-time reliability decreases abruptly. Once the breakpoint volume is exceeded, the decrease in travel-time reliability (increase in the variance) is so extreme and abrupt as to suggest it is a vertical function, with a nonsingular relationship to further volume increases. The breakpoint volume varies significantly between facilities and even within the same freeway facility (by location and direction of travel on the same facility). The breakpoint volume does not appear to be a fixed ratio of the theoretical capacity of the subject section of the facility. The breakpoint in reliability generally occurs at a counted volume significantly lower than the theoretical capacity of the facility computed per the Highway Capacity Manual (HCM). This is partly because the breakpoint volume computed in this analysis is the average hourly volume counted over a peak period and not the peak 15-minute demand as used in the HCM capacity.

  But this peaking effect does not entirely explain the difference. Part of the reason that the breakpoint volume is significantly lower than the theoretical capacity is because most sections of freeway are upstream of a bottleneck and, thus, are impacted by downstream congestion backing up into the subject section long before the subject section's HCM capacity is reached. Further, the effect of traffic-influencing events – especially incidents – effectively lower capacity when they occur and over time, cause reliability to degrade. This effect manifests itself in lower breakpoint volumes than for capacity related strictly to physical features. Finally, even for bottlenecks, the data suggests that the reliability breakpoint occurs long before the theoretical HCM capacity of the bottleneck is reached.

- **Sustainable Service Rates on Freeways.** Just as travel times vary over time, it has been noted that capacity is not a fixed value but also varies over time. The same factors that influence reliability also affect capacity variability. Incidents and work zones reduce overall roadway capacity by blocking lanes and shoulders and by affecting driver behavior (lower speeds and variable following distances due to "rubbernecking"). Weather conditions also affect driver behavior in similar ways. Capacity probably is not affected by the amount of demand (volume) as is reliability, but it is affected by the nature of that demand. That is, at a microlevel when volumes are very close to theoretical capacity, variability in driver behavior, small bursts of demand at merge areas (e.g., on-ramps), and the distribution of trucks at specific places and times all probably cause flow to breakdown at different demand levels. The research did not specifically tease out these factors, but all of them are imbedded in the final capacity distributions. The team developed a large set of capacity distributions that look roughly like travel-time distributions but reversed: the tail of the distribution is skewed to the left (lower capacity values) rather than to the right. Because these distributions were developed from year-long data measurements, they include the effect of the influencing factors, resulting in capacity values that could be used in a stochastic framework to model congestion and reliability. It also is a useful construct for accounting for reliability within future versions of the *Highway Capacity Manual*.

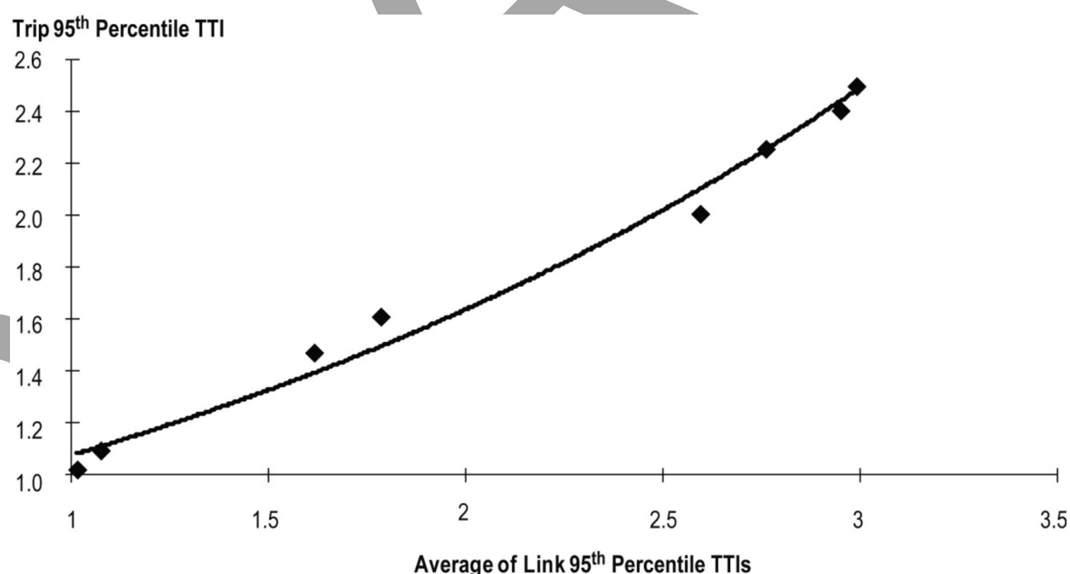
- **Travel-Time Distributions on Urban Freeways, Signalized Arterials, and Rural Freeways.** An analysis of travel-time distributions for different time slices and congested levels revealed the following characteristics:
  - All distributions feature a tail that is skewed to the right (i.e., higher travel times). Most of these abnormally high travel times can be attributed to one or more of the sources of congestion, that is, they occur in the presence of an event(s) and/or high demand.
  - Uncongested periods are characterized by a sharp peak of travel-time frequencies near the free-flow speed.
  - When congestion dominants the time slice (e.g., peak hour, peak period), the travel-time distribution becomes more broad and less peaked.
  - Travel-time distributions on signalized arterials are uniformly broad in shape, even for relatively low levels of congestion, presumably because of signal delay at even low volumes and interference from side traffic.

- As trips become longer, the travel-time distributions assume the typical uncongested shape.

- **Vulnerability to Flow Breakdown**. Examination of the five-minute data at individual stations (groups of detectors in a direction on a highway segment) reveals that just 20 to 45 minutes before the start of what is considered the normal peak period, there is an upsurge in the 95th percentile travel times. This upsurge begins prior to the uptick in average travel times and indicates that this window of time is vulnerable to flow breakdown. These windows are extremely important for operators to focus on as breakdowns during this time will strongly influence the duration and severity of the peak.

- **Reliability of Urban Trips Based on the Reliability of Links.** For extended travel on urban freeways ("trips" of 10 to 12 miles in length), the reliability of the entire trip can be predicted as a function of the reliability of the links that comprise the trip. Figure ES.5 shows an example using the 95th percentile travel time indices. While not specifically tested, it should be possible to construct trip reliability for trips that include other types of highways in addition to freeways, subject to the issue of time dependency for long trips.

Figure ES.5 Trip versus Link Reliability
95th Percentile TTI



Before/After Studies on Selected Study Sections

The primary goal of the research was to develop relationships for predicting the change in reliability due to improvements. The best way to accomplish this is with controlled before/after studies. However, such analyses are substantially more challenging than what is typically done because of the data requirements: to establish reliability empirically, 6 to 12 months of data is required, with 12 months being the preferred data collection period. This means a long period of continuously collected data is required both before and after the improvement. So, instead of designing traditional before/after experiments, the team concentrated on collecting continuous traffic data from areas we knew from previous experience had quality data, "interesting" congestion, and good records of event data. At a minimum, this would provide the best data for developing cross-sectional statistical relationships. As it turned out, we were able to identify 17 cases of improvements that coincided with the data we had identified, although the types of improvements were somewhat limited. The 17 cases were as follows:

- Ramp meters – 4;
- Freeway service patrol implementation – 2;
- Bottleneck improvement – 3;
- General capacity increases – 5;
- Aggressive incident clearance program – 2; and
- HOT lane conversion – 1.

The analysis produced reliability adjustment factors that can be applied to the various improvements (Table ES.6). The adjustment factors for a specific type of improvement vary slightly, presumably because background (baseline) conditions are somewhat different. Users are directed to the detailed descriptions of the studies in Appendix B to select the conditions most appropriate for their situation.

A global finding from the before/after analyses is that ***ALL*** forms of improvements – including capacity expansion – affect ***BOTH*** average congestion and reliability in a positive way (i.e., average congestion is reduced and reliability is improved). Conceptually, this makes sense: one of the seven sources of congestion/reliability identified earlier was the amount of base capacity. All things being equal, more capacity (in relation to demand) means that the roadway is able to "absorb" the effects of some events that would otherwise cause disruption. The size of this effect was greater than we had originally anticipated. What this means for the profession is that, to the extent that reliability is valued above and beyond typical/average travel time, a large part of the benefits of capacity expansion projects has been missed in historical analyses.

Table ES.6 Summary of Urban Freeway Before/After Studies

No.	Urban Area	Highways Covered	Improvement	Reliability Impacts (Peak Period)
1	Los Angeles	I-210	Ramp Metering: Design, field implementation, and evaluation of new advanced on-ramp control algorithms on westbound direction of I-210.	• Slight increases in average travel time and Planning Time Index (PTI) were observed. However, subsequent to this evaluation, the algorithms have been adjusted.
2	Bay Area	I-580	Ramp Metering.	• 22% reduction in average travel time. • 20% reduction in PTI.
3	Seattle	SR 520	Ramp Metering.	• 11% reduction in average travel time. • 12% reduction in PTI.
4	Atlanta	I-285, Northern Arc	Ramp Metering.	• 9% reduction in average travel time. • 7% reduction in PTI. • 3% increase in sustainable service rate.
5	Atlanta	All freeways inside beltway perimeter	Incident Management: Incentive program for reducing large truck crash incident duration (90 minutes).	• 13% reduction in large truck crash incident duration. • 9% reduction in lane-hours lost per large truck crash.
6	Los Angeles	I-710	Incident Management: Evaluation of pilot project to deploy towing service for big-rig tractor trailers.	• 10% reduction in average travel time. • 20% reduction in PTI.
7	San Diego	I-8	Incident Management: Expansion of the existing Freeway Service Patrol Beat-7 on I-8.	• 3% reduction in average travel time. • 4% reduction in PTI.
8	San Diego	SR 52	Incident Management: Expansion of the existing Freeway Service Patrol.	• 20% reduction in average travel time. • 10% reduction in PTI.
9	Minneapolis-St. Paul	I-94	Capacity Expansion: Add third lane in each direction.	• 43% reduction in average travel time. • 46% reduction in PTI.
10	Minneapolis-St. Paul	I-494	Capacity Expansion: Add third lane in each direction.	• 31% reduction in average travel time. • 16% reduction in PTI.

No.	Urban Area	Highways Covered	Improvement	Reliability Impacts (Peak Period)
11	Minneapolis-St. Paul	I-394	Capacity Expansion: Add auxiliary lanes westbound.	• 35% reduction in average travel time. • 38% reduction in PTI.
12	Minneapolis-St. Paul	Highway 169	Capacity Expansion: Convert signalized intersections to diamond interchanges.	• 16% increase in average travel time. • 11% reduction in PTI.
13	Minneapolis-St. Paul	Highway 100	Capacity Expansion: Add third lane northbound. Add auxiliary lane southbound. Convert Highway 7 interchange from a clover leaf to a folded diamond.	• 20% reduction in average travel time. • 30% increase in PTI.
14	Seattle	I-405 Southbound	Capacity Expansion: Addition of one general purpose lane.	• 11% reduction in average travel time. • 11 reduction in PTI.
15	Seattle	I-405 Northbound	Capacity Expansion: Addition of one general purpose lane.	• 42% reduction in average travel time. • 35% reduction in PTI.
16	Seattle	I-405/SR 167 Interchange	Capacity Expansion: Grade separation ramp connecting the southbound I-405 off-ramp with the southbound SR 167 on-ramp.	• 20% reduction in average travel time. • 23% reduction in PTI.
17	Minneapolis-St. Paul	I-394	HOT lane conversion.	• 8% reduction in average travel time. • 30% reduction in PTI.

Note: Complete results are given in Appendix B.

[a] Long study segment: 16 miles; study section influenced by downstream bottleneck.

Cross-Sectional Statistical Modeling

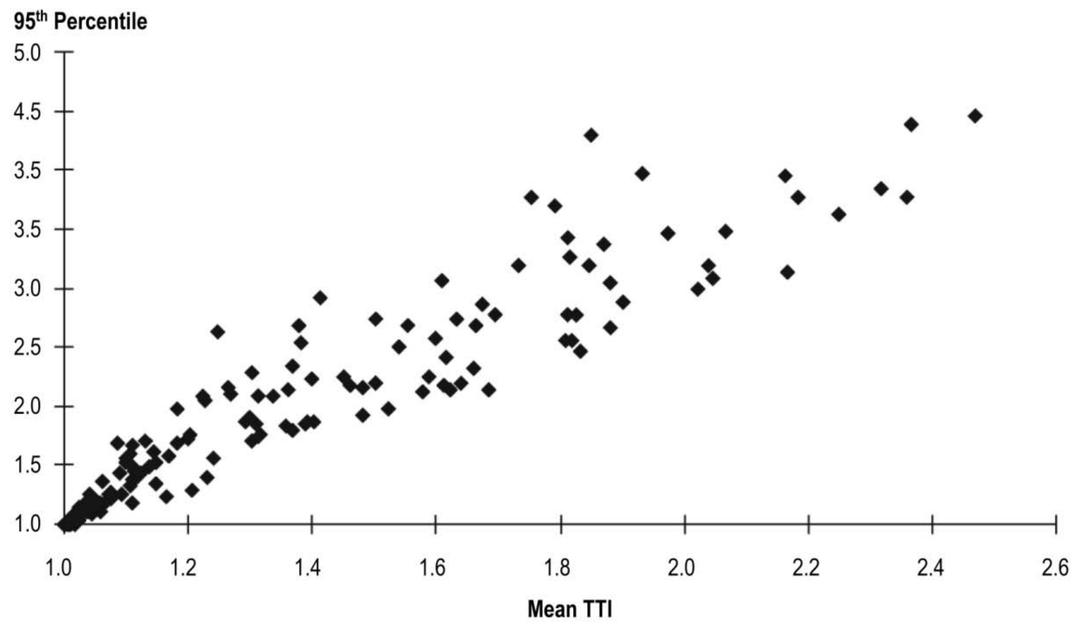
Going into the project, the team realized that only a limited number of before/after studies would be possible. Therefore, much of the effort for the study went into the creation of a cross-sectional dataset from which statistical models could be developed. The final analysis data set for the statistical modeling is highly aggregated: each record represents reliability, traffic, and event data summarized for a section for a year. This structure must be used: reliability is measured as the variability in travel times over the course of a year. As such, the cross-sectional model is a macroscale model. It does not seek to predict what the travel time for a particular set of circumstances. (For example, what is the expected travel time if incident and demand characteristics for a given day are known.) Rather, it seeks to predict the overall travel-time characteristics of a highway section in terms of both mean and reliability performance. It is, therefore, appropriate for adaptation to many existing models and applications that seek to do the same, and can serve as the basis for conducting cost/benefit analysis. It is not appropriate for real-time travel-time prediction.

Two model forms were developed: simple and complex. The simple model form relates all of the reliability metrics to the mean Travel Time Index (TTI) for all three highway types studied (urban freeways, rural freeways, and signalized arterials). These relationships are convenient for many applications that produce mean travel-time-based measures as output (e.g., traditional travel demand forecasting models, the *Highway Capacity Manual*). Because the mean TTI developed from the research data includes the effects of all the possible influences of congestion, which produces a mean value greater than model results which usually are for "typical" (nonextreme) conditions, an adjustment factor was developed to convert model output to the overall mean TTI so that the relationships can be applied. An example of the strong relationship between the mean TTI and 95^{th} percentile TTI is shown in Figure ES.6.

A more detailed model form also was developed that related reliability measures to the factors that influence reliability. A series of statistical predictive models were developed that related the reliability metrics over highway sections (multiple links, usually four to five miles long) to:

- The critical demand-to-capacity ratio (maximum from the individual links);
- Lane-hours lost due to incidents and work zones combined (annual); and
- Number of hours where rainfall was >= 0.05" (annual).

Figure ES.6 Section-Level Relationship for Mean TTI and 95th Percentile

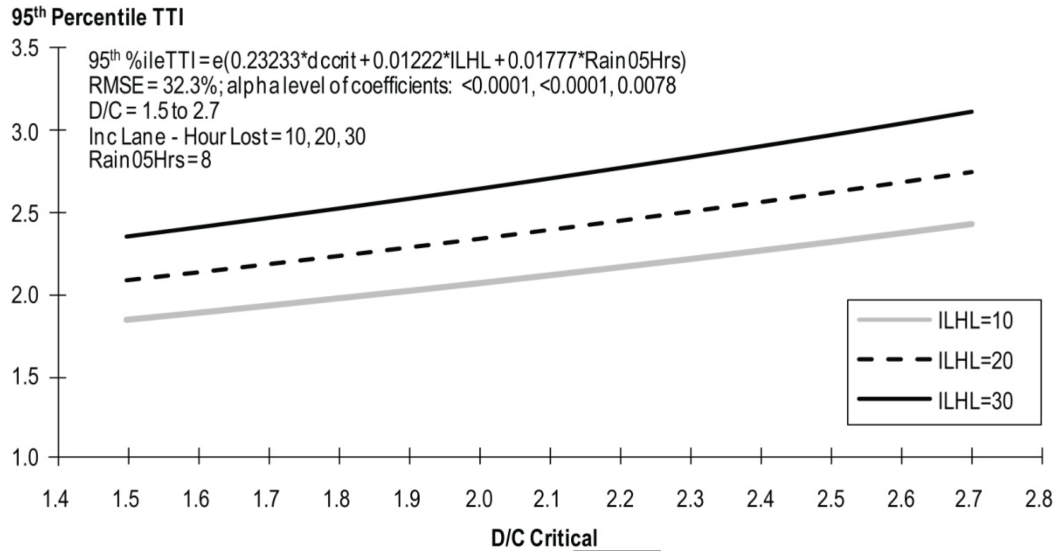


Models were developed for the peak hour, peak period, mid-day, and weekday time periods. An example of one of the predictive equations is shown in Figure ES.7. Guidance also was developed on how to estimate demand, capacity, and lane-hours lost from readily available data. For example, incident lane-hours lost is the product of number of incidents, lanes blocked per incident, and average incident duration:

- Number of incidents, which can be estimated as:
  - Incident rate x VMT:
    - » Where incident rate = Crash Rate/0.22.
- Lanes blocked per incident:
  - 0.476 if shoulders and policy is to move incidents to shoulder;
  - 0.580 if lane-blocking incidents are not moved to shoulder; and
  - 1.140 if usable shoulders are unavailable.
- Average incident duration.

Guidance also was provided on how improvements affect changes in the models' independent variables. The model structure is flexible and can easily incorporate new research on the effects of transportation improvements on reliability.

Figure ES.7 95th Percentile Predictive Equation for Peak Period



Congestion-by-Source

An assignment of congestion causality was made for the measured delay in the Seattle data (Table ES.7). Taken at face value, this simple summary table supports the commonly heard statement that "incidents and crashes cause between 40 and 60 percent of all delay." In reality, a considerable portion of the delay associated with incidents and crashes also is "caused" by large traffic volumes. Therefore, the amount of delay "caused" by incidents is actually less than can be reasonably assigned by simply observing the occurrence of events. There were numerous examples in the analysis data set of significant crashes and other incidents that caused little or no congestion because of when they occurred. These showed that without sufficient volume, an incident causes no measurable change in delay.

In the Seattle area, many incidents take place during peak periods, causing already existing congestion to grow worse, the result of the interwoven effects of incidents, bad weather, and traffic volumes on travel times. In addition, all types of disruptions to normal roadway performance (rain, crashes, and noncrash incidents) cause congestion to start earlier and last longer during the peak period, while increasing travel times during the normally congested times. Incidents and other disruptions also can cause congestion to form during times of the day that are normally free from congestion. However, congestion only forms when the disruption lowers functional capacity below traffic demand. Thus volume, relative to roadway capacity, is a key component of congestion formation, and in urban areas it is likely to be the primary source of congestion. Disruptions then significantly increase the delay that the basic volume condition creates.

Table ES.7 Percentage of Delay by Type of Disruption Influencing that Congestion

Causes of Congestion Ongoing Disruptions that Influence Congestion Duration and Severity	Percentage of Delay	Maximum Percent Within a Corridor	Minimum Percent Within a Corridor
No cause indicated	37.1%	74.2%	14.3%
Incident-influenced queues are present	23.9%	48.2%	1.0%
Crash-influenced queues are present	6.0%	25.3%	1.7%
Rain is present	8.4%	25.8%	2.0%
Both a crash and an incident have influenced queues that are present	9.2%	23.9%	0.5%
Both rain and an incident have influenced queues that are present	5.0%	8.9%	0.0%
Both rain and a crash have influenced queues that are present	1.6%	8.7%	0.2%
Rain, a crash, and an incident have influenced queues that are present	2.4%	13.6%	0.0%
Queues from a ramp – cause unknown – have influenced mainline queues	5.1%	37.3%	0.0%
Construction activity has influenced queues	0.6%	16.2%	0.0%
Construction and queues from a ramp – cause unknown – have influenced mainline queues	0.0%	0.2%	0.0%
Construction and an incident have influenced queues present	0.2%	2.6%	0.0%
Construction and a crash have influenced queues present	0.1%	1.4%	0.0%
Construction and rain have influenced queues	0.1%	4.6%	0.0%
A crash, an incident, and construction have influenced queues that are present	0.1%	1.2%	0.0%
Construction, rain, and an incident have influenced queues that are present	0.0%	0.5%	0.0%
Construction, rain and a crash have influenced queues that are present	0.0%	0.7%	0.0%

The fact that traffic volume is the basis of congestion also has an impact on how various traffic disruptions affect travel patterns. Not only does traffic volume affect whether an incident causes congestion, but it affects how long that congestion lasts once the primary incident has been removed. The Seattle data showed that in the morning peaks, disruptions have a more noticeable effect on the timing of the end of the peak period, while in the evening the opposite is true.

In summary, analysis of 42 roadway segments in the Seattle area showed that a majority of travel delay in the region is the direct result of traffic volume demand exceeding available roadway capacity. Whenever they occur, incidents, crashes, and bad weather add significantly to the delays that can be otherwise expected. The largest of these disruptions play a significant role in the worst travel times that travelers experience on these roadways. However, the relative importance of any one type of disruption tends to vary considerably from corridor to corridor.

In peak periods, incidents add only marginally (percentage-wise) to total delay, but they do SHIFT when and where those delays occur, as well as who suffers from those delays. That is, many incidents shift where a normally occurring bottleneck occurs, freeing up some roadway sections, while causing others to suffer major increases in congestion. But taken as a total, if it already is "normally congested," the added delay from incidents is modest (at least in Seattle) compared to the daily delay from simply too many vehicles for the available physical capacity.

In congested urban areas, traffic incidents are often more about causing more unreliable traffic patterns than they are about causing increases in total delay. While the total delay value does goes up, the big change is often that shift in WHO gets delayed. For an individual severe incident, many of travelers may value the extra (unplanned) delay very highly, and are very likely to remember these extreme cases. Some of that (total) delay is offset by other travelers who reach their destination early – their trip is downstream of the incident-caused bottleneck and volume has probably been metered by that bottleneck.

The Significance of Demand for Reliability Estimation

A major result of the research was the finding that demand (volume) is an extremely important determinant of reliability, ***especially in terms of its relation to capacity***. Demand's interaction with physical capacity is the starting point for determining congestion. Conceptually, the research team initially postulated that the effect of most events are determined by the level of demand under which they occur. (If an incident or work zone blocks a traffic lane, the impact will only be felt if volumes are high enough to be affected by the loss capacity.) However, we did not expect demand to have as strong an effect as the analyses indicated. Throughout the different analyses we conducted for the L03 research, demand kept emerging as a significant factor. The case for the strong effect of demand/ volume is summarized as follows.

- The Atlanta trend analysis revealed that roughly a three percent drop in demand significantly improved both average congestion level and reliability between 2007 and 2008.
- The before/after studies of capacity improvements produced a strong improvement in reliability, not just average congestion. We believe the mechanism for this improvement is capacity in relation to demand simultaneously (the demand-to-capacity or volume-to-capacity ratios), so a change in either will produce the same effect. (This was subsequently verified in the cross-sectional statistical models.)

- The Seattle congestion-by-source analysis which revealed that a substantial portion of delay could not be attributed to an event, even with careful consideration of off-section conditions and special events. This leaves only demand as the sole cause. The Seattle analysis also shows that incidents during low demand periods have only a small effect on congestion.
- The mid-day cross-sectional models did not show lane-hours lost due to incidents and work zones as a statistically significant independent variable, indicating that under low-volume conditions (i.e., conditions where volumes are low relative to the available physical capacity), the annual effect of disruptions is small. Extreme disruptions (multiple lane closures) clearly will have an effect on an individual day, but over the course of a year these events are rare and do not appear to "move" the annualized reliability metrics very much at all.
- The peak hour and peak period cross-sectional models showed that the demand-to-capacity ratio was a stronger contributor to the model than lane-hours lost.

The influence of demand is probably related not only to sheer volume of traffic but its characteristics. As volumes approach theoretical capacity, traffic flow becomes unstable and increasingly susceptible to breakdown due to small changes. These small changes can occur at a point substantially less than theoretical capacity and when they occur near potential bottleneck areas such as on-ramps, weaving areas, and lane-drops, we postulate that their effect is enhanced.

In addition to variations in demand as a source of unreliable travel times, evidence also exists that physical capacity also is variable. The research team observed that throughout the course of a year, due to disruptions and other factors that can occur on a highway segment. However, the work of Brilon and preliminary research conducted by other SHRP 2 contractors suggest that ***capacity varies even in the absence of disruptions.***

Why would physical capacity vary? We believe that fluctuations in traffic conditions at a microscale are the most likely causal factors. These small changes could be related to:

- **Driver Behavior –** One or a few vehicles can behave aberrantly (e.g., sudden unexplained stops);
- **Truck Presence –** A small increase in trucks in the traffic stream at a given point in time and space could have a detrimental effect; and
- **"Microbursts of Merging Traffic" –** A small but intense influx of vehicles from an on-ramp could be enough to cause flow breakdown.

There are several implications of the finding that demand and capacity will strongly influence travel-time reliability:

- The mechanism for demand's and capacity's influence on travel-time reliability can be seen in the before/after studies. Consider the distribution of travel times that occur on a routinely congested highway segment over the course of a year. In terms of the distribution, they will reduce nearly all the travel times in the congested portion of the distribution. Capacity additions and demand reductions will improve congestion on nearly all days; they are always present in the roadway environment. Strategies geared to disruptions (e.g., incident management) will only affect congestion when those disruptions appear, and they will not appear during every congested period of every day. In other words, only selected travel times in the congested portion of the distribution will be reduced.
- It is clear that traditional capacity projects improve reliability, and failure to account for this effect in economic analyses has excluded benefits to users.
- Demand management strategies, such as pricing, also will lead to improvements in reliability.
- Accounting for volumes in relation to available capacity can provide a tool for efficiently allocating operations strategies, particularly incident management. That is, times and locations that are most vulnerable to flow breakdowns can be targeted.

Reliability as a Feature of Congestion

- The intertwined relationship between demand, capacity, and disruptions documented in the L03 research leads to another major conclusion: ***reliability is a feature or attribute of congestion, not a distinct phenomenon.*** Because any influence on congestion will lead to unreliable travel reliability cannot be considered in isolation. Going into the research, the project team's thinking – and that of the profession in general – was that reliability related primarily to disruptions and the operational treatments aimed at those disruptions. Our analysis showed that even in the absence of disruptions, a substantial amount of variability (i.e., unreliability) in travel times exists for recurring-only (bottleneck-related) conditions. Therefore, the most inclusive view of travel-time reliability is that it is part of overall congestion. Just as congestion can be defined by extent and severity, it can also be defined as how it varies over time. Operational treatments are clearly effective in dealing with unreliable travel, but so are other congestion relief measures.

Recommendations for Future Research

Based on our research, the team also offers the following suggestions for future research.

- **Detailed Examination of Reliability Causes and Prediction on Signalized Arterials.** Because of data limitations in the number of signalized arterials with continuous travel-time data collection, the amount of data on those that did, lack of continuous volume data to match against the available travel-time data, and no information on incident and work zone characteristics, only simple analyses using travel-time data could be undertaken for this study. However, since we completed the data collection for the research, it is very clear that data availability is about to increase dramatically. Private vendors of vehicle probe data have improved their data processing methods and increased the sources of travel-time data in just the past 18 months. As a result, many states already have purchased private vendor probe data statewide primarily for traveler information applications. As with freeway detector data, these data have value in developing performance measures and supplying research studies after the fact. We expect the trend to continue as new sources – perhaps even those from consumer sources – continue to be added to their products. In addition, new and relatively inexpensive technologies for collecting travel times on signalized highways – such as Bluetooth readers and vehicle signature detectors – offer great potential for new forms of traffic management applications by public agencies.

- **Determine How Demand (Volumes) Can Be Effectively Collected Systemwide.** The study was fortunate that traditional urban freeway detectors collect both speed and volumes. However, if the other sources of speed/travel-time data discussed above become widespread, there will be no companion volume measurements until the number of vehicles that are detected approach 100 percent. The L03 research has shown that demand is a very important determinant of reliability. Further, from an operations viewpoint, emerging methods such as active traffic management (ATM) are likely to require more – not less – data (travel times and volumes) to feed their control processes.
- **Consistency in Data Collection for Incidents and Work Zones.** The study labored mightily to find and process incident and work zone data to match against the traffic measurements. The duration of blockages – recognizing that the nature of blockages can change over the course of a single event – is the critical piece of data required. Also, consistency in geocoding of events, traffic detectors, and roadway features would greatly enhance future research. An extra complication is the fact that private vendors (at least the two we used in the research) use the Traffic Message Channel standard for geolocation, a standard that is almost never used by public agencies. To avoid the large amount of manual intervention endured by the study – which would be even more onerous for public agencies trying to deal with the issues systemwide rather than on selected study sections – some consideration should be given to how all of these data should be collected, organized, and related to each other. This may require the development of new standards or the extension of existing ones.
- **Development of Alternative Reliability Concepts for Extreme Events.** As developed in this research, the concept of reliability is part of the urban congestion problem. That is, it has been studied on highways that experience

routine congestion from both recurring and nonrecurring sources. The working definition used was that reliability is a description of how travel times vary over time. It was noted that extreme events (disruptions) – such as major snow/ice storms, hurricane evacuations, and full highway closures – do not have a statistical significance in trying to predict reliability, which, by definition, occurs over the course of a year. Because they are so rare, they only shift the annual travel-time distribution by a small amount. However, these extreme events are extremely important to both transportation agencies and travelers, even if their occurrence is rare. If the urban congestion-based reliability concepts cannot describe these events, then an alternative should be explored.

- **Standard Processing Methods for Developing Congestion and Reliability Performance Measures.** In order to conduct the research, data processing procedures had to be developed to develop reliability performance metrics. These metrics are likely to be used on their own in many other transportation applications. However, a large amount of leeway exists in how the metrics can be developed from field data. As congestion performance monitoring becomes more widespread, and perhaps even Federally mandated, the need to produce consistent metrics will become critical.
- **Improved Methods for Microlevel Weather Data Collection.** The weather data used in the study was admittedly crude in terms of location. The assumption is that the closest National Weather Service station observations apply to the study sections, when they could be several miles apart. This probably led to misallocation of rainfall occurrence for at least some cases, but major weather fronts are most likely accounted for in the data. However, we believe that better methods can be explored. In lieu of deploying weather stations at regular intervals, which would be prohibitively expensive, one method that seems to have promise is the automated processing of time-lapse radar information to obtain precipitation data.
- **Reliability of Trips.** At the beginning of the study we selected the "extended highway section" as the basic unit of analysis: a relatively homogenous highway section in terms of geometrics covering several miles, typically four to five miles, for urban sections. (Much longer sections were used for the few rural freeway sections we used.) The reasons for this were related to both practicality and usability: this is the level at which the data were available and can be used by many existing applications. However, the reliability of entire trips is likely to be quite different due to a number of factors. First, the study sections were selected because they had relatively high volumes and were at least moderately congested during peak times (Jacksonville's sections were less congested). So, in terms of an entire trip that a user might make, they represent the worst conditions that can be encountered. This means that a trip-based travel-time distribution is likely to gravitate towards one that shows less congestion and better overall reliability. An additional complication is the scheduling component: if a "trip" can start within a window of time as

opposed to a specific time, users can in theory improve the travel time and reliability of their trip. Research is needed on these subjects and specifically how they impact investment decisions. That is, the facility focus as suggested by the L03 perspective leads to a certain set of investments (improvements). If we change the focus to the entire trip (that is, we manage trips in addition to facilities), how do the investment decisions change?

- **Before/After Studies for Demand Management, Active Traffic Management, and Institutional Aspects of Incident Management.** Reliability style (long before and after periods) should be undertaken as these types of projects are deployed. In addition to observing changes in congestion and reliability, these studies also should report the changes in the independent variables for the L03 cross-sectional statistical models (demand, capacity, and the characteristics of incidents and work zones). The study also noted that various degrees of institutional arrangements and policies related to incident management should have a positive effect on incident duration, which can then be related to reliability via the statistical models. The idea is that, beyond the deployment of equipment, the success of incident management will be determined by how agency agreements and policies translate to reductions in incident duration in the field.
- **Real-Time Predictive Models.** A potentially useful corollary to the macrolevel reliability relationships developed in the L03 effort is the development of models that relate congestion level ***on a specific day*** to the contributing factors. This is not really reliability – it is travel-time prediction for a given set of circumstances – but it would provide useful tool for traffic managers. The L03 dataset could be used as a starting point for this research, although based on our experiences with the congestion-by-source analysis, more microlevel data on traffic flow and events might be necessary (e.g., 30-second to one-minute volumes and speeds. Specifically, the microlevel examination of traffic flow breakdown would provide great insight into the causes of congestion.
- **Expand on the Concept of Whole Year Capacity.** The L03 research demonstrates that capacity varies substantially. The concept of whole year capacity, touched on in the L03 exploratory analyses, is worth pursing further. Because many predictive models – including travel demand forecasting and macroscopic and mesoscopic simulation models use the concept of capacity as a starting point for determining congestion, using whole year capacity may an entry point for incorporating reliability into these models. That is, instead of using a fixed capacity, model runs can use whole year capacity distributions stochastically. Because the whole year capacity distributions developed from empirical data include all of the possible influencing factors, they represent a more realistic picture of how capacity actually behaves.

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1.0 Introduction

1.1 Project Background

The fundamental objective of SHRP 2 Project L03 is to develop predictive relationships between highway improvements and travel-time reliability. In other words, how can we predict what effect an improvement will have on reliability? Alternately, how can we characterize reliability as a function of highway, traffic, and operating conditions? A variety of challenging issues have been confronted in addressing this objective.

Travel-time reliability is a significant aspect of transportation system performance. Reliability is important to travelers and transportation practitioners for a variety of reasons:

- From an economic perspective, reliability is highly important because travelers must either build in extra time to their trips to avoid arriving late or suffer the consequences of being late. This extra time has value beyond the average travel time used in traditional economic analyses. Recent work has documented the fact that reliability has value to travelers and that their behavior is influenced by it (*1*, *2*).
- Because of the extra time required in planning trips – and the uncertainty about what travel times will actually be for a trip – reliability influences decisions about where, when, and how travel is made.
- Due to the extra economic cost of unreliable travel on users, transportation planners and operators need to include these costs in the project planning, programming, and selection processes. This is particularly true of strategies that deal directly with roadway events (e.g., incidents). In the past, most assessments of these types of strategies have missed this important aspect of travel.

Travel-time reliability is a new concept to which much of the transportation profession has had only limited exposure. Use of travel-time-based performance measures in planning and operations applications has taken on greater significance in the last few years. Congestion has been growing nationwide and planners increasingly have become involved in short-term activities such as performance monitoring as well as operations and management strategies. These activities have been elevated in importance by transportation agencies in order to be responsive to the demands of the public and state legislatures. Both anecdotal and technical studies indicate that average congestion levels have – and are continuing – to grow in our cities. In their 2005 report, Texas TTI researchers found that congestion levels in 85 of the largest metropolitan areas have grown in almost every year in all population groups from 1982 to 2003 (*3*).

Recently, anecdotal and empirical information suggest that congestion levels have eased. In their 2007 report, TTI researchers noted:

> Congestion, by every measure, has increased substantially over the 25 years covered in this report. The most recent two years of the report, however, have seen slower growth or even a decline in congestion. Delay per traveler – the number of hours of extra travel time that commuters spend during rush hours – was 1.3 hours lower in 2007 than 2005. This change would be more hopeful if it was associated with something other than rising fuel prices (which occurred for a short time in 2005 and 2006 before the sustained increase in 2007 and 2008) and a slowing economy. This same kind of slow growth/decline over a few years occurred in the early 1990s when spending and growth in the high-tech and defense sectors of the economy declined dramatically. The decline means congestion is near the levels recorded in 2003, not exactly a year remembered for trouble-free commuting (*4*).

However, talking about typical or average conditions in a transportation system that experiences wide fluctuations in performance tells only one part of the story. The notion of *travel-time reliability* – how consistent (or variable) travel conditions are from day to day – has taken on increasing importance. The variation in travel times now is understood as a separate component of the public's and business sector's frustration with congestion problems. Reliability is a major part of system performance and of travelers' perceptions of performance. It has not been widely used to describe performance, but increasingly agencies are recognizing its value in assessing their own performance and in communicating performance to the public.

How should travel-time reliability be defined? In terms of highway travel, the F-SHRP Reliability Research Program defined reliability this way (*5*):

> … from a practical standpoint, *travel-time reliability can be defined in terms of how travel times vary over time* (e.g., hour-to-hour, day-to-day). This concept of variability can be extended to any other travel-time-based metrics such as average speeds and delay. For the purpose of this study, travel-time variability and reliability are used interchangeably.

A slightly different view of reliability is based on the notion of a *probability or the occurrence of failure* often used to characterize industrial processes. With this view, it is necessary to define what "failure" is in terms of travel times; in other words, a threshold must be established. Then, one can count the number of times the threshold is not achieved or exceeded. These types of measures are synonymous with "on-time performance" since performance is measured relative to a pre-established threshold. The only difference is that failure is defined in terms of how many times the travel-time threshold is exceeded while on-time performance measures how many times the threshold is not exceeded.

In the work performed for NCHRP Project 3-68, it is noted that the variability and failure definitions have a common underlying theme – they both imply that a ***history or distribution of travel times*** exists (*6*). The history over which travel times are measured must be sufficiently long so as to capture the variations that occur due to the random and planned events that occur on the roadway system. Once this distribution is established, it is possible to construct any number of measures to describe its size and shape. This leads to a more general definition of travel-time reliability:

> Travel-time reliability is defined as the level of consistency in travel conditions over time and is measured by describing the distribution of travel times that occur over a substantial period of time.

In recent years, some non-U.S. reliability research has focused on another aspect of reliability – the *probability* of "failure," where failure currently is defined in terms of traffic flow breakdown. A corollary is concept of "vulnerability" which could be applied at the link or network level: this is a measure of how vulnerable the network is to breakdown conditions (*7*).

To understand travel-time reliability, it is essential to understand the factors that cause travel times to be unreliable. Previous work indicates that reliability is determined by the variability in conditions that travelers encounter from day to day. Therefore, reliability metrics tell you that variability exists in the system – they do not tell you what is causing it. The original F-SHRP Reliability Research Plan identified the "Seven Sources of Congestion" as the factors that cause travel times to be unreliable and contribute to total congestion: incidents, inclement weather, work zones, special events, traffic control device timing, demand fluctuations, and inadequate base capacity. These categories were developed to move away from the recurring/nonrecurring nomenclature that has been in wide use but is not detailed enough for the purpose of SHRP 2 research.

Both operational strategies and capacity expansion projects were postulated to affect reliability and both were studied in the research. Many operational strategies are aimed specifically at the factors that cause unreliable travel (e.g., incident management, work zone management). Note, however, that one of the "Seven Sources" affecting reliability is inadequate base capacity. The effect of physical capacity on congestion is well established and has been the focus of analytic procedures for the past several decades (e.g., the HCM). Physical capacity also affects the reliability since it interacts with all the other sources. For example, consider an incident that blocks one lane of traffic. Its effect is much greater if there are only two lanes available than if three or more were available. So, adding physical capacity definitely will have an effect on reliability.

Travel-time measurements are critical to any definition of reliability and reliability metrics. Travel time is the starting point for sound congestion measurement because it reflects the actual experience of system users. When measured directly, it also is independent of theoretical capacity concerns – such as what happens in oversaturated conditions. Further, once travel time is obtained, a whole family of additional measures can be created using other basic information about the system (e.g., volume, free-flow speed). Delay is one example of the metrics that naturally flow from travel-time measurements.

1.2 Document Organization

The Final Report is organized as follows. It summaries material in the Phase 1 and Phase 2 Reports but does not present all of the material in those reports. These summaries are primarily in Sections 2.0, 3.0, and 4.0, although new material has been added to those sections. Sections 5.0, 6.0, and 7.0 present all new material. The sections are as follows:

- **Section 2.0 – Preparatory Analyses**. This section presents the literature review, lists improvements that have the potential for improving reliability and presents the experimental design for the main analyses conducted.
- **Section 3.0 – Data Collection, Assembly, and Fusion**. This section provides a description of the data used in the exploratory analyses (Section 4.0), congestion-by-source analysis (Section 5.0), before/after studies (Section 6.0) and statistical analysis (Section 7.0), including sources and processing procedures.
- **Section 4.0 – The Empirical Measurement of Reliability**. This section presents the results of several exploratory analyses undertaken to gain a better understanding of reliability and to set the parameters for the three main analyses that follow (Sections 5.0, 6.0, and 7.0). It includes a list of reliability performance metrics used in the research and that can be used in other applications.
- **Section 5.0 – Estimating Congestion by Source**. This section looks at a detailed analysis of the contributing factors for congestion using a specially created dataset from Seattle.
- **Section 6.0 – Before/After Studies of Reliability Improvements**. This section summarizes the results of studies undertaken before and after different types of improvements were implemented.
- **Section 7.0 – Cross-Sectional Statistical Analysis of Reliability**. This section presents the results of statistical analyses that developed predictive models of reliability as a function of key factors.
- **Section 8.0 – Application Guidelines.** General guidance on how the methods can be applied is provided, including caveats. It should be noted that adaptation of the methods to specific applications will require customization.
- **Section 9.0 – Conclusions and Recommendations**.
- **Appendix A – Data Elements and Structure for the Statistical Analysis Dataset**.

- **Appendix B – Before/After Analyses of Reliability Improvements.**
- **Appendix C – Computation of Influence Variables, Seattle Analysis (Mechanisms for Determining When an Incident Affects Travel Time and Travel-Time Reliability).**
- **Appendix D – Seattle Analysis: Variable Definitions.**
- **Appendix E – Summary of Weather Data Tests Seattle Analysis**.
- **Appendix F – Statistics Related to the End of Congestion, Seattle Analysis.**

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2.0 Preparatory Analyses

2.1 Introduction

The project was organized in three Phases:

- **Phase 1: Foundational Research –** The effort was documented in the Phase 1 Report and included:
  - A literature review;
  - Identification of the reliability metrics to be used in the research;
  - Defining the improvement strategies that have an effect on travel-time reliability;
  - Specifying an experimental design for the research;
  - Identifying the types of data that need to be collected to conduct the research; and
  - Defining an Analysis Plan for conducting the research, including the model forms to be investigated.
- **Phase 2: Data Collection and Preliminary Analyses –** The effort was documented in the Phase 2 report and included:
  - A description of the datasets that were assembled; and
  - Exploratory analyses on the data to establish fundamental concepts for the detailed analyses.
- **Phase 3: Reliability Prediction Models –** The Phase 3 effort is documented for the first time here in the Final Report.

A synopsis of the work conducted in Phases 1 and 2 is presented in this report. Much more detail is available in the Phase 1 and Phase 2 reports.

This section presents selected analyses from the Phase 1 and Phase 2 Reports, as a way to set the stage for the presentation of the original research. The subsections presented herein are as follows:

- **Literature Review –** An assessment of previous work on travel-time reliability;
- **Improvements that Affect Reliability –** A qualitative assessment of the improvement types that potentially can affect reliability; and
- **Experimental Design –** A discussion of the main factors that affect reliability and how they were organized in the research.

2.2 Literature Review

2.2.1 Reliability Performance Metrics

The recognition that travel-time reliability is a problem is being reflected by changes to traditional monitoring programs that examine average or "typical" congestion; regions are understanding those studies must be supplemented with tracking efforts that include day-to-day measures as well (*1*). The National Transportation Operations Coalition (NTOC) Performance Measurement Initiative, for example, identified Travel-Time Reliability (Buffer Time) as one of the 14 key measures for operations programs (*2*). Data and analysis procedures, however, are not progressing as fast as the recognition of the problem.

Table 2.1 displays several transportation agencies that have included travel-time reliability as a portion of their mobility measurement in their performance evaluations. Some of the evaluations are performed on a corridor basis while others are done on a systemwide or statewide basis.

Table 2.1 Reliability Measures in Selected Transportation Agencies

Agency	Reliability Metrics Used	Data Source	Coverage
Freeway			
Georgia Regional Transportation Authority (for annual mobility performance in Atlanta) and Georgia DOT (*3*), (*4*)	Buffer Index Planning Time Index	GDOT and Local	Facilities
Florida DOT (*5*)	Buffer Index On-Time Arrival	FDOT and Local	Facility Statewide
Southern California Association of Governments (for goods movement study) (*6*)	Buffer Index	Caltrans and Local	Facility
Washington State DOT (for performance monitoring and traveler information) (*7*)	95th Percentile Travel Time	WSDOT and Local	Facility (time is the sum of link times)
National Transportation Operations Coalition (NTOC) (for performance measure initiative): Potential case study with I-95 Corridor Coalition (*2*)	Buffer Index	Various Agencies	To be determined
Arterials			
NCHRP 3-68	Buffer Index	Various Agencies	Facilities
PRUEVIIN	Coefficient of Trip Time Variation	WSDOT	Facilities
Private Companies – Inrix and Traffic.com	–	Private	Facilities
Maryland SHA and Delcan-NET	–	Private	Facilities
Freight			
American Transportation Research Institute (FHWA freight performance measurement) (*8*)	Buffer Index	Private	State- and national-level Interstates
Missouri DOT	–	ATRI	I-70 across state

Note: This table only includes those cases in which reliability measures have been endorsed or adopted by a public entity responsible for operating and/or maintaining transportation systems (i.e., table does not include recommendation or use of performance measures by academic or research groups).

NCHRP Project 3-68 identified several measures of travel-time reliability that provide a basis for selecting measures for the research; these are (*4*):

- Buffer Index – The difference between the 95th percentile travel time and the average travel time, divided by the average travel time.
- Planning Time Index – The 95th Percentile Travel Time Index. (The Travel Time Index (TTI) is the ratio of the actual travel time to the ideal or free-flow travel time. Thus, a TTI of 1.2 indicates that the trip takes 20 percent longer than it would under ideal conditions.)
- Percent of trips with space mean speeds <= 50 mph.
- Percent of trips (section or O/D) with space mean speeds <= 30 mph.

Tu, van Lint, and van Zuylen stated that travel-time reliability measures can be classified into five types: 1) statistical range methods; 2) buffer time methods; 3) so-called "tardy-trip" measures; 4) probabilistic measures; and 5) so-called "skew-width" methods (*10*). The first three of these were first defined by Lomax et al. (*11*). Probabilistic measures are the same category as the failure-based or on-time measures and have been proposed for use in Florida, in combination with a buffer time measure (*12*). The skew-width methods are based on the observation that most travel-time distributions are skewed to the right, as shown in Figure 2.1. It has been suggested that travel times follow either a log-normal distribution or gamma distribution with an adequately scaled shape parameter (*13*).

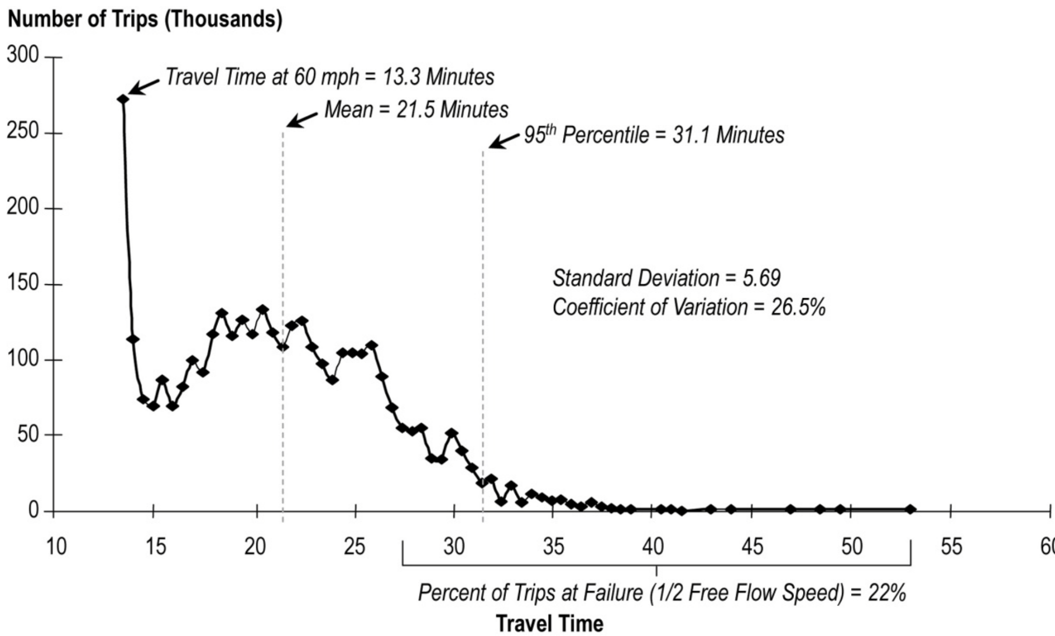
In traditional statistics, two standard measures are used to express the "unevenness" of distributions:

- **Skewness** is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point.
- **Kurtosis** is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case (*14*).

Van Lint and van Zuylen noted that buffer time and "Misery Index" measures based on the mean may not be appropriate because of the underlying skewed distribution (*15*). They also defined two measures that describe the size and shape of the travel-time distribution:

1. A **Skewness Statistic**, defined as (90th percentile-median)/(median-10th percentile); and
2. A **Width Statistic**, defined as (90th percentile-10th percentile)/median.

Figure 2.1 Travel-Time Reliability is Determined by the Distribution of Travel Times
Example Measures Only



Note: Analysis of NavGAtor data (Atlanta, Georgia): I-75 Northbound from I-285 to Wade Green Road (13.33 miles). 5:00 to 7:00 p.m. Weekdays, 2004.

Total number of trips for time period = 3,485 million (each point on the line represents the number of trips grouped by 30-second travel-time intervals). Note that about eight percent of trips (275,000 out of 3.485 million) occur at free-flow during this period.

2.2.2 Freight Efforts

In terms of economic value, reliability is probably more important to freight carriers and shippers than to personal travelers. With the rise in "just-in-time" deliveries (largely as a replacement to extensive warehousing), providing dependable (reliable) service has become extremely valuable. Conversely, failure to provide dependable service can increase costs significantly.

An example of how reliability affects truck freight operations is the chemicals supply chain. Increases in transportation reliability play an important role in reducing inventory in the chemicals supply chain. Because of the many nodes, up to one-third of chemical inventory is in transit at any point. Inventory managers keep safety or buffer stock to cushion against variability of inbound arrivals, and the amount of safety stock increases with the degree of unreliability and the number of stocking locations. However, capacity to receive chemical stocks is limited by the size of the liquid storage silos. Balancing capacity with demand is a challenge. As one industry consultant explains: "If the tank is full, there's no place to put it and you pay demurrage [storage charges] on the railcar. But if the vessel is early, you have wait time or dead freight." As transportation reliability decreases, wait time, dead freight, and cost increases (*16*).

Conceptually, reliability for trucks is no different than for personal travel – it is measured the same way (the travel-time distribution) with the same metrics (e.g., Buffer Index). Also, all roadway, demand management, and operations improvement types (except for those that specifically target trucks such as lane and service restrictions) affect both truck and personal travel. A practical difference is the length of the trip. Much truck travel is intercity in nature and, therefore, traverses long sections of rural highways that are not routinely congested. This means that in terms of the entire trip, only a small portion is within urban areas where most of the delay and associated unreliability occur. As discussed above, we intend to concentrate on how the reliability of facilities operates.

In 2002, The American Transportation Research Institute (ATRI) partnered with the Federal Highway Administration (FHWA) to develop methods for measuring freight performance on U.S. highways (*8*). With the Freight Performance Measurement (FPM) project, ATRI demonstrated that it is possible to collect roadway operational data for trucks using satellite technology and that the data could be rendered unidentifiable through a cleansing process. The trucking companies wanted some assurance (primarily caused by safety and security concerns) that their individual trucks could not be tracked once the "identity cleansing" process had been performed. The FPM results were deemed successful in identifying freight significant corridors, in developing measures for evaluating the performance of full highway corridors as well as providing information on individual segments within these corridors.

2.2.3 Missouri Department of Transportation

The Missouri Department of Transportation (MoDOT) has developed a set of performance measures that it uses to grade their activities and system performance. The measures are housed in a report known as Tracker (*17*). Tracker reports average truck speed as one of its freight performance measures. The average truck speed is updated monthly for the entire length of I-70 across Missouri as well as I-70 nationwide. This speed estimate is supplied as a monthly average to MoDOT by ATRI and the FPM database (see American Transportation Research Institute above).

2.2.4 Washington State Department of Transportation

A research project by the Washington State Transportation Center (TRAC) analyzed options for collecting travel-time data for trucks to determine the benefits provided by freight mobility projects in Washington State (*18*). The report identifies two types of travel-time data that need to be collected for trucks. The first is the average travel time experienced while making routine trips. The second type of travel time demonstrates what happens when trucks experience severe, unexpected delay. The report states that collecting truck travel times using floating car techniques is not practical to gather enough data to show truck trip reliability. Additionally, the travel times had to be collected for trip lengths longer than just the affected portion of a corridor where improvements had been made. Since some trucks would change their travel patterns to make use of the improved roadway, the travel time between truck origin/destination pairs should be used to determine the effect of the improvement on delay reduction for the area.

2.2.5 Texas Department of Transportation Work Zone Studies

The Texas Transportation Institute developed two case studies using archived speed data and more detailed work zone data in Houston and San Antonio in an ongoing TxDOT research project (*19*). This study related detailed information on work zone start/stop times, weather information, and crash information to determine the delay that is caused by the work zone.

2.2.6 PRUEVIIN

A research effort in the Seattle area developed a technique to combine regional travel demand models and commercially available traffic simulation software into a scenario-based framework (*20*). The Process for Regional Understanding and Evaluation of Integrated ITS Networks (PRUEVIIN) has two main features. First, it uses state-of-the-art traffic simulation models to identify the impacts of Intelligent Transportation Systems (ITS) on a transportation system under "average" conditions. Second, it provides a method to incorporate system variability which links the simulation analysis to the travel demand modeling framework. This second feature allows the evaluations to include realistic conditions – inclement weather, collisions, vehicle breakdowns, work zones, etc. – rather than to model the "expected" or "best-day" conditions. In one analysis, the coefficient of trip-time variation was calculated by examining the variation in travel times across each of the different modeled scenarios for a specific trip. As the coefficient gets larger, the variability of trip times increases and the lower the reliability for the trip. PRUEVIIN demonstrates that reliability measures can be generated without enormous amounts of travel-time data collection and may provide a means of obtaining travel-time reliability measures on arterial streets where data can be scarce.

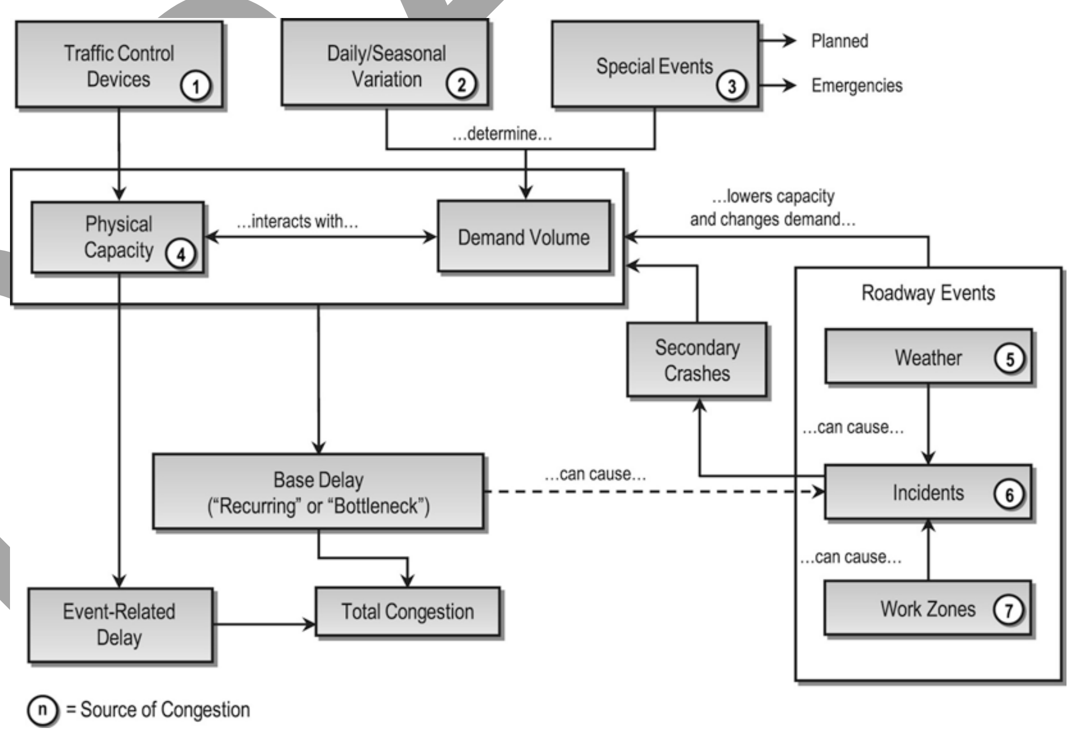
2.2.7 Inrix and Traffic.com

Some private companies have been collecting travel-time data on freeways and arterial streets in many U.S. cities for several years. Inrix (*21*) and Traffic.com (*22*) collect travel-time data by tracking fleets of probe vehicles in each area utilizing GPS tracking. Additionally, they obtain data from DOT web sites and other sources of speed data to supplement the probe vehicle data. They produce real-time travel speed estimates that are posted to web sites and provided to the media in the majority of these areas. This real-time data is generally archived and could be used to calculate travel-time reliability on arterial streets. There have not been many independent analyses performed on the GPS tracking travel-time data from these two sources so there is a great deal of uncertainty as to the composition of the data. The Maricopa Association of Governments (MAG, the Metropolitan Planning Organization for the Phoenix urban area), undertook a study to compare private vendor travel-time data (two firms) to their own sources (freeways detectors and floating car runs) (*23*). The evaluation indicated that on freeways, both companies' historical average speeds compared favorably with eight accurate loop detector freeway locations maintained by Arizona. The evaluation found that on arterial streets, both companies' historical average speeds compared favorably with MAG traffic speed data.

2.2.8 Beyond Reliability: The "Seven Sources"

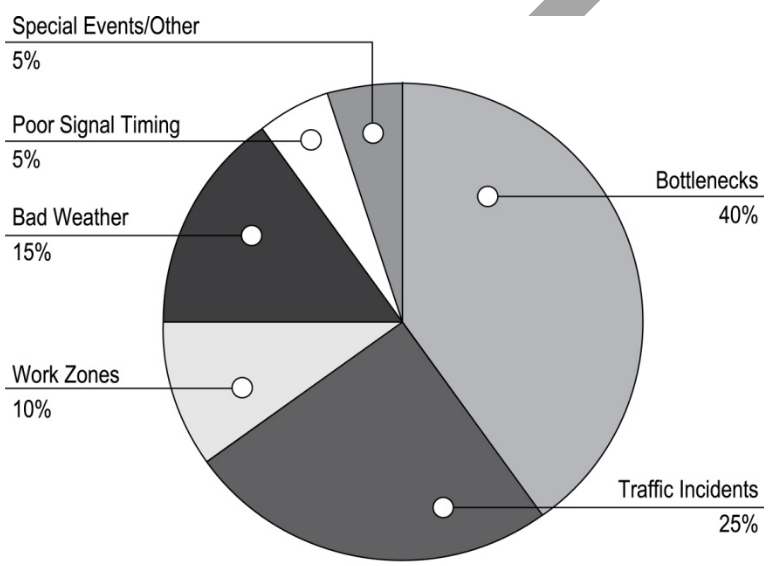
Reliability metrics provide an understanding of how dependable or variable travel conditions are – they do not tell you what the cause of the variability is. In this sense, reliability measures are top-level "outcome" measures. A deeper understanding of what is causing unreliable travel (and congestion, in general) is useful because it indicates which general areas or specific strategies should be emphasized. The original research plan for the SHRP 2 Reliability areas recognized this and identified the "seven sources of congestion." Figure 2.2 shows how these seven sources interact to produce total congestion. Reliability is an aspect of total congestion and is greatly influenced by the complex interactions of traffic demand, physical capacity, and roadway "events."

Figure 2.2 A Model of Congestion and Its Sources



Our understanding of how source contributes to total congestion (as well as reliability) is limited, although the current research will attempt to determine this analytically. National estimates have been produced by FHWA (Figure 2.3), but these were determined by consensus rather than analysis. The FHWA estimates also are meant to be a national snapshot, not indicative of individual corridors or highways. For example, in rural conditions, any delay that does occur will nearly always be a function of events rather than a bottleneck. In urban conditions, especially on a facility with a dominant bottleneck, most of the delay will be determined by the bottleneck.

Figure 2.3 Delay by Source
National Estimates



Source: Reference (*24*).

2.3 Improvements that Affect Reliability

Tables 2.2 through 2.4 show the Effects Matrix for the three major categories of improvement. The list is not exhaustive but rather is illustrative. The assessment of "Significance of Expected Effect on Reliability" is based on the team's initial subjective judgment about the magnitude of the strategy's effect on reliability – it does not reflect the results of any of the research conducted for the project.

Table 2.2 Congestion Strategy Effects Matrix – Add Capacity

Strategy	Expected Effect on Reliability	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Add Capacity – Freeways			
New Freeways	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
Widen Freeways	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
New Toll Roads	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
New Toll Lanes on Existing Roads	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, simulation	Medium
Interchange Improvements	Add capacity at bottleneck, reduce potential for secondary incidents	HCM, simulation	Medium
New HOV/Managed Lanes	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, simulation	Medium
Truck Only Lanes	Add new system capacity, reduce demand on adjacent freeways and arterials, reduce level of incident impacts, and reduce crash potential by eliminating auto/truck speed and braking differential	HCM, simulation	Medium
Add Capacity – Arterials			
New Arterials	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
Widen Arterials	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
Street Connectivity	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	simulation	Medium
Grade Separations	Reduce delay at intersections and reduce crash potential	HCM, simulation	Medium
HOV/Managed Lanes	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, simulation	Medium

Table 2.3 Congestion Strategy Effects Matrix – Operational Improvements

Strategy	Substrategies Included	Congestion Sources Affected	Strategy Implementation Factor Affects	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Operational Improvements – Freeways					
TMC Operations	Integrated real-time incident management, verification, detection, and traveler information	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High
Service Patrols	Must include incident scene management methods	Reduces delay due to incidents	Reliability affected by geographic coverage, vehicle route density, congestion level, and program aggressiveness	IDAS	High
On-Scene Incident Management Improvements	Response agency coordination and training	Reduces delay due to incidents	Reliability affected by program aggressiveness	IDAS	Medium
Remote Verification (CCTV)	Camera views available to multiple agencies and in TMC	Reduces delay due to incidents	Reliability affected by geographic coverage, equipment density, and program aggressiveness	IDAS	High
Event Management	Incident management coordination among agencies, and event ingress/ egress planning and coordination	Reduces delay due to special events	Reliability affected by geographic coverage, equipment density, congestion level and program aggressiveness	IDAS	Medium
Ramp Metering	Ramp meter algorithms based on real-time traffic information	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS, Simulation	High
Lane Controls	Dynamic message sign over lanes to close lanes in advance of incidents	Reduces delay to incidents, special events, and work zones	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS, Simulation	High
Managed Lanes	HOV lanes, HOT lanes, truck only lanes, and TOT lanes	Reduces delay due to incidents and bottlenecks	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	Simulation	High

Strategy	Substrategies Included	Congestion Sources Affected	Strategy Implementation Factor Affects	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Operational Improvements – Freeways (continued)					
Electronic Toll Collection	Toll payment by electronic toll tags	Reduces or eliminates delay at toll booths	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	Simulation	High
Real-Time Traveler Information	Pretrip information by 511, web sites, subscription alerts; en-route information on DMS, 511, real-time navigation systems	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High
Work Zone Management	Active management in TMC coverage areas, real-time information from portable equipment in non-ITS areas	Reduces delay in work zones	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS, Simulation, QuickZone	High
Road Weather Information Systems	Weather information supplied to TMCs from roadside weather stations	Reduces delay to incidents and weather	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High
Road Weather Pretreatment	Application of anti-icing chemicals on defined road segments to prevent/ retard icing	Reduces delay to incidents and weather	Reliability affected by geographic coverage, equipment density, and program aggressiveness	IDAS	Medium
Variable Speed Limits	Dynamic message signs to change speed limits based on current conditions	Reduces delay due incidents, weather, special events, and work zones	Reliability affected by geographic coverage, equipment density, and program aggressiveness	Simulation	High
Ramp Improvements	Construct additional ramp lanes, lengthen ramps,	Reduces delay due to bottlenecks	Reliability affected by extent of improvement	Simulation	Medium
Ramp Closures	Close entrance ramps in areas with closely spaced ramps	Reduces delay due to bottlenecks	Reliability affected by extent of closures and ramp spacing	Simulation	Medium
Bottleneck Removal	Add auxiliary lanes, improve road geometrics	Reduces delay due to bottlenecks	Reliability affected by geographic coverage and congestion level	Travel demand model, Simulation	High
Integrated Multimodal Corridors	Integrated control of freeways and arterials within a corridor	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Reliability affected by geographic coverage, equipment density, and program aggressiveness	Travel demand model, Simulation	High

Strategy	Substrategies Included	Congestion Sources Affected	Strategy Implementation Factor Affects	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Operational Improvements – Freeways (continued)					
Advanced Technology for Freight Management	Fleet management, advanced vehicle location, real-time truck traveler information, roadside permitting/ inspection, and weigh-in-motion	Reduces truck delay	Reliability affected by geographic coverage, equipment density, and program aggressiveness	IDAS	Medium
Operational Improvements – Arterials					
Geometric Improvements	Reduce grade and curvature	Reduces delay due to incidents and bottlenecks	Reliability affected by geographic coverage and congestion level	HCM, HERS	Low
Intersection Improvements	Add turn lanes, improve intersection geometrics	Reduces delay due to bottlenecks	Reliability affected by geographic coverage and congestion level	Simulation, HCM	Low
One-Way Streets	Convert two-way streets to one-way	Reduces delay due to bottlenecks	Reliability affected by geographic coverage and congestion level	Travel demand models, Simulation	Medium
Access Management	Reduce driveways on arterials, provide interparcel access	Reduces delay due to bottlenecks	Reliability affected by geographic coverage and congestion level	Travel demand models	Medium
Advanced Signal Systems	Centrally controlled signals, advanced detection,and advanced signal control strategies	Reduces delay due poor signal timing	Reliability affected by geographic coverage, equipment specifications, and program aggressiveness	Simulation	High
Signal Retiming/ Optimization	Regularly scheduled signal optimization programs	Reduces delay due poor signal timing	Reliability affected by geographic coverage, equipment specifications, and program aggressiveness	Simulation	High
Changeable Lane Assignments	Reversible lanes	Reduces delay due to bottlenecks	Reliability affected by geographic coverage and congestion level	Simulation	Medium
HOV By-Pass Ramp	Provide by-pass lanes for HOVs and buses at entrance ramps	Reduces delay due to ramp bottlenecks	Reliability due to congestion level	Simulation	Medium
Parking Restrictions	Restrict parking on arterial streets during peak hours	Reduces delay due to bottlenecks	Reliability affected by geographic coverage and congestion level	Simulation	Medium
Incident Management	Incident management coordination among agencies focused on arterials	Reduces delay due to incidents	Reliability affected by geographic coverage, vehicle route density, congestion level, and program aggressiveness	IDAS	Medium

Strategy	Substrategies Included	Congestion Sources Affected	Strategy Implementation Factor Affects	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Operational Improvements – Arterials (continued)					
Event Management	Incident management coordination among agencies and event ingress/ egress planning and coordination	Reduces delay due to special events	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	Medium
Road Weather Information Systems	Weather information supplied to TMCs from roadside weather stations	Reduces delay to incidents and weather	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High
Remote Verification (CCTV)	Camera views available to multiple agencies and in TMC	Reduces delay due to incidents	Reliability affected by geographic coverage, equipment density, and program aggressiveness	IDAS	High
Real-Time Traveler Information	Pretrip information by 511, web sites, subscription alerts; en-route information on DMS, 511, and real-time navigation systems	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Reliability affected by geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High

Table 2.4 Congestion Strategy Effects Matrix – Demand Management

Category	Strategy	Substrategies Included	Expected Effect on Reliability	Existing Methodology to Calculate Effects	Significance of Expected Effect
Travel Alternatives	Public education on aggressive driving	Public Service Announcements, Driver training, and brochures	Reduce crashes due to aggressive driving, fewer incidents	None	Low
Travel Alternatives	Reduction in trips/diversion to other modes/other times	Transit trip itinerary planning, real-time transit information, and commercial vehicle fleet scheduling	Reduce trips and reduced congestion	Travel demand modeling	Medium
Land Use	"Smart Growth" policies	Transit-oriented design, access management, street connectivity, bike/pedestrian facilities, and mixed use development	Reduce trips and reduced congestion	Travel demand modeling	Medium
Pricing	Reduction in trips or time shift due to pricing	Toll roads, HOT lanes, time-of-day pricing, cordon pricing, parking pricing, and HOV parking	Reduce trips and reduced congestion	Travel demand modeling	Medium
HOV	Rideshare programs	Vanpool/carpool programs, Transportation Management Associations,	Reduce trips and reduced congestion	Travel demand modeling	Medium
Freight	Truck only toll (TOT) lanes	Toll lanes exclusively for trucks and time-of-day pricing	Removes trucks from general purpose lanes, reduces truck/auto conflicts, reduces crashes, and reduces congestion in general purpose lanes by removing slower trucks	Simulation	Low
Freight	Lane restrictions	Restrict left lanes from use by trucks	Reduces truck/conflicts in restricted lanes, reduces crashes, reduces congestion in restricted lanes	Simulation	Low
Freight	Delivery restrictions	Restrictions on deliveries in peak hours	Reduces congestion in restricted areas during peak hours	Travel demand modeling	Low

2.4 Experimental Design

2.4.1 Types of Analyses Conducted

Three main forms of analysis were undertaken, as described below. In addition, a large set of exploratory analyses were conducted prior to the primary analyses as part of Phase 2 (see Section 4.0); these were undertaken to identify the parameters necessary to conduct the primary analyses.

1. **Before/After Analysis –** Since the major objective of the research is the development of models that can predict the change in reliability due to improvements, before/after analysis is the most appropriate experimental design. (Here, the "before" period is a period of time prior to implementing the improvement and the "after" period is a time period after the improvement has been implemented.) Ideally, before/after analysis is applied with a control group to help account for the influence of background factors. In this approach, the same highway section or network is studied with and without the improvement. However, it was recognized early in the research that it would be impossible to study all the possible improvement types in the field due to data limitations. Therefore, a second approach was developed that could handle reliability prediction:
2. **Cross-Sectional Analysis –** Patterned after classical experimental design, this essentially establishes a matrix of factors and their levels. Observations ideally are taken at each combination of factors. As previously noted, strict control of all factors were not achievable and there were missing combinations, which precluded studying interactions directly from the field data. Statisticians refer to this situation as a *quasi-experimental design*. In this approach, experimental design is used to ensure that a range of conditions are represented in the data.
3. **Congestion by Source Analysis –** Identifying the contributing factors to congestion and reliability (the "seven sources") is a major concern for the transportation profession. Table 2.5 shows some results from previous studies. The primary issue is how to split up delay so that each source that is present gets a share. The first decision is how much delay would have occurred in the absence of the event. Then, what are reasonable splits when multiple sources are at work. Further complicating matters are that inclement weather and work zones can increase the likelihood of a crash – should the resulting delay be charged completely to the weather or work zone category, or shared with the incident category.

Table 2.5 Results from Previous Studies Identifying Congestion by Source

Statistics	Study			
	Dowling (25)	NCHRP 3-68 (*26*)	Kwon et al. (*27*)	CDTC (*28*)
Metro Area	Los Angeles	Seattle	San Francisco	Albany
Routes	I-10	I-405, I-90, SR 520	I-880	I-87, I-90
Freeway Miles	10 miles	42 miles	45 miles	15 miles
Amount of Data	7 days	4 months	6 months	1 year
Total Delay				
Recurring Delay	69%	71%	80%	72%
Nonrecurrent Delay	31%	29%	20%	28%
Nonrecurrent Sources				
Percent Incident	31%	16%	13%	28%
Percent Work Zone	Not studied	Not studied	Not studied	Not studied
Percent Weather	Not studied	9%	2%	Not studied
Percent Special Events	Not studied	Not studied	5%	Not studied
Percent High Volume	Not studied	4%	Not studied	Not studied

2.4.2 Factors Considered

The Experimental Design is detailed in Table 2.6. The top-level design in Table 2.6 shows the overarching factors that will be studied. ***Note that the purpose of this experimental design is not to specify a classic factorial experiment***. The amount of locations needed to cover all possible factorial combinations would be prohibitive. Rather, the experimental design is used to ensure that a range of conditions is covered by the data and to identify the important factors and levels of those factors that are **desirable, but not necessarily achievable.** The combinations of factors that result will, therefore, be dependent on what data are able to be assembled. However, it will be useful to document what the experimental design matrix looks like after data have been assembled. This then will provide a basis for seeing what interactions can be studied.

Table 2.6 Experimental Design

Factors	Levels	Highway Type: Urban Freeways	Highway Type: Urban Signalized Arterials	Highway Type: Rural Freeways
Area Size	Small/Medium	●	●	
	Large/Very Large	●	●	
Base Congestion[a]	Low (AADT/C <7)			●
	Moderate (AADT/C ~9)	●	●	
	Severe (AADT/C ~12)	●	●	
Number of Lanes	4	●	●	●
	6	●	●	
	8+	●	●	
Base Crash Rate[b]	Low	●	●	●
	High	●	●	●
Percent Trucks	< 10%	●	●	●
	> 10%	●	●	●
Traffic Variability[c]	Low	●	●	●
	High	●	●	●
Traffic Signal Density	< 2/mi		●	
	2-5/mi		●	
	> 5/mi		●	
Proximity to Major Bottleneck	< 1 mile downstream from segment	●		
	> 5 miles downstream from segment	●		
Improvement Types	Incident Management	●	●	●
	Work Zone Management	●	●	●
	Weather Management[d]	●		●
	Traffic Device Control[e]	●	●	
	Demand Management	●	●	
	Special Event Management	●	●	
	Traveler Information	●	●	●
	Physical Expansion/Changes	●	●	●

[a] "C" in AADT/C is two-way hourly capacity.

[b] Categories will be based on comparison to each states average crash rate by type of highway.

[c] For urban highways, this will be determined based on the coefficient of variation (CV) of weekday peak-period travel. For rural highways, the CV of 24-hour volume will be used.

[d] Provisional; will depend on what is being covered in other research activities such as FHWA's Road Weather Research and Development Program.

[e] Ramp meter control on freeways; signal control on signalized arterials.

This approach is obviously a compromise, but it was decided early in the study that if empirical data were used, then the team would have to access data already being collected by transportation agencies. The reason for this is that a long history of travel-time data is needed to establish reliability, and the cost of undertaking special instrumentation to collect these data would have been exorbitant. Thus, the team identified areas where our past experience indicated that data were of sufficiently high quality to undertake the research.

Originally, it was thought that rural two-lane highways also could be studied, but data availability currently is nonexistent and we want to focus new data collection efforts on signalized highways, where reliability (and congestion) is a greater issue.

One key factor that is common to all improvement types and any predictive relationship of reliability is ***traffic "pressure" or demand level.*** In Table 2.7, the AADT/C ratio is used as a general measure of congestion level to ensure that roadways at all levels are considered in the analysis. AADT/C also may be used directly as an independent (predictor) variable in reliability relationships, but doing so masks the peaking characteristics of the facility. Other indicators of traffic pressure may include single or multiple hour v/c ratios. Variations in traffic demand variability also influence traffic pressure.

Accurately characterizing traffic demand is a critical part of the research. Our data collection plan is clearly oriented to facility-level rather than corridor- or system-level analysis. Existing continuous data collection activities by public agencies – on which the research will heavily rely – is concentrated on major facilities, usually freeways; data on parallel nonfreeways is scarce to nonexistent. During times of severe congestion, traffic demand can be suppressed by travelers switching to alternative routes or delaying their trips. We handled this effect by carefully measuring traffic demand on the test facilities as a way to control for diversion effect; original data collection to capture diversion is cost-prohibitive for this study, given the wide range of conditions we need to address.

The "Proximity to Major Bottleneck" requires elaboration. If a major bottleneck (e.g., freeway-to-freeway interchange) is immediately downstream of the study segment, then it will tend to dominate congestion on it. (Queues will routinely form on the study segment.) It is, therefore, important to note both the presence and characteristics (e.g., capacity) of a nearby downstream bottleneck. If the bottleneck is upstream of the study segment, then flow onto the study segment will be limited or "metered," because of the lower discharge rate from an oversaturated bottleneck. This is not really a problem except that the study segment may not ever receive enough demand to cause recurring congestion.

Additional subfactors vary by type of improvement or type of source delay being considered. The key is ensuring that a spread of conditions is represented:

- **Incidents –** Presence of a "usable" shoulder on each side of the highway; levels of incident management that lead to low-/medium-/high-average incident durations.
- **Work Zones –** Nature of geometric change, translated into HCM-based capacity loss to account for multiple combinations (such as lane narrowing with and without shoulder loss): < 5 percent/5 to 15 percent/15 to 30 percent/30 to 50 percent/50 to 75 percent.
- **Traffic Signals –** Type of progression: actuated/central control/adaptive.

Spatial Measurement Scale: Facility-Based. Because all (or nearly all) of the data are based on measurements taken at the level of the roadway (not the trip), the focus of the work was to define reliability at the facility level. This provides the most practical results for implementation, at least in the short run. We will investigate several spatial levels:

- Urban Links (distance between signalized intersections and freeway interchanges);
- Urban "Facility Segments" (distance between multiple signalized intersections and multiple freeway interchanges):
  - Two to five miles for freeways; and
  - One to three miles for arterials.
- Rural Extended Sections (long stretches of rural highways, probably 30 to 200 miles in length).

Temporal Measurement Scale. Reliability measurements for the following time periods were captured and used in the analysis:

- Peak hour and peak direction (based on maximum volume);
- Peak period (to encompass typical commuting times that include most delay, broken down by a.m./p.m. and directionality);
- Mid-day or overnight;
- Daily (to encompass all delay); and
- Weekday versus weekend.

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3.0 Data Collection, Assembly, and Fusion

3.1 INTRODUCTION

The research team decided at the beginning of the project that an empirical approach would be used to develop predictive relationships for reliability. The alternative would have been to conduct a large number of simulation-based experiments. However, we had conducted several previous projects using empirical data and were confident that these data could be used successfully in the research. Another reason for pursuing this approach is the large amount of empirical data that would be assembled that could not only be used in this project but would have value for future research. (Such an approach is not without risk – real-world data can be subject to measurement error, and it was clear that the extremely large amount of data that would be needed could not be uniquely collected by the project, thus the data collection itself was outside of our control.) Continuous travel-time data collected for a sufficiently long period of time is an absolute requirement for empirical studies of reliability, as reliability is defined by how travel times vary over a considerable time span. Going into the study, we estimated that a complete year of data is required to establish reliability, given the myriad of factors that influence it.

The majority of the effort conducted in the project was the creation of analysis datasets. Dataset creation involved obtaining, cleaning, and integrating data collected primarily by public agencies, but also private vendors. The research team selected agencies which had a long history of data collection and based on our experience with past projects, had data of the coverage and quality required to undertake the research. The challenges in this approach were twofold: 1) processing, reviewing, and reducing the raw data down to summary measurements for the analysis; and 2) matching the different types of data geographically.

Assembling empirical data from different locations around the country proved to be challenging, but manageable. Traffic data is relatively consistent from location to location, but incident and work zone data does not seem to follow any standard definitions in terms of definitions or content. Fusion of the event data with the traffic data also posed problems and in some cases these had to be matched manually.

3.2 Traffic and Travel-Time Data

3.2.1 Urban Freeways

The project team assembled urban freeway data from traffic management centers (TMC) that were considered to be at the forefront of maintaining quality traffic data. Other considerations in selecting the cities were the availability of incident data from the TMCs, the presence of before/after improvement situations, and a fairly long history of archiving data. Table 3.1 summarizes the cities and Table 3.2 summarizes the study sections. The locations of the sections appear in Figures 3.1 through 3.7. Full detail on the characteristics of the study sections is provided in the Phase 2 Report.

Several sections were used in the before/after analyses (Section 6.0 of this report; highlighted in bold in Table 3.2). All of these sections were considered in the exploratory analyses (Section 4.0) and the statistical modeling (Section 7.0). A separate dataset of urban freeways was compiled for the Seattle area for the congestion-by-source analysis; this dataset is documented at the end of this section.

Table 3.1 Urban Freeway Study Section Summary

City	Number Directional Study Sections	Total Directional Mileage
Houston	13	58.80
Minneapolis	16	62.63
Los Angeles	3	50.27
San Francisco Bay Area	4	19.98
San Diego	6	28.04
Atlanta	10	54.66
Jacksonville	8	17.71
Total	60	292.09

Note that Seattle freeways are not included in Table 3.2. Seattle data were used in the Congestion-by-Source analysis and before/after studies (see Section 5.0 for a description).

The urban freeway data set was the most complete of all the datasets assembled for the project. In addition to traffic data, all of the sections also had incident and weather data available.

Table 3.2 Urban Freeway Study Sections

Number	City	Route	Directions Covered	Beginning Landmark	Ending Landmark	Length (Miles)	Time Period Covered
1	Houston	U.S. 290 Northwest	Eastbound	Barker Cypress	FM 1960	4.05	1/1/2006-12/31/2007
2	Houston	U.S. 290 Northwest	Eastbound	FM 1960	Sam Houston	5.10	1/1/2006-12/31/2007
3	Houston	U.S. 290 Northwest	Eastbound	Fairbanks-N Houston	W 34th	5.35	1/1/2006-12/31/2007
4	Houston	U.S. 290 Northwest	Westbound	Pinemont	Sam Houston	4.45	1/1/2006-12/31/2007
5	Houston	U.S. 290 Northwest	Westbound	Sam Houston	FM 1960	4.25	1/1/2006-12/31/2007
6	Houston	U.S. 290 Northwest	Westbound	FM 1960	Barker Cypress	4.90	1/1/2006-12/31/2007
7	Houston	I-45 Gulf	Northbound	Nasa Road 1	Dixie Farm Road	5.10	1/1/2006-12/31/2007
8	Houston	I-45 Gulf	Northbound	Dixie Farm Road	Fuqua	2.80	1/1/2006-12/31/2007
9	Houston	I-45 Gulf	Northbound	Edgebrook	Broadway	4.70	1/1/2006-12/31/2007
10	Houston	I-45 Gulf	Northbound	Woodridge	Scott Street	4.15	1/1/2006-12/31/2007
11	Houston	I-45 Gulf	Southbound	Scott Street	Woodridge	4.15	1/1/2006-12/31/2007
12	Houston	I-45 Gulf	Southbound	Broadway	Edgebrook	4.70	1/1/2006-12/31/2007
13	Houston	I-45 Gulf	Southbound	Dixie Farm Road	Nasa Road 1	5.10	1/1/2006-12/31/2007
14	Minneapolis-St. Paul	I-35 W	Northbound	W 106th Street	South of I-494	3.47	1/1/2006-12/31/2007
15	Minneapolis-St. Paul	I-35 W	Southbound	South of I-494	W. 106th Street	3.64	1/1/2006-12/31/2007
16	Minneapolis-St. Paul	I-35 W	Northbound	T.H. 36	I-694	3.37	1/1/2006-12/31/2007
17	Minneapolis-St. Paul	I-35 W	Southbound	I-694	T.H. 36	3.29	1/1/2006-12/31/2007
18	Minneapolis-St. Paul	T.H. 36	Eastbound	Fairview Avenue	I-35E	4.41	1/1/2006-12/31/2007
19	Minneapolis-St. Paul	T.H. 36	Westbound	I-35 East	Fairview Avenue	4.35	1/1/2006-12/31/2007
20	Minneapolis-St. Paul	I-35 E	Northbound	West 7th Street	I-94	3.48	1/1/2006-12/31/2007
21	Minneapolis-St. Paul	I-35 E	Southbound	I-94	W. 7th Street	3.59	1/1/2006-12/31/2007
22	Minneapolis-St. Paul	T.H. 77	Northbound	T.H. 13	I-494	3.43	1/1/2006-12/31/2007
23	Minneapolis-St. Paul	T.H. 77	Southbound	I-494	T.H. 13	3.43	1/1/2006-12/31/2007
24	Minneapolis-St. Paul	I-94	Eastbound	Highway 100	I-494	7.00	09/2000-09/2001 and 11/2004-11/2005
25	Minneapolis-St. Paul	I-94	Westbound	I-494	Highway 100	7.00	09/2000-09/2001 and 11/2004-11/2005
26	Minneapolis-St. Paul	I-494	Eastbound	Highway 100	Highway 5/312	4.00	05/2002-05/2003 and 11/2005-11/2006
27	Minneapolis-St. Paul	I-394	Westbound	Highway 100	Highway 169	3.17	07/2004-07/2005 and 11/2005-11/2006
28	Minneapolis-St. Paul	Highway 169	Southbound	T.H. 62	I-494	2.00	06/2005-06/2006 and 11/2006-11/2007

Number	City	Route	Directions Covered	Beginning Landmark	Ending Landmark	Length (Miles)	Time Period Covered
29	Minneapolis-St. Paul	Highway 100	Northbound	36th Street	I-394	2.80	04/2005-04/2006 and 11/2006-11/2007
30	Los Angeles	I-210	Westbound	Foothill Highway and Ventura Freeway Interchange	S. Asuza Avenue and Foothill Freeway Interchange	13.63	10/2000-12/2002
31	Los Angeles	I-710	Northbound	Interchange: I-710 and I-5	I-710 and W. Ocean Boulevard	18.32	04/2004-06/2006
32	Los Angeles	I-710	Southbound	Interchange: I-710 and I-5	I-710 and W. Ocean Boulevard	18.32	04/2004-06/2006
33	Bay Area	I-880	Northbound	Oak Street Ramps	I-980 Ramps	1.35	01/2008-12/2008
34	Bay Area	I-880	Southbound	Oak Street Ramps	I-980 Ramps	1.35	01/2008-12/2008
35	Bay Area	I-580	Eastbound	Eden Canyon Ramps	1st Street and I-580 Interchange, Livermore	8.64	06/2002-07/2004
36	Bay Area	I-580	Westbound	Eden Canyon Ramps	1st Street and I-580 Interchange, Livermore	8.64	06/2002-07/2004
37	San Diego	SR 52	Eastbound	Santo Road Ramps	SR 52 and SR 125 Interchange	5.96	06/2004-12/2006
38	San Diego	SR 52	Westbound	Santo Road Ramps	SR 52 and SR 125 Interchange	5.96	06/2004-12/2006
39	San Diego	I-5	Northbound	Del Mar Heights Road Ramps	Carmel Valley Road Interchange	3.38	06/2001-08/2006
40	San Diego	I-5	Southbound	Del Mar Heights Road Ramps	Carmel Valley Road Interchange	3.38	06/2001-08/2006
41	San Diego	I-8	Northbound	North 2nd Street Interchange	Lake Jennings Park Interchange	4.68	06/2004-08/2006
42	San Diego	I-8	Southbound	North 2nd Street Interchange	Lake Jennings Park Interchange	4.68	06/2004-08/2006
43	Atlanta	I-75	Northbound	I-285	Roswell Road	5.19	01/2006-12/2008
44	Atlanta	I-75	Southbound	I-285	Roswell Road	5.19	01/2006-12/2008
45	Atlanta	I-75	Northbound	I-20	I-85	4.43	01/2006-12/2008
46	Atlanta	I-75	Southbound	I-20	I-85	4.43	01/2006-12/2008
47	Atlanta	I-285	Eastbound	I-75	GA 400	6.50	01/2006-12/2008
48	Atlanta	I-285	Westbound	I-75	GA 400	6.50	01/2006-12/2008
49	Atlanta	I-285	Eastbound	GA 400	I-85	6.03	01/2006-12/2008
50	Atlanta	I-285	Westbound	GA 400	I-85	6.03	01/2006-12/2008
51	Atlanta	I-75	Northbound	Roswell Road	Barrett Parkway	5.18	01/2006-12/2008
52	Atlanta	I-75	Southbound	Roswell Road	Barrett Parkway	5.18	01/2006-12/2008
53	Seattle	SR 520	Eastbound/Westbound	I-5	I-405	7.00	01/2006-12/2008
54	Seattle	SR 520	Eastbound/Westbound	I-405	SR 202	5.50	01/2006-12/2008
55	Seattle	I-90	Eastbound/Westbound	I-5	West End Floating Bridge	1.24	01/2006-12/.2008
56	Seattle	I-90	Eastbound/Westbound	West End Floating Bridge	I-405	4.76	01/2006-12/2008
57	Seattle	I-90	Eastbound/Westbound	I-405	West Lake Sammamish	4.00	01/2006-12/2008

Number	City	Route	Directions Covered	Beginning Landmark	Ending Landmark	Length (Miles)	Time Period Covered
58	Seattle	I-90	Eastbound/Westbound	West Lake Sammamish	West of High Point Road	6.37	01/2006-12/2008
59	Seattle	SR 167	Northbound/Southbound	15th Street NW	SR 516	3.70	01/2006-12/2008
60	Seattle	SR 167	Northbound/Southbound	SR 516	I-405	6.10	01/2006-12/2008
61	Seattle	I-405	Northbound/Southbound	I-5 Tukwila	SR 167	2.30	01/2006-12/2008
62	Seattle	I-405	Northbound/Southbound	SR 167	112th Avenue S.E.	7.70	01/2006-12/2008
63	Seattle	I-405	Northbound/Southbound	112th Avenue S.E.	I-90	2.20	01/2006-12/2008
64	Seattle	I-405	Northbound/Southbound	I-90	SR 520	3.40	01/2006-12/2008
65	Seattle	I-405	Northbound/Southbound	SR 520	SR 522	8.40	01/2006-12/2008
66	Seattle	I-405	Northbound/Southbound	SR 522	I-5 Lynnwood	6.50	01/2006-12/2008
67	Seattle	I-5	Northbound/Southbound	South 320th Street	I-405 Tukwila	10.40	01/2006-12/2008
68	Seattle	I-5	Northbound/Southbound	I-405 Tukwila	Albro Place	6.60	01/2006-12/2008
69	Seattle	I-5	Northbound/Southbound	Albro Place	SR 520	7.80	01/2006-12/2008
70	Seattle	I-5	Northbound/Southbound	SR 520	Northgate	4.10	01/2006-12/2008
71	Seattle	I-5	Northbound/Southbound	Northgate	Snohomish/King County Line	5.40	01/2006-12/2008
72	Seattle	I-5	Northbound/Southbound	Snohomish/King County Line	128th S.W.	8.10	01/2006-12/2008
73	Seattle	I-5	Northbound/Southbound	128th SW	Marine View Drive	8.40	01/2006-12/2008
74	Jacksonville	I-95	Northbound	Phillips Hwy	SR 202	5.16	03/2008-12/2008
75	Jacksonville	I-95	Southbound	Phillips Hwy	SR 202	5.16	03/2008-12/2008
76	Jacksonville	I-95	Northbound	SR 202	Atlantic Blvd	4.56	03/2008-12/2008
77	Jacksonville	I-95	Southbound	SR 202	Atlantic Blvd	4.56	03/2008-12/2008
78	Jacksonville	I-95	Northbound	U.S. 23	SR 111 (Edgewood)	3.85	03/2008-12/2008
79	Jacksonville	I-95	Southbound	U.S. 23	SR 111	3.85	03/2008-12/2008
80	Jacksonville	I-95	Northbound	SR 111	I-295	4.13	03/2008-12/2008
81	Jacksonville	I-95	Southbound	SR 111	I-295	4.13	03/2008-12/2008

Notes: Houston data is based on toll tag-equipped probe vehicles and is comprised of direct travel-time measurements. The remaining locations' data are comprised of roadway-based sensors measurements of volume, speed, and lane occupancy.

Sections in bold were used in the before/after analysis. All sections were considered by the statistical modeling.

Figure 3.1 Atlanta Base Map

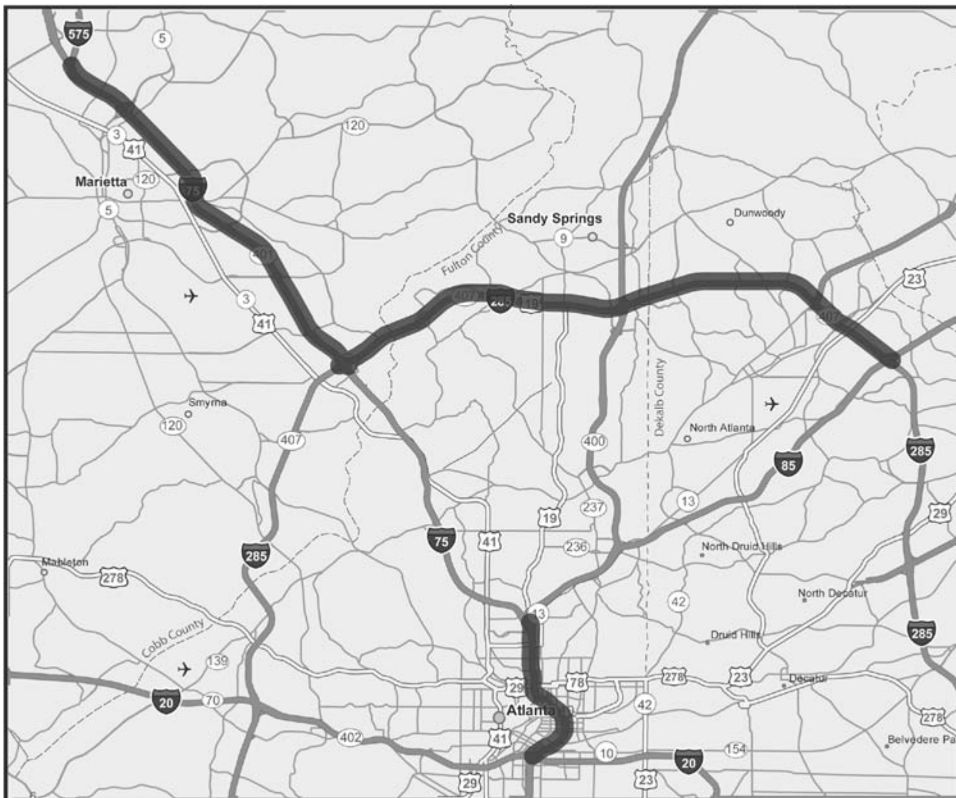


Figure 3.2 Houston Base Map

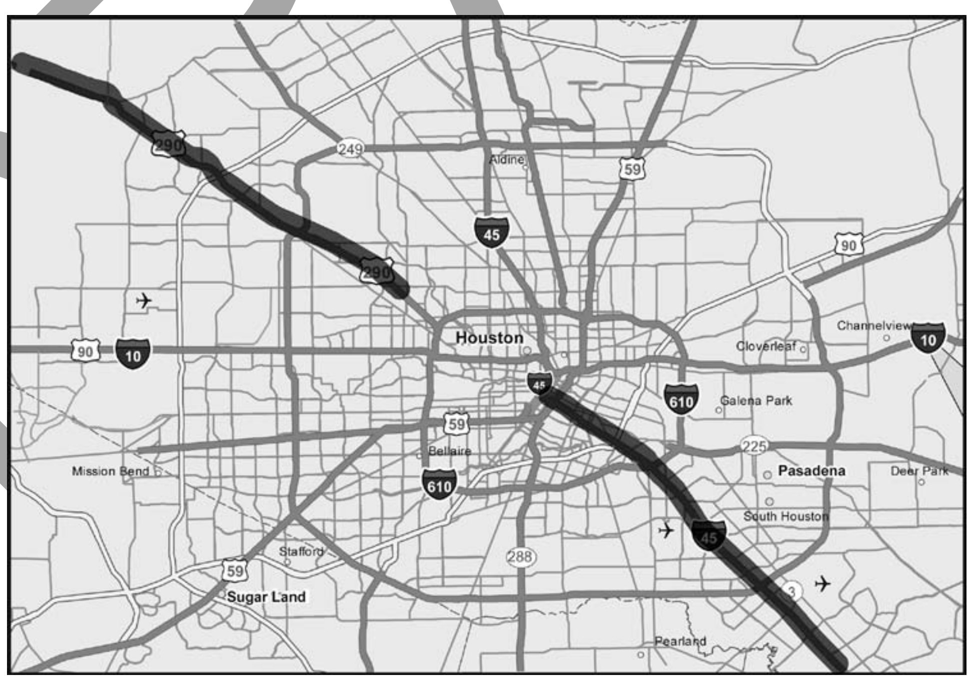


Figure 3.3 Minneapolis-St. Paul Base Map

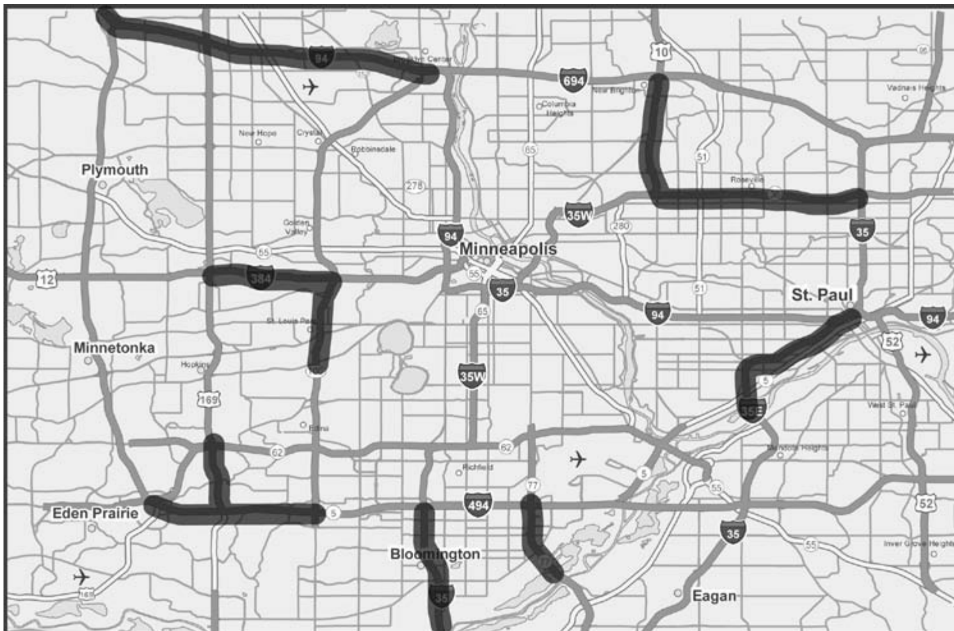


Figure 3.4 San Francisco Bay Area Base Map

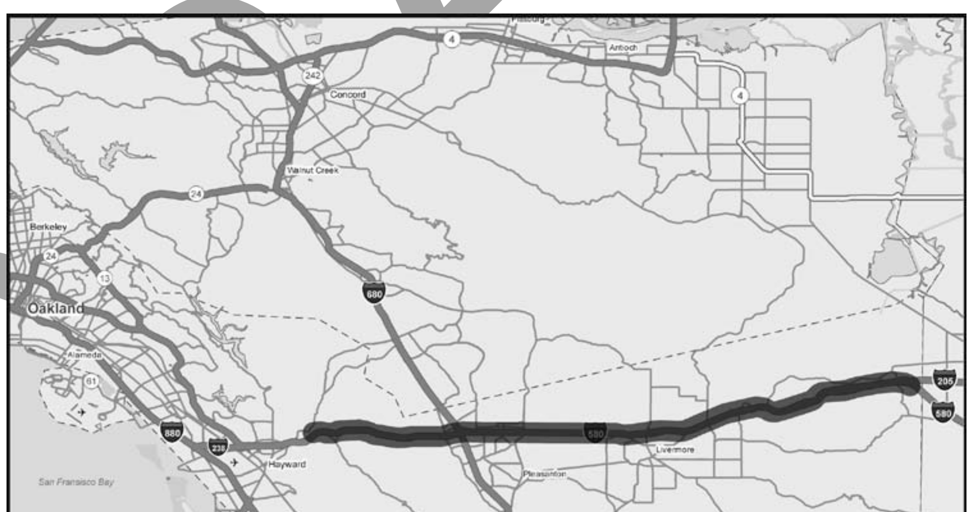


Figure 3.5 Los Angeles Base Map

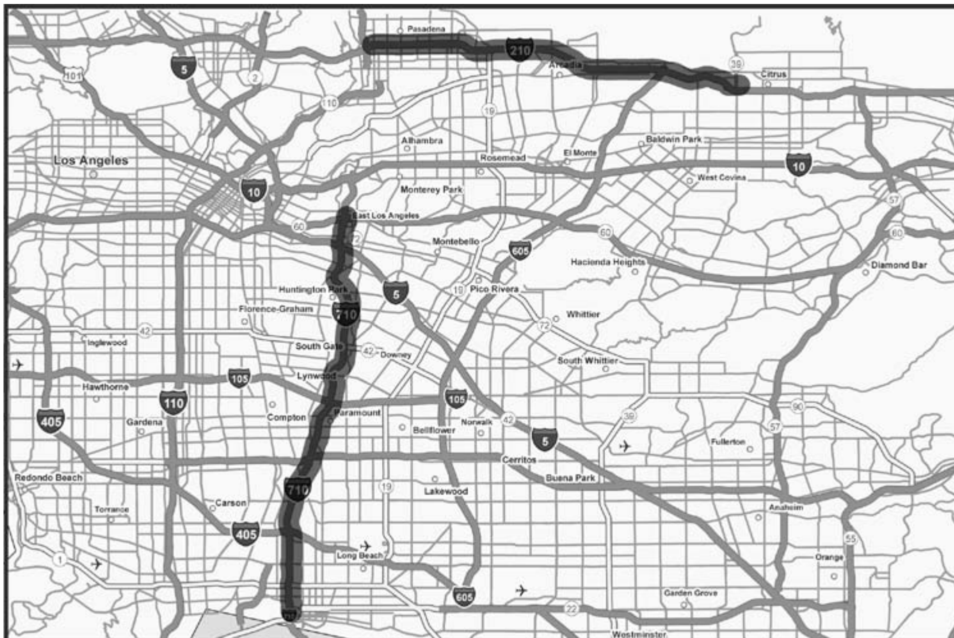


Figure 3.6 San Diego Base Map

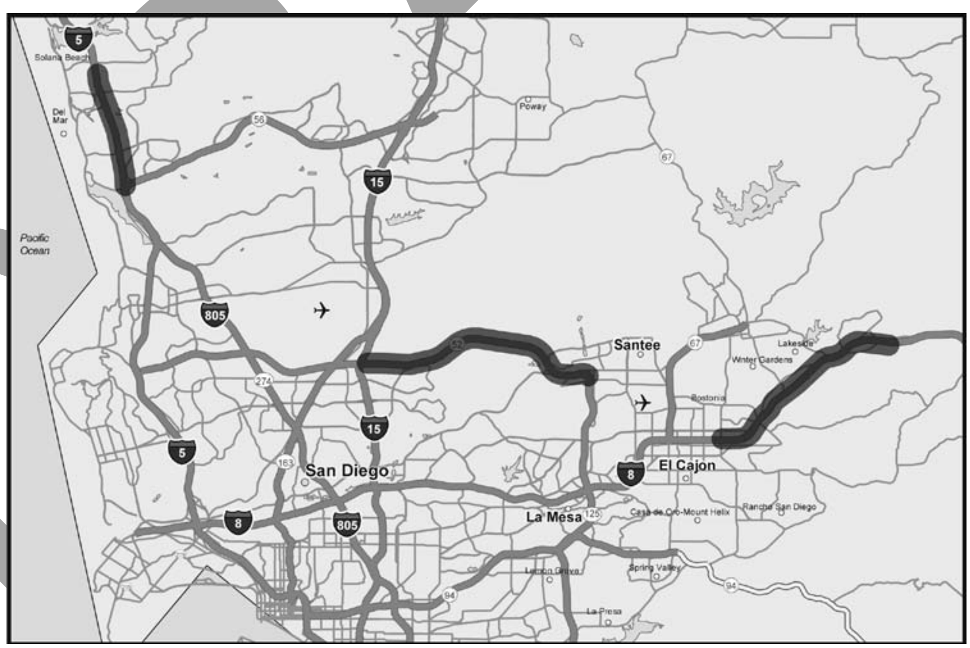
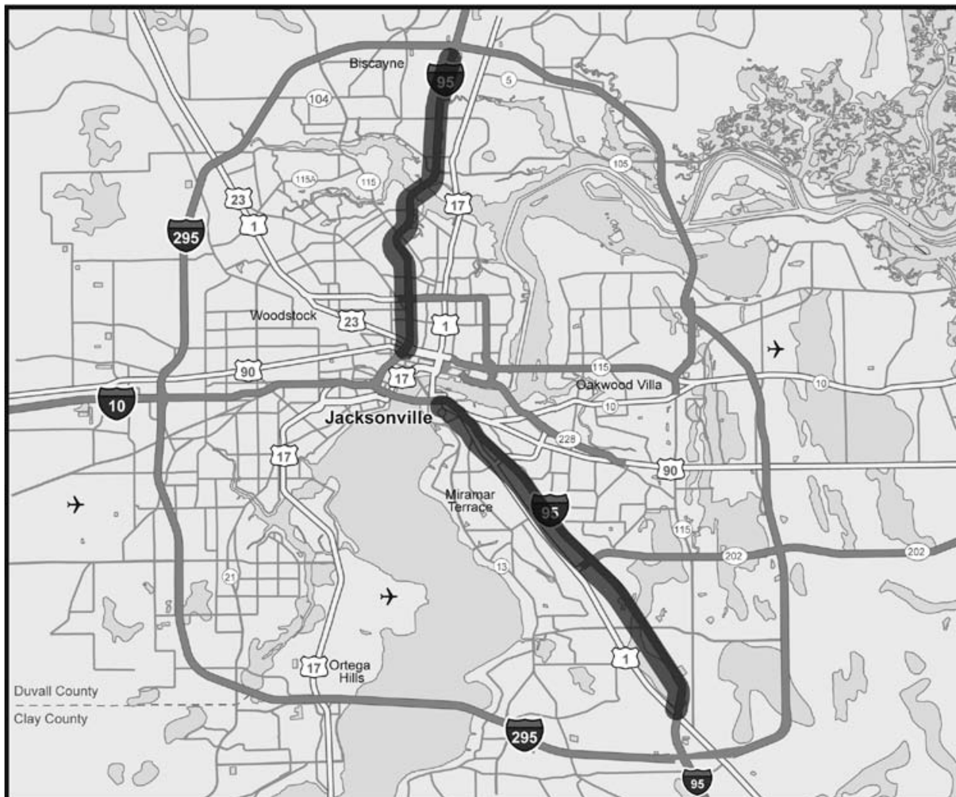


Figure 3.7 Jacksonville Base Map



3.2.2 Signalized Arterials

Table 3.3 shows the data assembled for signalized arterials. Data were derived from both public and private sources and several technologies. The privately provided data were purchased from Inrix, which has nationwide agreements with private fleets to capture travel-time information. Inrix sells these data primarily for real-time traveler information to both private and public entities (such as the I-95 Corridor Coalition), but also archives the data for other uses. In late 2007, the Research Team asked Inrix to review their data quality and to provide suggestions for arterial sections which they felt had the best quality of data and the highest sample sizes. However, upon review of the data, it was determined that the Inrix data for signalized arterials had an insufficient number of samples to define reliability for the research (See Appendix G of the Phase 2 Report). The net result is that only the two arterials in Orlando could be used for the analysis. It should be noted there are several private vendors offering travel time data on the market. We have observed that over time sample sizes have grown substantially as the vendors increase the sources for their data, increasing their value as a resource for future reliability research.

3.2.3 Rural Freeways

Table 3.4 presents the sections for which rural freeway travel-time data were assembled. The Inrix data was deemed to have sufficient sample sizes for the two locations indicated.

Table 3.3 Signalized Arterial Study Sections

City	Arterial	From	To	Length (Miles)	Travel-Time Data: Data Technology	Travel-Time Data: Period
Orlando	Sect 1: SR 50 Eastbound	Florida Turnpike	SR 408W	6.85	Tag-Based Probe	March 2008+
	Sect 2: SR 50 Westbound	SR 408W	Florida Turnpike	6.85	Tag-Based Probe	March 2008+
	Sect 3: U.S. 441 Northbound	SR 417	SR 408	10.67	Tag-Based Probe	March 2008+
	Sect 4: U.S. 441 Southbound	SR 408	SR 417	10.67	Tag-Based Probe	March 2008+
	Sect 5: U.S. 441 Northbound	SR 408	N. John Young Parkway	4.35	Tag-Based Probe	March 2008+
	Sect 6: U.S. 441 Southbound	N. John Young Parkway	SR 408	4.35	Tag-Based Probe	March 2008+
Los Angeles	Santa Monica Boulevard	I-405	N. Gardner Street	6.9	GPS Probe (Inrix)	2006/2007
Phoenix	E. Camelback Road	44th Street	Highway 51	4.2	GPS Probe (Inrix)	2006/2007
Minneapolis	Washington Avenue	County Highway 153	U.S. 65	3.4	GPS Probe (Inrix)	2006/2007
Miami	U.S. 1	17th Avenue	Le Jeune Road	3.8	GPS Probe (Inrix)	2006/2007
Houston	Westheimer Road	W. Sam Houston	I-610	6.9	GPS Probe (Inrix)	2006/2007

Note: Probe tag technology provide direct estimates of travel time over the segment. Inrix-provided data are supplied as speed estimates by link (approximately one-half- to one-mile long). Only the Orlando sections were used in the analysis because of sample size limitations on the other sections.

Table 3.4 Rural Freeway Study Sections

State	Route	From	To	Length	Travel-Time Data: Data Technology	Travel-Time Data: Period
Texas	I-45	Exit 213, Navarro County	Exit 267, Ellis County	54.1	GPS Probe (Inrix)	2006/2007
South Carolina	I-95	South Carolina/Georgia Border	SR 68, Hampton County	38.2	GPS Probe (Inrix)	2006/2007

3.3 Incident and Work Zone Data

3.3.1 Incident and Work Zone Characteristics

Data on the basic characteristics of incidents were available from three sources and are used to varying degrees, depending on the team's assessment of data sources for each city's situation. First, incident data were available from a private vendor, Traffic.com, for the research. The incident and event data were provided to the project team by Traffic.com at no cost from their Traveler Information Management System (TIMS). The TIMS data provided a standardized source of information for traffic incidents, events, scheduled and unscheduled construction, and other events that could affect traffic conditions (such as severe weather or transit delays).

The incident data are gathered directly by Traffic.com observers using numerous sources of information, such as video images, aircraft, mobile units, and police and emergency communication frequencies. In some cities, Traffic.com observers are stationed on the floor of the regional traffic management center. In other cities, Traffic.com observers are mobile or are stationed in a connected operations center.

The incident data from Traffic.com was chosen for this study because it has several unique attributes:

- All reported incidents are entered; however, Traffic.com does attempt to confirm reports and will indicate in their system when the reported incident has been confirmed. Thus, we have the ability to view both reported incidents as well as confirmed incidents.
- The Traffic.com incident data was collected by an independent entity that is not involved in the traffic or emergency management process. It was reasoned that Traffic.com staff could gather more complete and accurate data because information gathering and reporting was their sole focus (whereas public agency traffic managers typically must manage incidents/crises and record relevant information at the same time). Additionally, the Traffic.com incident data is routinely reviewed to ensure quality data entry by Traffic.com observers.
- The Traffic.com incident data contains the sequence of events as an incident is reported, responded to, and cleared. For example, an incident record is updated and appended at any time in which the status or conditions of the incident change. This information provides more specificity about the incident.
- The Traffic.com incident data provided consistent data attributes in all of this study's cities. Additionally, the Traffic.com incident data had unambiguous location referencing as well.

The following incident attributes were used in this study:

- **Unique Traffic Item Identifier –** A unique identifier for each record/ observation.
- **Unique Original Traffic Item Identifier –** A unique identifier for the original traffic incident. This identifier does not change as information about the same incident is updated.
- **Metropolitan Area –** Unique city identifier.
- **Roadway and Location Identifier –** Unique combination of identifiers for the location.
- **Type of Traffic Item –** Possible entries include:
  - ACCIDENT;
  - ALERT;
  - CONGESTION;
  - DISABLED VEHICLE;
  - MASS TRANSIT;
  - MISCELLANEOUS;
  - OTHER NEWS;
  - PLANNED EVENT;
  - ROAD HAZARD;
  - SCHEDULED CONSTRUCTION;
  - UNSCHEDULED CONSTRUCTION; and
  - WEATHER.
- **Verification –** An indication of whether the incident/event has been verified.
- **Number of Lanes Blocked –** Numeric entry for number of travel lanes that are blocked.
- **Start and Ending Time –** The combination of these attributes provides incident duration. The start time is the time when the lane or shoulder blockage began; the end time is when the blockage was cleared.

Second, data collected by TMC operators (entered into consoles at the TMC) and/or entered by freeway service patrols (FSP) were available for some cities. The type of data collected by these entities varies, but they for the most correspond to Traffic.com data; the key items of location, duration, and lane blockage are the same. The sources of incident data used in the urban freeway analysis are as follows:

- **Atlanta –** TMC data is primary source (includes work zones and special events), checked against both Traffic.com and GDOT crash data.
- **Houston –** Traffic.com data was found to match TMC (Transtar) incident data very well, and since it contains work zones and special events, is the source of incident information.
- **Minneapolis –** Traffic.com data.
- **San Diego, Los Angeles, and San Francisco (Bay Area) –** Traffic.com data.
- **Seattle –** Special data set, a fusion of TMC and police CAD data.
- **Jacksonville –** TMC data.

3.3.2 Incident Activity Data

Areas with incident management differ substantially in the institutional arrangements and policies that govern day-to-day operations. Many of these are subjective and do not lend themselves to quantification (which we need for our statistical modeling). Initially, it was thought that the approach being taken in SHRP 2 Project L06, *Institutional Architectures to Advance Operational Strategies*, could be used. The L06 approach is based on adapting the Capability Maturity Model (CMM) developed for software engineering to operations activities in transportation agencies. (The **Capability Maturity Model** in software engineering is a model of the maturity of the capability of certain business processes. A maturity model can be described as a structured collection of elements that describe certain aspects of maturity in an organization, and aids in the definition and understanding of an organization's processes (http://en.wikipedia.org/wiki/Capability_Maturity_Model). It was hoped that the resulting levels could be used as indicators of the "degree of sophistication" in policies and institutional arrangements with regard to incident management. Unfortunately, Project L06's CMM is too general and nonspecific to incident management to be of use in our statistical modeling. Instead, we used the Traffic Incident Management (TIM) Self-Assessment procedure developed by FHWA to indicate the sophistication of incident management arrangements for modeling purposes. This has the advantages of capturing a wide range of activities in a single numeric score and being in widespread among operators to facilitate application of the final models. The TIM Self-Assessment consists of three primary assessment areas:

1. Program and Institutional Issues;
2. Operational Issues; and
3. Communications and Technology Issues.

Composite scores are given for each of these areas (there are multiple attributes in each area) as well as a single overall score. We explored using both the individual scores as well as the overall score in the modeling. Unfortunately, self-assessment scores were only available for three cities, which were not enough for model development. Preliminary – but inconclusive – results are presented, though.

3.4 WEATHER DATA

Overview

The weather data for SHRP 2 L03 project were obtained from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). NCDC is the world's largest active archive of weather data. NCDC produces climate publications and responds to data requests from all over the world.

The National Climatic Data Center offers a wide range of climate products and services. One of the surface climate products that NCDC offers is the Local Climatological Data. The Center also offers marine and upper air data.

The Local Climatological Data product consists of hourly, daily, and monthly climatological summaries for approximately 1,600 U.S. locations. However, Daily Summary forms are not available for all stations. After January 2005, the Local Climatological Data have been processed through automated quality control processing. About 480 first-order stations also undergo additional quality control after the end of the month.

Data Access

Similar to other NCDC products and services, the Local Climatological Data is available on a variety of media, including on-line access, CD-ROMs, DVDs, computer tabulations, maps, and publications. An annual subscription is available for on-line access of the Local Climatological Data. The details of how to subscribe to the Local Climatological Data can be found at https://ols.nndc.noaa.gov/subscriptions.html. Free access to NCDC data is granted to certain users, such as academic and educational users, using reverse domain lookup (for details, see Free Access). The Local Climatological Data for specific locations and specific timeframe can be downloaded at http://cdo.ncdc.noaa.gov/qclcd/QCLCD?prior=N. ASCII format download of this data for all stations are available at http://www5.ncdc.noaa.gov/ulcd for unlimited subscription customers and FREE domains. Final Data loads occur on a monthly basis, usually overnight. Data gaps may exist during the timeframe of previous and current final data loads.

Data Format and Description of Hourly Data

Hourly data files were used for the research. The basic weather elements in the hourly data files are:

- Sky condition – Cloud height and amount (clear, scattered, broken, and overcast) up to 12,000 feet;
- Visibility (to at least 10 statute miles);
- Basic present weather information – Type and intensity for rain, snow, and freezing rain;
- Obstructions to vision – Fog, haze;
- Pressure – Sea-level pressure, altimeter setting;
- Ambient temperature and dew point temperature;
- Wind – Direction, speed and character (gusts, squalls);
- Precipitation accumulation; and
- Selected significant remarks, including variable visibility, precipitation beginning/ending times, rapid pressure changes, pressure change tendency, wind shift, and peak wind.

3.5 Geometric, Operating, and Improvement Data

Geometric data were obtained from satellite imagery (lane configurations) and the 2007 Highway Performance Monitoring data. Operating and improvement data were obtained directly from the state DOTs. The most important data in this category are those elements related to calculating capacity for each individual link.

3.6 Data Processing Procedures

3.6.1 Urban Freeway Data Processing

Data for all urban freeway sections were centrally processed to ensure consistency. The procedures used are summarized in Figure 3.8 and includes the following steps:

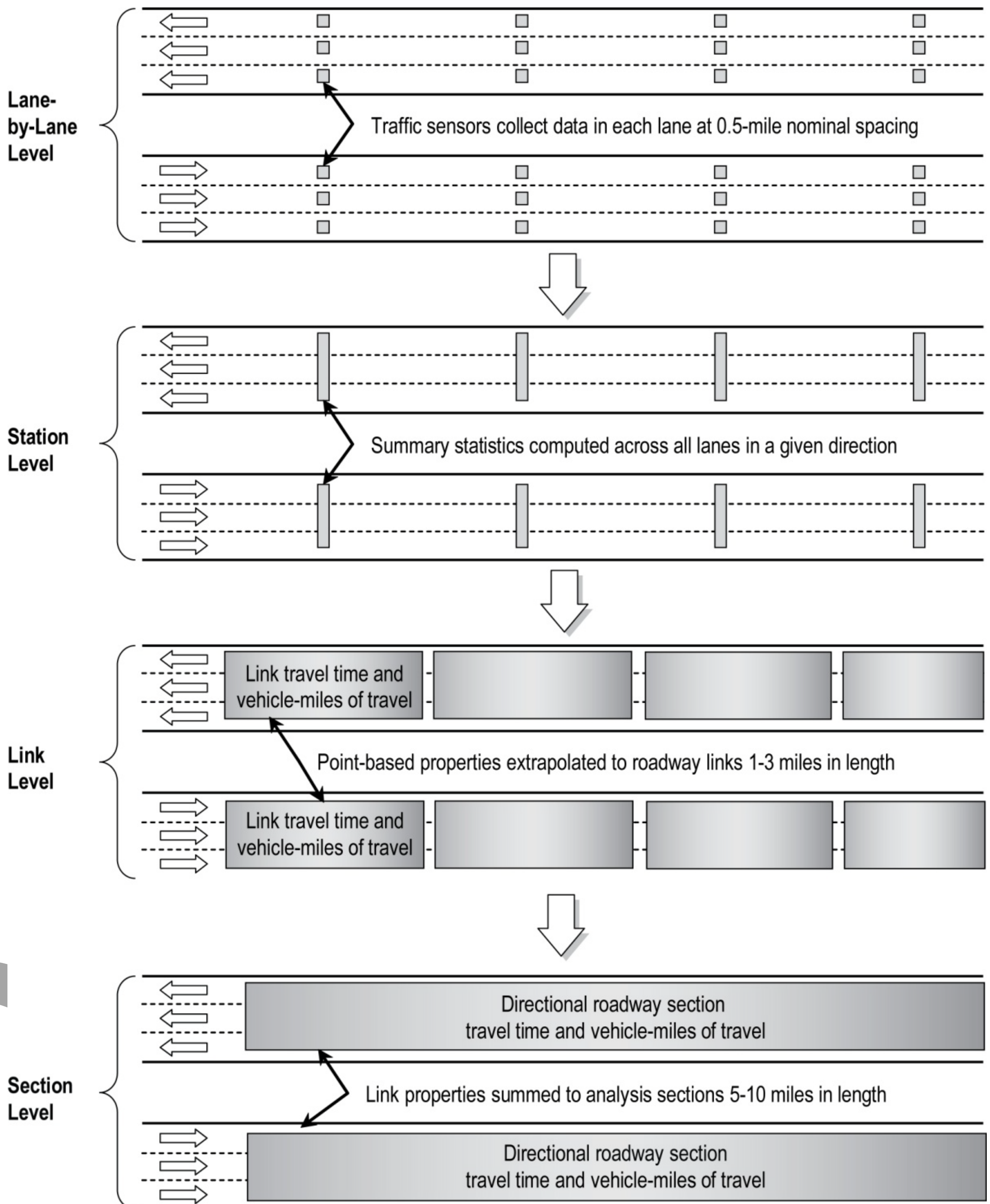
- The processing begins with quality control of the data as received from the TMCs. The data quality checks used are those developed for FHWA (*1*).
- Data are aggregated to five-minute-by-lane summaries. Aggregation rules follow those in a forthcoming ASTM standard (*2*).
- Two levels of spatial aggregation is done on the five-minute interval data:

1. **Station Level –** Aggregated laterally over all lanes in a direction; and
2. **Section-Level –** Station-level data aggregated longitudinally for all stations on a study section.

The aggregation process is shown in Figure 3.8.

- From the Section-Level data, a procedure for estimating the start and end times of the peak hour and peak period is applied; this procedure is detailed in Section 4.6 of this report. Analysts then review the start and end times, and make adjustments based on local knowledge.
- Section-Level statistics are computed for each time slice to be used in the analysis:
  - Peak Hour (weekdays only);
  - Peak Period (weekdays only);
  - Counter Peak Hour (weekdays only; the opposite time slice from the peak hour – if the peak hour is in the morning, then the counter peak is in the afternoon);
  - Mid-day;
  - Week Day (all hours of the day); and
  - Weekend/Holiday (all hours of the day).

Figure 3.8 Study Sections Mapped to Original Experimental Design Matrix



Source: Reference (*3*).

3.6.2 Signalized Arterial Data Processing

Calculating travel-time and reliability statistics from toll tag-equipped probe vehicles is straightforward – travel times are measured directly so there is no need for transformations as shown in Figure 3.8. Data quality control is different, however. Because of the opportunities for vehicles to make incomplete trips through a section of arterial (such as stopping at adjacent land uses), some travel times will be detected as being excessively high. As a result, probe data quality controls have been focused on eliminating outliers. In the FHWA's Mobility Monitoring/Urban Congestion Report Project (Reference 27), the quality control criterion for probe data is two consecutive travel times cannot change more than 40 percent. Another method proposed by researchers at University of Washington is that a travel time cannot be more than one standard deviation above or below the moving average of the 10 previous entries.

These methods work well for freeway data where probe data coverage is high. However, probe data on arterials are considerably sparse. Many of the outliers in arterial data will pass through this method undetected because there are not enough immediate adjacent observations. Instead of relying on continuous observations, arterial data quality control focused more on the overall spread of the data. Examination of the arterial data has led us to develop the following QC processing rules, all of which were applied to the data.

1. Visual inspection removes any days that have extremely low or high travel times.
2. Rank all travel time for a section, and treat any value greater than the 75th percentile plus 1.5 times the interquartile distance, or less than the 25th percentile minus 1.5 times the interquartile distance as an outlier. This technique is robust because it uses the quartile values instead of variance to describe the spread of the data.
3. Two consecutive travel times cannot change more than 40 percent.
4. A travel time cannot be more than one standard deviation above or below the moving average of the 10 previous entries. These 10 previous entries must be continuous and valid data.

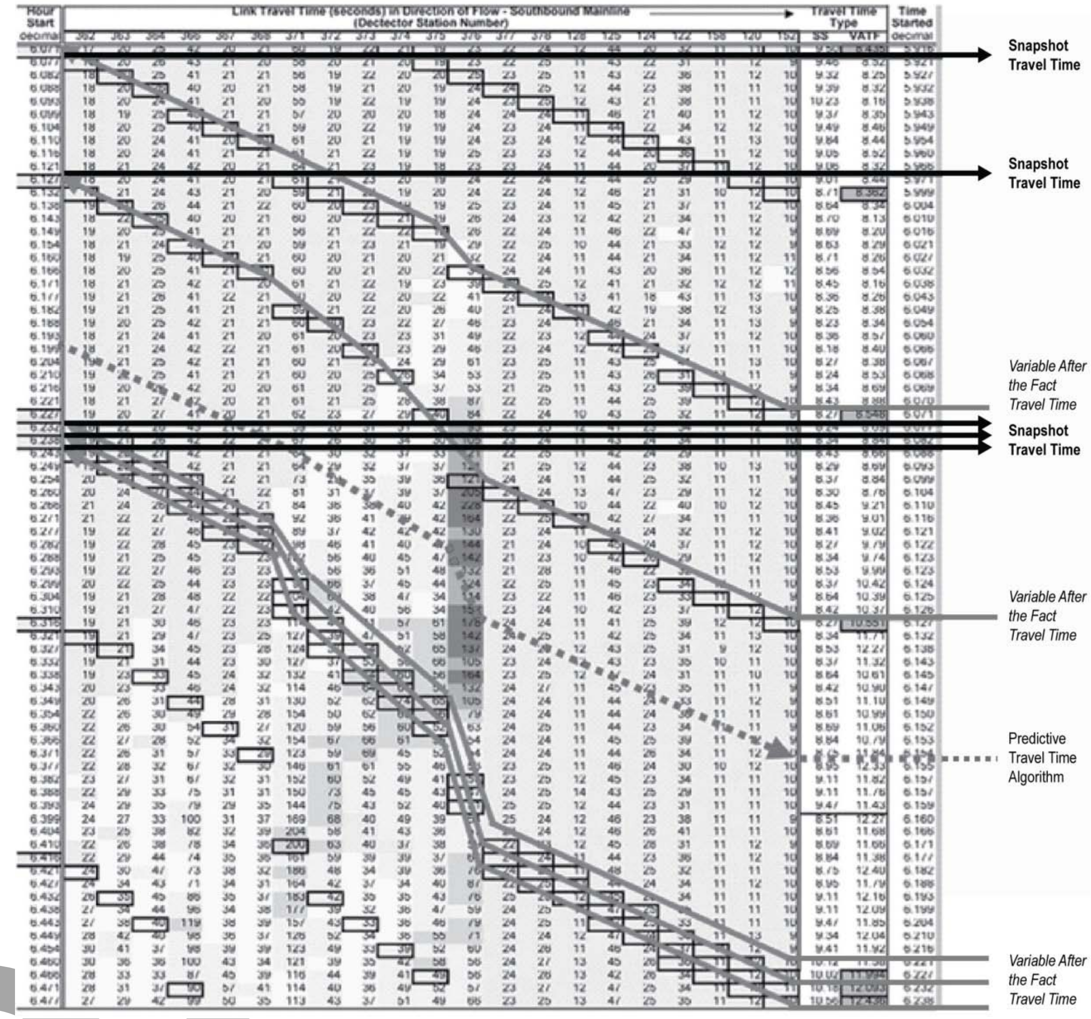
3.6.3 Rural Freeway Data Processing

The rural freeway relies on speed data supplied by Inrix on traffic message channel (*4*) links. From a processing standpoint, we treat the Inrix data in the same way as for detector data. However, because the Inrix data is provided by relatively short links, and many links comprise the very long rural segments used in the research, a trajectory-based method was used to estimate travel times for the entire segment. The vehicle trajectory method "traces" the vehicle trip in time and applies the link travel time corresponding to the precise time in which a vehicle is expected to traverse the link. For example, a section travel time that begins at 7:00 a.m. will use a link travel time for 7:00 a.m. to 7:05 a.m. at the trip origin, but could use a link travel time from 7:05 a.m. to 7:10 a.m., or 7:10 a.m. to 7:15 a.m. at the trip destination. The vehicle trajectory method attempts to more closely model the actual link travel times experienced by motorists as they traverse the freeway system. Figure 3.9 shows how the vehicle trajectory method works compared to the "snapshot" method used for the much shorter urban freeway sections. In the trajectory method, the vehicle "stair steps" through the time/distance matrix (rows are time, columns are distance along the route, indicated by detector location); these are shown as the grey arrows moving up from right to left. Thus, the travel time/speed at any given location depends on what time the vehicle is at that location. The snapshot method simply takes all the travel times/speeds for a time slice along the entire route (black arrows moving straight across from left to right), i.e., speeds are not considered to be time-dependent.

3.6.4 Calculation of Free-Flow Speed

The distribution statistics for the Travel Time Index (TTI) depend on measuring travel time relative to an ideal or free-flow speed. Deviation from the free-flow speed indicates that congestion occurs. For urban freeways, the research team used a constant value for all sections: 60 mph. This is a well-established threshold for measuring congestion on urban freeways. For signalized highways and rural freeways, the situation is more complex due to variation in speed limits and signal-influenced delay, even at very low volumes. For these sections, we used the 85th percentile speed as the free-flow speed. In all cases, if section speeds were higher than the free-flow speed, the TTI was set to 1.0; no "credit" was given for going faster than the free-flow speed.

Figure 3.9 The Snapshot and Vehicle Trajectory Methods of Estimating Travel Times from Spot Speeds



Source: Reference (5).

3.7 FINAL DATASET FOR STATISTICAL ANALYSES

As can be seen in the preceding discussion and figures, a large array of datasets at various levels of spatial and temporal aggregation have been created. The end result of the processing and fusing is the dataset used in the statistical analyses. This dataset is highly summarized – this is a requirement because reliability is defined over a long period of time to allow all the factors to exert influence on it. Each "observation" in the statistical analysis dataset is for an individual section for an entire year for each of the daily time slices studied: peak hour, peak period, mid-day, weekday, and weekend/holiday. The dataset contains the following data types, and the data are meant to capture characteristics for an entire year on the study section. Appendix A shows the variables in the final dataset.

Reliability Metrics

- Mean, standard deviation, median, mode, minimum, and percentiles (10th, 80th, 95th, and 99th) for both the travel time and the Travel Time Index.
- Buffer indices (based on mean and median), Planning Time Index, Skew Statistic, and Misery Index.
- On-time percents for thresholds of: median plus 10 percent, median plus 25 percent; and average speeds of 30 mph, 45 mph, and 50 mph.

Operations Characteristics

- Areawide and section-level service patrol trucks (average number of patrol trucks per day).
- Areawide and section-level service patrol trucks per mile (average number of patrol trucks per day divided by centerline mile).
- Traffic Incident Management Self-Assessment scores.
- Quick clearance law (yes/no).
- Property damage only move-to-shoulder law (yes/no).
- Able to move fatalities without medical examiner (yes/no).
- TMC staff per mile covered.
- Number of ramp meters, DMSs, and CCTVs.

Capacity and Volume Characteristics

- Start and end times for the peak hour and the peak period.
- Calculated and imputed VMT.
- Demand-to-capacity and AADT-to-capacity ratios:
  - Average of all links on the section; and
  - Highest for all links on the section.
- AADT-to-capacity ratios for downstream bottlenecks, by ramp merge area.

Incident Characteristics

- Number of incidents (annual).
- Incident rate per 100 million vehicle-miles.
- Incident lane-hours lost (annual).

- Incident shoulder-hours lost (annual).
- Mean, standard deviation, and 95th percentile of incident duration.

Work Zone Characteristics

- Number of work zones (annual).
- Work zone lane-hours lost (annual).
- Work zone shoulder-hours lost (annual).
- Mean, standard deviation, and 95th percentile of work zone duration.

Weather Characteristics

- Number of (annual) hours with precipitation amounts greater than or equal to: 0.01 inches, 0.05 inches, 0.10 inches, 0.25 inches, and 0.50 inches.
- Number of (annual) hours with measurable snow.
- Number of (annual) hours with frozen precipitation.
- Number of (annual) hours with fog present.

Assigning Incidents to Study Sections

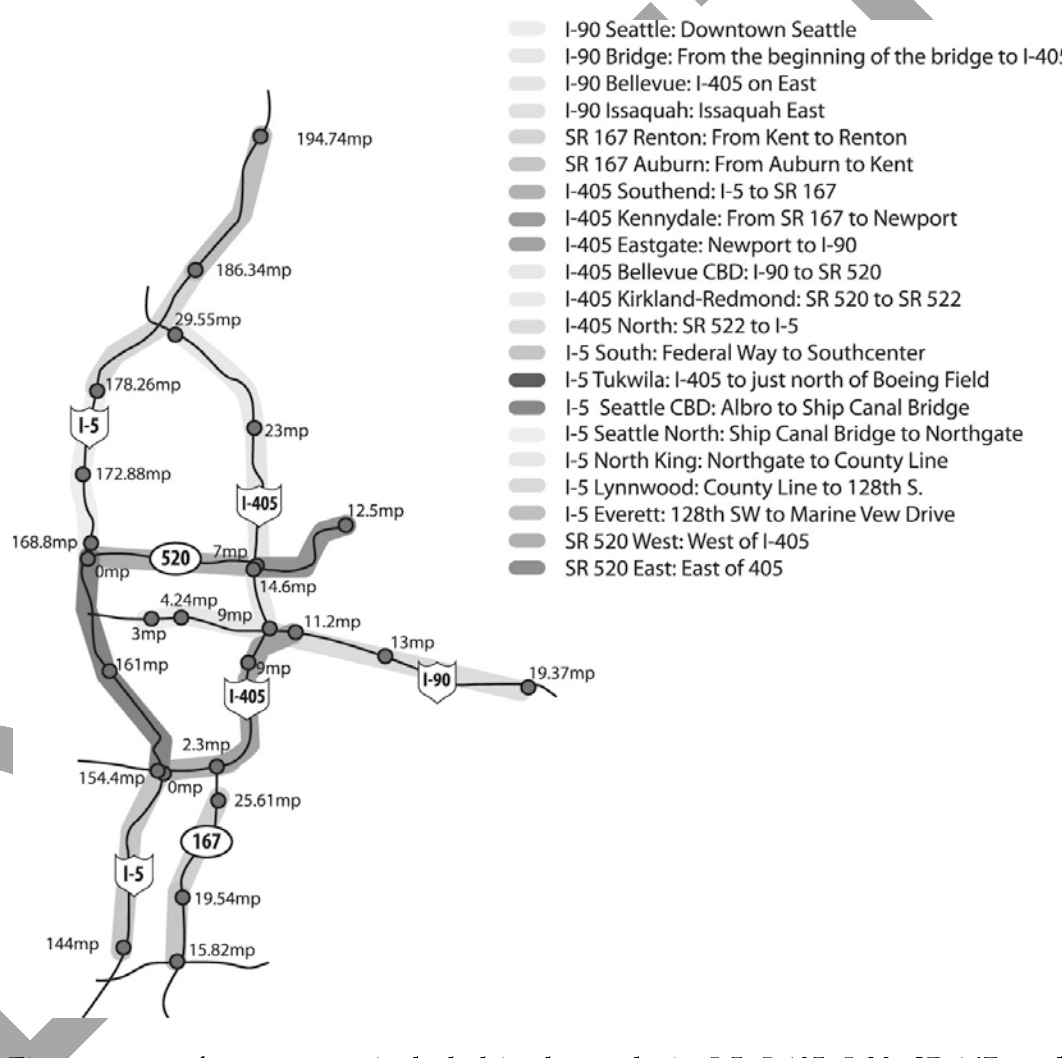
Incidents were assigned spatially to the study sections based on the linear referencing in the traffic and incident data sets. Only incidents that actually occurred on the section were included. Clearly, incidents that occur immediately downstream of the study section that influence flow on the study section. Likewise, there are incidents that occur at the extreme upstream end of the section that influence other sections. The decision to include only on-section incidents was based on application of the statistical models – it is far easier for practitioners to develop section-specific data than to have to compile off-section data as well. Also, the goal of the statistical modeling is not to build a deterministic model of traffic flow but to try to capture the cumulative, annual flow characteristics of a section.

For the peak hour, peak period, and mid-day time slices, incidents were assigned to the time slice if it began in the time slice, ended in the time slice, or spanned the time slice. To capture the effect of incidents that occur immediately before the start of the time slices, a 15-minute window was allowed. The lane-hours lost calculation is based on those that are lost ***solely within the period.*** For example, consider a peak hour of 7:30 to 8:30 a.m. If an incident begins at 8:00 and lasts to 9:15 (a total duration of 75 minutes), only the lane blockages in the 8:00 to 8:30 period count.

3.8 DESCRIPTION OF THE SEATTLE STUDY AREA

This section provides a very brief description of the portions of the Seattle freeway system included in the congestion-by-source analyses; more detail is provided in Appendices C and D. Figure 3.10 illustrates the 21 study sections. Each of these roadway segments was studied by direction, leading to the analysis of 42 study sections.

Figure 3.10 Map Illustrating Seattle Study Sections



Five separate freeways are included in the analysis, I-5, I-405, I-90, SR 167, and SR 520. They are broken into multiple segments based on a combination of geometric and travel patterns. The segmentation of each roadway is described briefly below.

3.8.1 Freeway I-5

I-5 is divided into six segments, named from south to north: South, Tukwila, Seattle CBD, Seattle North, North King, Lynnwood, and Everett. Their basic attributes are discussed below.

South is the longest segment. It is primarily four-lanes wide, with an HOV lane on the left side and travels from the southern edge of WSDOT's instrumented roadway system to the southern I-5/I-405/SR 518 interchange. Its traffic is heavily directional (relative to its capacity). It contains a very large hill located at the northern end of the segment. The hill can affect congestion southbound in the evening peak period due to slow speeds of buses and trucks climbing the grade, especially those entering I-5 from I-405 and SR 518. Both directions of traffic can be affected by downstream congestion.

Tukwila the next segment to the north goes from the southern I-5/I-405 interchange to just north of Boeing Field also is mostly four general purpose lanes wide, with one inside HOV lane. The northern end of Boeing Field is the approximate end of the back-up from much of recurring congestion that occurs both in the a.m. and many p.m. peak periods. Much of that congestion stems from bottlenecks occurring in the next roadway section to the south. In the southbound direction of travel this segment tends to be relatively congestion free (the congestion tends to be bottlenecked north of it, in the downtown sections). It does occasionally suffer from back-ups in the downstream segment, when very severe congestion getting onto I-45 NB combined with queuing on the South Center Hill can interfere with traffic flow. Otherwise, most congestion is commonly caused by disruptions of some kind.

The **Seattle CBD section** is the next section to the north. This section contains a significant number of bottlenecks in closely spaced succession. Unfortunately, they are so closely spaced that it was not practical to divide them into separate roadway sections. At its southern end, this is a four-lane GP, one-lane HOV roadway. One of the GP lanes is dropped at the West Seattle freeway interchange. This is followed by the interchange with I-90, which includes a collector/distributor lane which also serves as a mechanism for separating downtown ramps from some of the mainline traffic flows. Immediately north of the I-90 interchange is the southern terminus of the I-5 Express lanes, a reversible roadway that primary operates southbound in the a.m. and northbound in the p.m. During this stretch of highway, the left hand HOV lane becomes a general purpose lane, and then becomes of Exit Only lane to the northbound Express lanes. When the Express lanes are operating southbound, these lanes become part of a left hand exit to downtown. Another of the through lanes also becomes an exit only ramp to downtown, leaving only two general purpose through lanes. (One additional lane exists as part of the collector distributor to I-90 and other downtown ramps.) This is another bottleneck location. This area is followed by a series of on and off ramps (including the on-ramp from the collector-distributor which provides the on-ramps from I-90) to downtown. This section of the freeway also moves underneath the State's convention center, as part of a short tunnel segment, with modest visibility and sight distances. The collector/distributor becomes the third lane when it rejoins the main roadway underneath the convention center, and then a fourth is added part way through downtown as an add-lane from one of the downtown ramps. No HOV lane exists on this stretch of freeway. Finally, as the roadway exits the downtown Seattle area, it reaches the end of this roadway segment, the SR 520 interchange. The right two lanes become exit only lanes to SR 520. These lanes are often stop-and-go during both peak periods due to congestion on SR 520. In addition, one final bottleneck appears in that last ramp from downtown (Mercer) is a left hand on-ramp, which sets up a C-class weave as many vehicles entering at Mercer, wish to be in the right hand lanes, in order to exit to SR 520.

In the southbound direction, all of these features exist. The only difference is that the Express lanes terminus is an add lane, located just south of the downtown core. Consequently, it has less impact on the overall freeway performance than the northbound terminus does. However, the C-class weave from SR 520 to Mercer (again a left hand on-ramp followed by a right hand exit lane) is a bottleneck, as are the effects of the downtown exit- and on-ramps.

The **North Seattle** roadway section is the next section to the north. This section starts at the I-5/SR 520 interchange, goes across the Ship Canal Bridge, and continues to the northern terminus of the Express lanes. This section of roadway has only modest routine northbound congestion. However, southbound, it is affected by a C-class weave from the NE 45th St and NE 50th St entrances to the SR 520 interchange. In addition, the Ship Canal Bridge is exposed to wind, adding to the factors which effect throughput on this roadway. This roadway is four-general-purpose-wide in the southern section, and becomes three-lanes wide with an add/drop to Lake City way (about half way through the study segment). No HOV lane exists in this section of the roadway. (Note that this study does NOT include Express Lanes themselves, which serve as the HOV facility – and as additional GP capacity – during the peak directional movements.)

The **North King** County section of the roadway starts with the northern entrance of the Express Lanes and then continues to the King/Snohomish County line. It is four lanes wide, with an HOV lane on the left. The HOV lane starts/ends with at the Express Lanes terminus. This roadway experiences routine congestion associated with that terminus in both directions. When the Express Lanes are operating northbound, considerable weaving takes place into/out of the left hand HOV lane. In addition, northbound, modest volumes of vehicles move from the left hand entrance to the general purpose exists on the right side of the freeway. Southbound, this section of roadway has minor merge related slowdowns both as vehicles decided to enter the Express lanes, and when the Express lanes are closed, as I-5 loses two lanes of capacity at that time (one GP lane and the HOV lane).

Lynnwood is the next section of I-5 to the north. This section of roadway goes from the King/Snohomish County line to SE 128th Street, and includes the northern I-5/I-405 interchange. This section of roadway has four general purpose lanes, and one-HOV lane. Additional lanes exist at the I-405 interchange to smooth flow between the freeways.

Everett is the final I-5 section. It is primarily three GP-lanes wide with an HOV lane on the left side. Of greatest significance for this study is the fact that in 2006, north of the instrumented roadway a major construction project was underway. This included the extension of the HOV lanes and significant redesign of the ramps in Everett. These construction activities did create some backups that extended back onto the Everett study section, mostly late at night, but occasionally on weekends.

3.8.2 Freeway I-405

The I-405 freeway is divided into six sections. From the south they are:

- South;
- Kennydale;
- Eastlake;
- Bellevue CBD;
- Kirkland-Redmond; and
- North.

The **South** section contains two general purpose lanes and one left-hand HOV lane. It extends from the I-405/I-5 interchange to the SR 167 interchange. Bottlenecks occur at both of these interchanges, with the most significant of those being the northbound movement. The southern end of this study segment also is significantly impacted by on- and off-ramps which lead to/from the South Center Mall. (Short ramp lengths and the narrow freeway lead to difficulty merging and the commensurate increase in traffic disruption from these ramps.)

The **Kennydale** section is among the most routinely congested sections in the region. It stretches from the SR 167 interchange to two miles south of the I-90 interchange. This stretch of road includes the merge (northbound) from SR 167 and diverge (southbound from I-405 to SR 167). Both of these movements cause major bottlenecks because they are routinely over capacity. North of the SR 167 interchange on I-405 are a series of ramps to/from the City of Renton, which create considerable ramp disruptions. The freeway then goes up and over a major hill (the Kennydale Hill) which can slow heavy trucks, and there is significant heavy truck traffic on this route as it is the primary route for travel from the region's major distribution centers to I-90 and all points east. Because the roadway is only two GP lanes and one-HOV lane through most of this entire section (there are some add/drop lanes), any slow moving vehicle is likely to create minor congestion. The roadway also is severely over-capacity especially northbound in the morning and southbound in the evening.

The **Eastlake** section of the freeway is a short two-mile segment, designed to examine the effects of I-90 interchange congestion. In the peak directions, this is a very congested segment. In the off-peak directions it flows well.

The **Bellevue CBD** section stretches from the I-90 interchange just south of the Bellevue CBD to the SR 520 interchange just north of the Bellevue CBD. Bellevue is the second largest city in the region, and a significant urban center. While considerable traffic uses I-405 to reach Bellevue, I-405 also serves a considerable pass through movement. For traffic coming from the north (including SR 520 which serves the Microsoft headquarters complex), I-405 is the primary connection to I-90 and the other bridge across Lake Washington. As a result of the combination of through movements and large Bellevue based ramp movements, and the congestion which occurs at the I-90 and SR 520 interchanges, this section of roadway also is routinely congested during peak periods.

The **Kirkland-Redmond** roadway section has a southern boundary at the SR 520 interchange and travels north to the SR 522 interchange. Unlike I-405 south of Bellevue – which while directional has a strong reverse direction movement – the Kirkland-Redmond section is very directional, southbound in the morning, northbound in the evening. The roadway changes width from three-GP lanes and one-HOV lane north of the NE 80th Street interchange to four-GP lanes and one-HOV lane between SR 520 and Kirkland. In addition to severe demand related congestion at most of the major on-ramps, the roadway study segment also has a very steep hill (uphill southbound) just south of the SR 522 interchange.

The **North** study segment is the last of the I-405 roadway segments. It is a two GP, one-HOV lane section that extends from SR 522 to the northern I-5/I-405 interchange. This section has no significant bottleneck points, but does have some simple capacity issues, primary southbound in the morning.

3.8.3 Freeway I-90

The I-90 roadway is divided into four segments from Issaquah to downtown Seattle. These are (moving from west to east) Issaquah, Bellevue, Bridge, and Seattle.

The **Issaquah** segment is a three-GP lane one-HOV lane roadway section that travels six miles from the city of Issaquah towards Bellevue. While there are no significant geometric bottlenecks on this study segment, it does contain three very high-volume ramps. The result is routine a.m. congestion westbound. In the evening, some off-ramp queuing can cause delays in the right-hand lanes of the roadway eastbound.

The **Bellevue** study segment covers the remaining distance between Issaquah and the I-405 interchange. Two additional on-ramps add traffic, although an additional lane is added in this section, before becoming a drop lane at the I-90 interchange. As with the Issaquah eastbound P.M. movement, this roadway section can be affected by significant off-ramp queuing to I-405 – in this case in the westbound A.M. peak period. On very bad days queues on I-90 from the downstream section of I-90 can also reach the western portions of this segment during the A.M. peak period.

The **Bridge** study section contains both I-90s Lake Washington floating bridge, and the stretch of I-90 that crosses Mercer Island, which also contains a short tunnel. A reversible express lane also sits in the middle of this study section. (The express lane section is not included in this analysis.) The eastern end of the express lane is located just to the west of I-405. The eastbound exist from the express lanes cause little disruption because of direct ramps from that facility to the I-405 interchange, and an add lane to the I-90 mainline. Westbound it causes congestion only when the Express lane is eastbound, in which case the HOV lane must merge into the three-GP lanes, causing a merge bottleneck. In addition to the ramps from Mercer Island to I-90, several other locations on this section of roadway can become bottlenecks under specific conditions. The most significant are the exit from the tunnel section – which leads to the bridge, and creates some visibility issues when the sun is at some angles, and the bridge itself which can suffer from considerable visual distraction.

The **Seattle** section is the last section on I-90. It covers from the western end of the floating bridge, through tunnels underneath Capital Hill, and to I-5, where I-90 ends. Westbound travelers can exit to downtown Seattle, or turn north or south on I-5. All three of these ramps can experience queues that extend back onto I-90 depending on the time of day, the types of events occurring in downtown Seattle, and the congestion found on I-5. Eastbound, this roadway section has only one entrance ramps, other than the ramps from I-5 or downtown. Merge congestion is therefore modest. However, back-ups from the Bridge section of I-90 can easily extend back onto this section creating congestion.

3.8.4 Freeway SR 167

This roadway is east of I-5, and travels in a north/south direction through the region's primary warehouse and distribution centers. It also serves a number of manufacturing areas as well as a growing residential population, especially to the far south. This roadway is divided into two study sections for this project, Auburn and Renton. The entire roadway contains two GP lanes and one-HOV lane. (That HOV lane is now an HOT lane, but in 2006, it was still a traditional HOV lane.)

The **Auburn** section extends from the SR 18 interchange (the southern end of the surveillance equipment, although not the end of the SR 167 freeway), to the City of Kent. This stretch of roadway has no major geometric bottlenecks northbound, but does suffer from on-ramp merge congestion due to high traffic volumes northbound in the a.m. Southbound in the p.m., it has a bottleneck at the southern terminus to the study section, where the HOV lane ends (becoming a GP lane), and one of the GP lanes becomes an Exit Only lane to SR 18. In addition, due to the restricted number of lanes, traffic south of this bottleneck can move very slowly in the P.M. peak, further worsening the queues observed southbound on the study section.

The **Renton** study section travels from Kent to the I-405 interchange. The I-405 interchange is a significant bottleneck. The ramp queues from northbound SR 167 to I-405 frequently back up onto SR 167 in both peak periods (although the A.M. peak is the primary movement) as I-405 simply does not have the capacity to accept the SR 167 traffic volumes. Southbound the SR 167 section also congests simply because of very high traffic volumes. There are no significant geometric causes for those delays.

3.8.5 Freeway SR 520

The final roadway in the study section is SR 520. This roadway also is divided into only two sections, called Seattle and Redmond.

The **Seattle** section goes from I-5 across the Lake Washington Floating bridge to I-405. This section is two general purpose lanes. There is an HOV lane only in the westbound direction, and that HOV lane ends in a lane drop at the approach to the bridge itself. The bridge has no shoulders. The lack of shoulders means any incident occurring on the bridge or on the bridge approaches blocks a lane. On the western end of the study section are two ramps, one of which leads to the University of Washington. This roadway operates near capacity in both directions over 13 hours each weekday. Because both directions are capacity constrained, the directional volumes are roughly equal throughout the day. The primary difference in the measured performance of the two directions for this roadway is the location of the bridge relative to the entire study section. Eastbound, the study section only travels a little over one mile from I-5 to the bridge itself, and all of this distance is a two-lane roadway. This means that the measured queue eastbound is never larger than roughly one mile. Once the queue grows larger than on G-mile, it extends onto I-5 – where its effects are felt in the southbound Seattle North study section or the northbound Seattle CBD study section. Conversely, in the westbound direction, the study section allows for the measured queue from the bridge deck to extend for more than three miles. In the heart of the P.M. peak period, this entire roadway section is routinely stop-and-go congestion.

The **Redmond** study section includes that section of SR 520 from I-405 east to the end of the freeway – a signalized intersection with SR 202 and other local roads. (The freeway branches into two parts as it ends, each of which ends at a signal.) The freeway passes by the Microsoft headquarters campus. Consequently, significant traffic volumes move towards the center of this study section in the A.M. peak period and away from the center of the study section in the P.M. peak period. In addition, the eastern end of the roadway serves a large residential population that travel to both Bellevue and Seattle. Thus the A.M. peak also contains a large westbound home to work movement that extends the length of the study section, while the P.M. peak contains a large work to home movement.

From a bottleneck perspective, there is one major bottleneck, the signalized intersections at the eastern end of the facility. The result of the signals is that significant congestion extends back from the eastern end of the facility during the P.M. peak period. In the morning, the lights simply serve to meter traffic entering the roadway, allowing the roadway to operate fairly well. The only other bottlenecks that occur are minor ramp delays leading to Microsoft (these can add considerable delay to travelers headed to Microsoft, but they do not significantly affect the main freeway lanes), and queues that originate on the Seattle section of SR 520, but that extend back onto the Redmond section. This happens, on average, at least once a week, usually as a result of crashes or other major traffic incidents on the Seattle section of the roadway.

References

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2. *Standard Specification for Archiving ITS-Generated Traffic Monitoring Data.* This standard is being published as of this writing and has tentatively been designated as ASTM E2665-08.

3. Turner, S., Margiotta, R., and Lomax, T., *Monitoring Urban Freeways in 2003: Current Conditions and Trends from Archived Operations Data,* Report No. FHWA-HOP-05-018 (December 2004), http://mobility.tamu.edu/mmp/FHWA-HOP-05-018/.

4. http://en.wikipedia.org/wiki/Traffic_Message_Channel.

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4.0 The Empirical Measurement of Reliability

4.1 Overview

As discussed in Section 3.0, the research team took an empirical approach to the problem of reliability estimation. Prior to conducting the three main analyses – before/after studies of reliability improvements, statistically based predictive relationships for reliability, and congestion-by-source – a number of exploratory analyses were conducted to: 1) explore the basic characteristics of reliability, and 2) to establish basic parameters and principles for measuring and analyzing reliability. These analyses form the basis for the more detailed analyses that follow, but they also offer valuable guidance on their own for others interested in measuring and studying reliability. We offer them in this section.

4.2 Recommended Reliability Metrics for the Research and General Practice

The research team concluded that all potentially useful reliability metrics communicate information about the size and shape of the underlying travel-time distribution – the history of travel times on a facility, corridor, or network. (The Phase 1 report more completely describes the wide range of possible reliability metrics.) As shown in Figure 4.1 travel times can be developed using a number of different methods, from direct measurement (top left) to purely synthetic means (top right). Also, a wide variety of other performance metrics can be developed from travel times, but is travel time the best primary metric to use? Travel times are not normalized and clearly will vary according to the length of the segment or trip being studied.

The original candidate reliability measures were the ones in use throughout the United States. However, during the research, research in Europe suggested other potentially useful measures. To examine how these concepts relate to those specified in the work plan, an analysis using 2006 freeway data from the Atlanta NaviGAtor system was conducted. The first concept tested was the notion that in a skewed distribution, the median is a better descriptor of central tendency than the mean. Table 4.1 shows that for all the highway sections studied, the mean and the median are very close. This is true for relatively uncongested sections (Travel Time Index {TTI} < 1.1) and congested sections (TTI > 1.4).

Figure 4.1 Travel Time is the Basis for Defining Mobility-Based Performance Measures

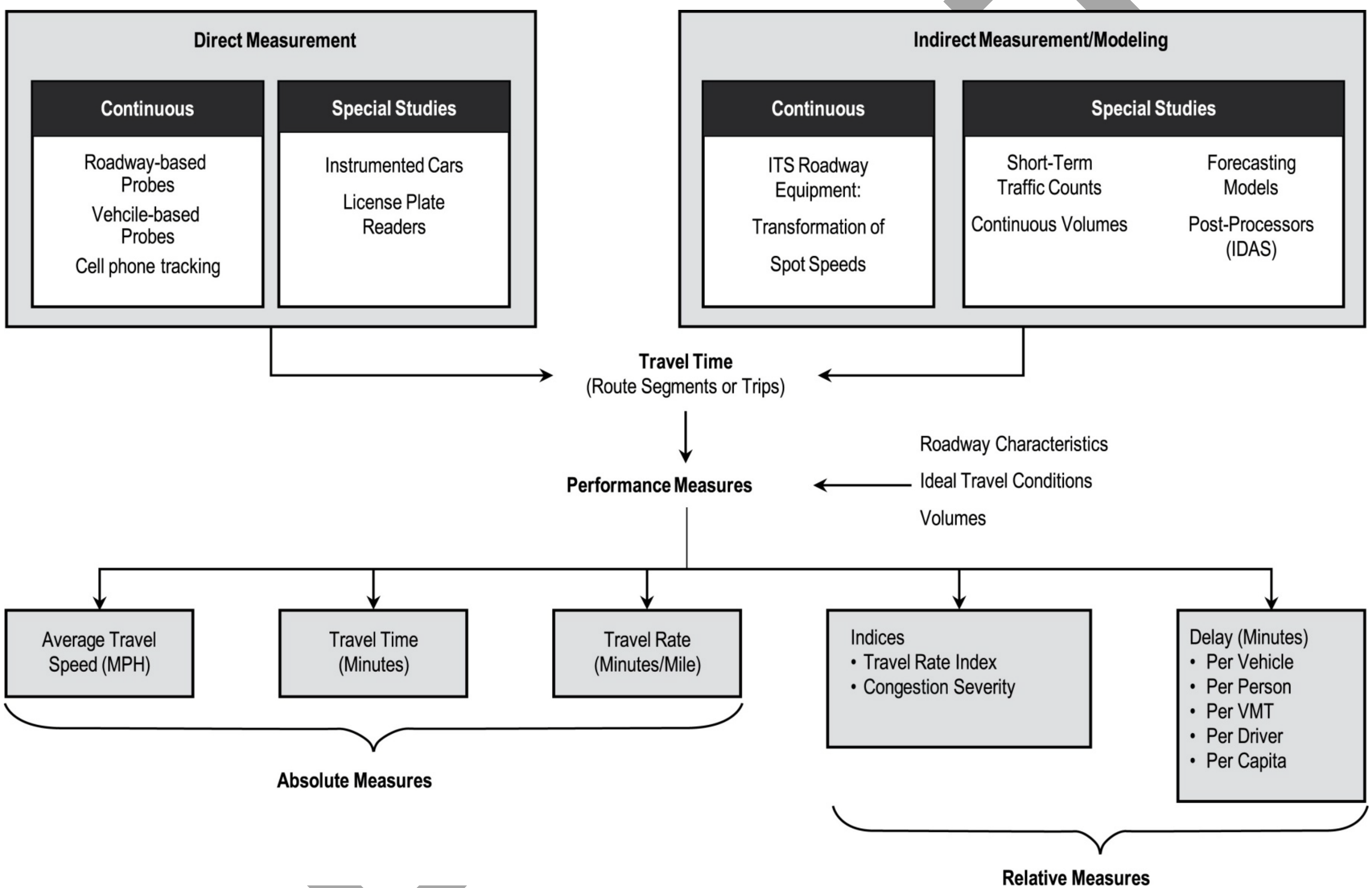
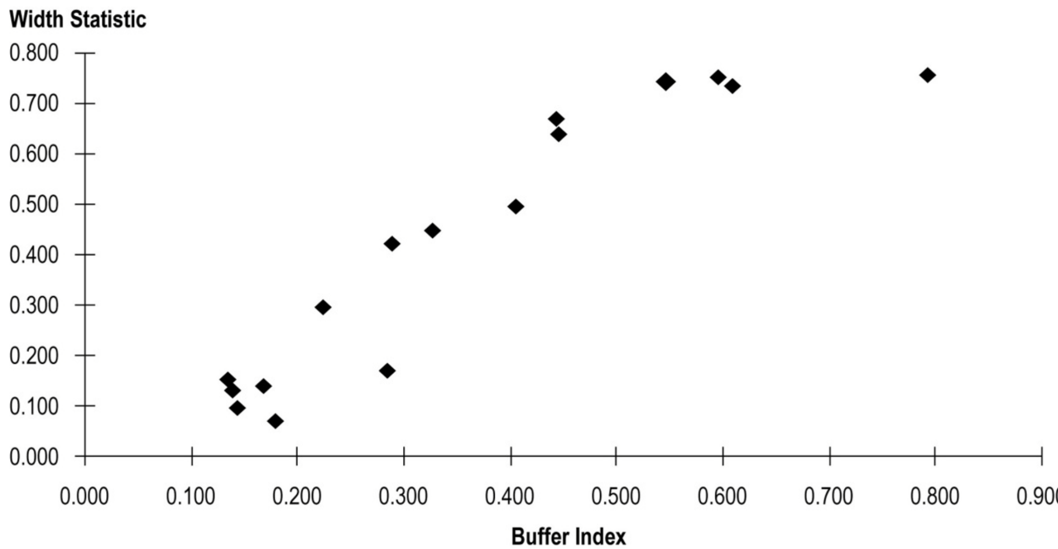


Table 4.1 Travel-Time Distribution Statistics
Atlanta Freeways, 2006 (4:00 to 7:00 p.m.)

Section	Section Length	Travel Time Index (TTI)	Mean Travel Time	Median Travel Time	95th Percentile Travel Time
I-75 Northbound: South of Hudson Road to I-85 Split	12.980	1.065	13.8	13.3	15.671
I-75 Northbound: South of I-85 Split to Brookwood Interchange	6.250	1.334	8.3	7.3	13.409
I-75 Northbound: Brookwood Interchange to Wade Green Road	18.290	1.619	29.6	28.8	42.803
I-75 Southbound: South of Hudson Road to I-85 Split	12.610	1.560	19.7	18.5	30.418
I-75 Southbound: South of I-85 Split to Brookwood Interchange	6.570	1.665	10.9	10.7	14.089
I-75 Southbound: North of Wade Green to Brookwood	16.760	1.056	17.7	17.1	20.140
I-85 Northbound: Camp Creek Parkway to I-75	2.590	1.171	3.0	2.7	5.439
I-85 Northbound: Brookwood Interchange to SR 316	17.430	1.570	27.4	27.0	36.305
I-85 Southbound: I-75 to Camp Creek Parkway	2.670	1.055	2.8	2.7	3.291
I-85 Southbound: SR 316 to Brookwood Interchange	18.690	1.248	23.3	23.0	28.537
I-285 Eastbound: Cobb Parkway to Chamblee Tucker	13.400	1.673	22.4	21.9	32.365
I-285 Westbound: Chamblee Tucker to Cobb Parkway	13.190	1.565	20.6	19.4	32.929
I-20 Eastbound: I-285 Westside to I-75/85	3.680	1.036	3.8	3.7	4.496
I-20 Westbound: I-75/85 to I-285 Westside	3.410	1.093	3.7	3.5	4.788
I-20 Eastbound: I-75/85 to Wesley Chapel	8.590	1.345	11.6	11.3	16.234
I-20 Westbound: Wesley Chapel to I-75/85	8.560	1.046	9.0	8.7	10.244

Further confirmation that using the mean in the Buffer Index calculation provides the same information as the Width Statistic is found in Figure 4.2. The strong positive relationship indicates that both measures are closely related and can be used interchangeably.

Figure 4.2 Buffer Index versus "Width Statistic"
Atlanta Freeways, 2006 (4:00 to 7:00 p.m.)



With regard to the skew of the travel-time distribution, we considered it to be useful to include such a measure in the current research. Use of this measure would largely be limited to researchers and technical personnel as its communication to laypersons is problematic, but having a way of characterizing the travel-time distributions of different facilities and time periods would be valuable.

As a further empirical test of reliability performance measures, we conducted an additional analysis using data from the Seattle area. The data for this research was obtained from the loop sensors maintained by the Washington State DOT along SR 520, an urban limited-access freeway running from Seattle to Redmond. The corridor has been divided into westbound and eastbound segments and segments west of I-405 (Bellevue to Seattle) and east of I-405 (Redmond to Bellevue). This particular data set is an excellent example for the study of reliability data because each of the four segments has a very different level and pattern of congestion. SR 520 westbound from Bellevue to Seattle experiences the highest level of congestion. Volumes are typically heavy throughout the day with congestion peaks in the A.M. and P.M. A two-mile-long floating bridge, with no shoulders, on the western end of the corridor is highly susceptible to incident induced congestion, adding to the existing volume saturation-related delays. On the eastbound section of this roadway from Seattle to Bellevue, volumes are similar to those found in the westbound direction, but because the bridge bottleneck is located at the beginning of the study corridor, the average travel times tend to be higher than those measured in the westbound direction. The eastbound travel is frequently congested throughout the day with substantial peaks in both A.M. and P.M.

Table 4.2 shows the number of observations, minimum, maximum, mean, standard deviation, and skewness statistics for the travel time in the P.M. peak period (3:00 p.m. to 7:00 p.m.) for each section of SR 520. Using the skewness and standard error of skewness, a z-value can be calculated. If the skewness is divided by the standard error of skewness (ses) is greater than 1.96; then, we can be 95 percent confident that the distribution is skewed. (The standard error of skewness is calculated as the square root of 6/n.) The ses values for the four sections in Table 4.2 are all roughly 0.02, since the sample sizes (number of observations) are the same. The skewness ranges from 10 to 100 times the standard error of skewness, indicating that the distributions are skewed.

Table 4.2 Travel-Time Statistics for P.M. Peak Period on SR 520

SR 520 Section	Number	Minimum	Maximum	Mean	Standard Deviation	Skewness
Westbound Bellevue to Seattle	12,350	409	2,975	1,088.8	441.3	0.27
Eastbound Seattle to Bellevue	12,095	409	2,861	598.8	203.8	2.26
Westbound Redmond to Bellevue	12,385	330	2,365	492.4	364.6	2.58
Eastbound Bellevue to Redmond	12,371	330	3,354	604.9	264.2	3.13

Although a few extreme values affect the mean and the maximum, a few extreme values do not impact the 80th, 90th, and 95th percentile calculations, therefore, the difference between mean and these percentiles is not as robust of a measure as it would be using median. Because travel-time data is by nature skewed, the measurement of travel-time reliability-based comparison to the median would be more appropriate (e.g., the Buffer Index).

A test was performed where all travel times affected by incidents and accidents were removed from the SR 520 dataset for the western portion of the corridor from Bellevue to Seattle. This simulated the benefits that could be gained if vehicle improvements eliminated all vehicle accidents and breakdowns. Table 4.3 shows the statistics that reflect these two conditions.

While improvements are seen in all direct measures of travel time, both indices report a "worsening of reliability." This is caused by the fact that the central condition has improved more than the extreme portions of the distribution. Thus the corridor is "less reliable." But from both a motorist's standpoint and a highway agency's standpoint, this would be a significant improvement in performance. Because both the central tendency and the actual extreme travel times improved, the corridor operates better as experienced by the traveler. Consequently, we are unconvinced that either of these indices effectively reports the changes illustrated by this experiment.

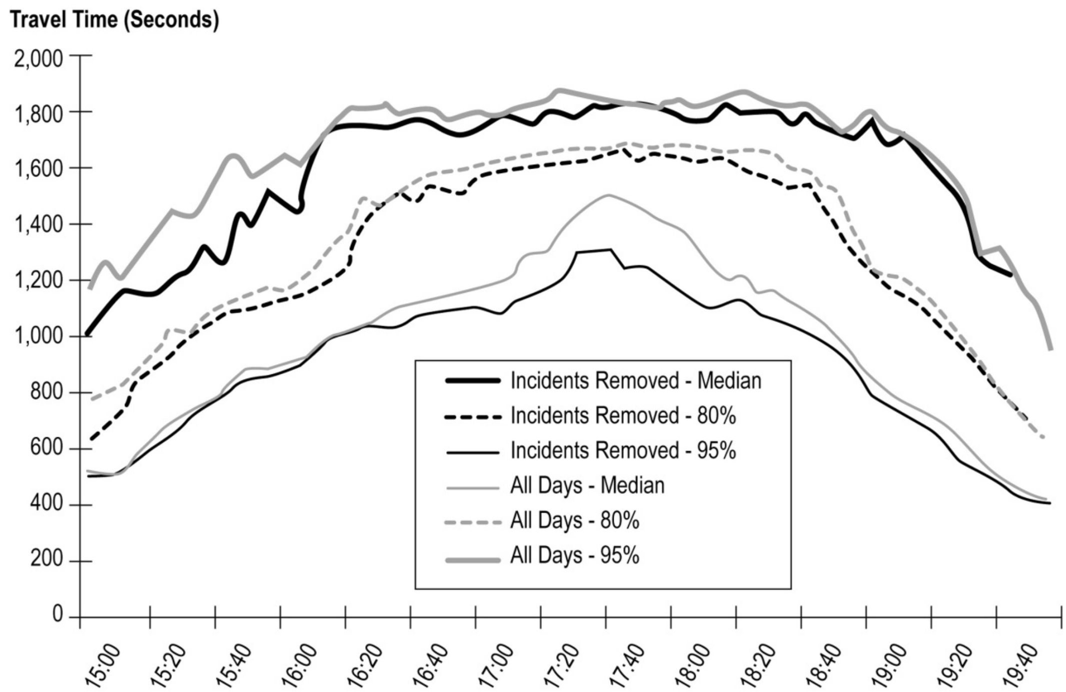
Table 4.3 Effect on Travel Times of Removing All Incidents and Accidents on SR 520
Bellevue to Seattle P.M. Peak Period (3:00 p.m. to 7:00 p.m.)

	Travel Times (Seconds) for Weekdays	Travel Times for Days With No Incident Effects	Difference (Seconds)
Mean	1,089	1,026	63
Median	1,063	1,006	57
80th Percentile	1,560	1,467	93
90th Percentile	1,687	1,651	36
95th Percentile	1,780	1,748	32
Misery Index	0.59	0.66	-0.07
Unreliability Skew	1.08	1.2	-0.12

Essentially the issue with choosing one number to explain a reliability distribution is that one number cannot explain the entire distribution. Rather than relying on only one percentile calculation or one index, several must be documented to effectively track travel times. By noting the 80th percentile value, the 90th percentile value, and the 95th percentile value in comparison to the median value (50th percentile value), the range in travel-time changes can be demonstrated from year to year. Each statistic can illustrate the change in a particular problem.

An example of the use of these statistics is given in Figure 4.3. This figure shows the westbound segment of SR 520 from Bellevue to Seattle. The grey lines are all weekday travel times in the P.M. peak period from 3:00 p.m. to 8:00 p.m. The black lines are the weekday travel times during the same time period with travel times during incident or accident conditions removed. Therefore, essentially the black lines represent the travel-time percentiles if no incidents or accidents occurred. Although this case serves as an excellent example of the shifting of the travel-time percentile lines. In this case, the median travel-time improves from 1,500 to 1,300 seconds at 5:30 p.m., the peak five-minute time period. The shift in the 95th percentile is more pronounced at the onset of the peak-period congestion from 3:00 p.m. to 4:00 p.m. The 50th, 80th, and 95th percentile travel times all have noticeable improvement over the "before" condition. At the same time, on this badly oversaturated roadway, it is quickly apparent that while incidents and accidents make travel both worse and more unreliable, they are by no means the primary cause of either congestion nor the only cause of unreliable travel.

Figure 4.3 Travel-Time Distributions on SR 520
Seconds



We conclude from this analysis that a few additions to the list of reliability metrics originally developed in Phase 1 are in order. Based on the skewness of the travel-time distributions, the median is a better central tendency statistic to use as a base value for travel time for indices. We, therefore, have made the following adjustments:

- Defined the two Buffer Indices, using both the mean and median as the reference value. (Note that the Skew Statistic already uses the median as their reference value.)
- Added the 80th percentile travel time as a reliability metric.
- Added the Skew Statistic.
- Defined some "on-time" measures by using the median rather than the mean.

The final set of reliability metrics appears in Table 4.4. Note that the Travel Time Index (TTI) rather than pure travel time is used as the primary measurement for the percentiles of the distribution. As a unitless index, the TTI is normalized for distance so that sections of different lengths can be compared. An alternative would have been to use the travel rate (minutes per mile, the inverse of space mean speed). What this means is that all the reliability measures used in this report are derived from the distribution of Travel Time Indices rather than raw travel time.

Table 4.4 Final Set of Reliability Metrics Used in the Research

Reliability Performance Metric	Definition	Units
Buffer Index (BI)	• The difference between the 95th percentile travel time and the average travel time, normalized by the average travel time. • The difference between the 95th percentile travel time and the median travel time, normalized by the median travel time.	Percent
Failure/On-Time Measures	Percent of trips with travel times <: • (1.1 * Median Travel Time); and • (1.25 * Median Travel Time). Percent of trips with space mean speed <: • (50 mph, 45 mph, 30 mph).	Percent
Planning Time Index	95th percentile Travel Time Index .	None
80th Percentile Travel Time Index	Self-explanatory.	None
Skew Statistic	The ratio of (90th percentile travel time minus the median) divided by (the median minus the 10th percentile).	None
Misery Index (Modified)	The average of the highest five percent of travel times divided by the free-flow travel time.	None

Note: The Buffer Index based on the mean is used in the analyses presented in this report.

4.3 Travel-Time Distributions and Reliability Performance Metrics

The Introduction presented several perspectives for defining reliability. For the purpose of the L03 research, functional definition chosen by the team is that ***reliability is defined as the variability of travel times on an extended highway section over the course of six months to one year for different time slices of the day.*** This definition allows direct measurement with the available data and is consistent with the current state of the practice in performance measurement and economic analyses.

A simple way to visualize reliability is to develop travel-time distributions and superimpose reliability metrics on them. Figures 4.4 to 4.8 show an example of this process for a 5.19-mile section in Atlanta for calendar year 2007, for multiple time slices: peak hour, peak period, mid-day, weekday (all hours), and weekend/holiday (all hours). (Throughout the analysis, we defined "holidays" as the major Federal holidays: New Year's Day, Martin Luther King Day, President's Day, Independence Day, Labor Day, Veteran's Day, Thanksgiving, and Christmas Day.) In peak times, this is a highly congested section, with an average Travel Time Index (TTI) over 2.0, which means that trips take over twice as long as they would under free-flow conditions. Several observations on these plots can be made that are generalizable to other locations, as we have found during the course of the research:

- The shape of the travel-time distribution for congested peak times (weekdays, nonholidays) is much broader than the sharp spike evident in uncongested conditions. The breadth of this broad "shoulder" of travel times decreases as congestion level decreases.
- Likewise, the tails of the distributions (to the right) appear more exaggerated for the uncongested time slices. However, note that the highest travel times occur during the peaks.
- Despite the fact that peaks have been defined, there are still a number of trips that occur at close to free-flow; more in the peak period than in the peak hour. This is probably due to the fact the peak times actually shift slightly from day-to-day as traffic demand can be shifted by events. Also, there are probably some days where overall demand is lower than other days.

Figure 4.4 Peak-Hour Travel-Time Distribution, Atlanta, I-75 NB, I-285 to SR 120
2007

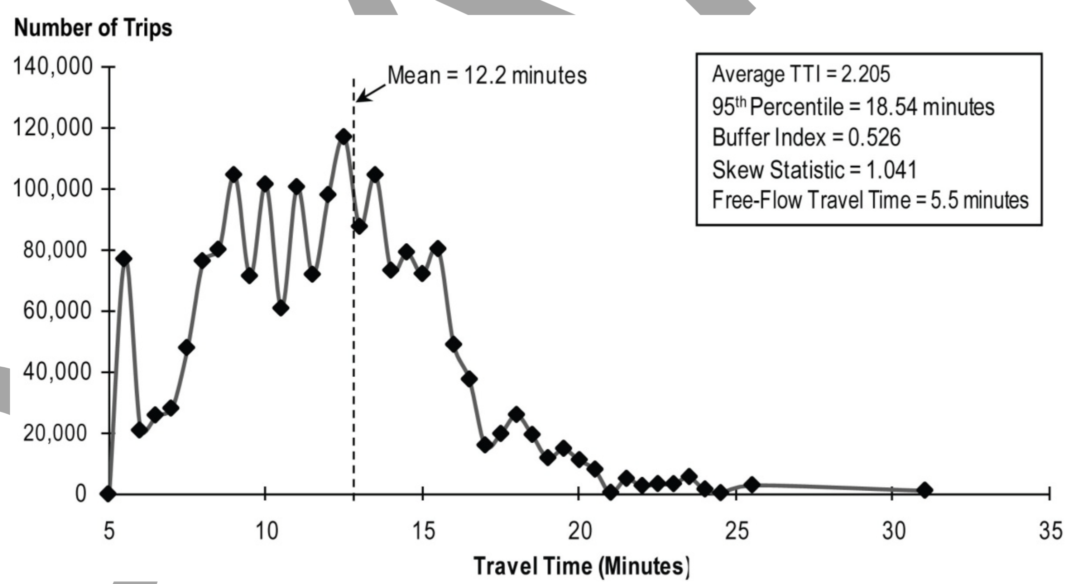


Figure 4.5 Peak-Period Travel-Time Distribution, Atlanta, I-75 NB, I-285 to SR 120
2007

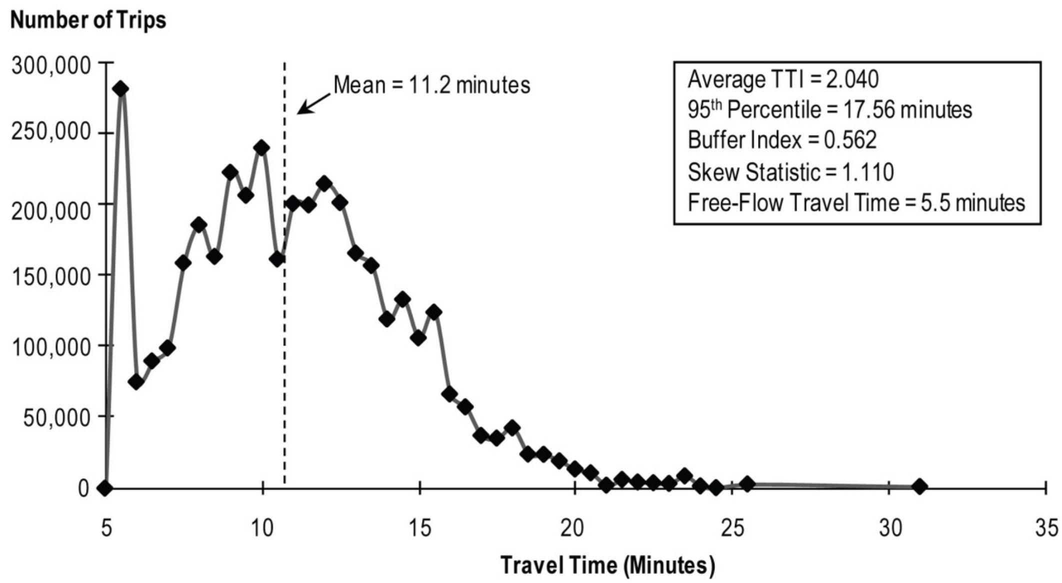


Figure 4.6 Mid-Day Travel-Time Distribution, Atlanta, I-75 NB, I-285 to SR 120
2007

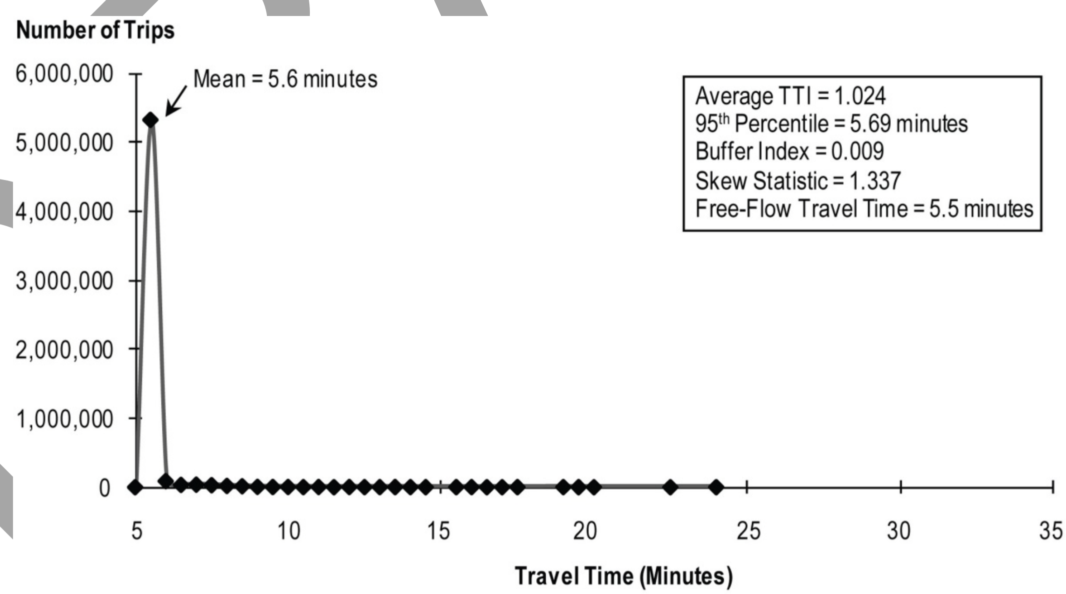


Figure 4.7 Weekday Travel-Time Distribution, Atlanta, I-75 NB, I-285 to SR 120
2007

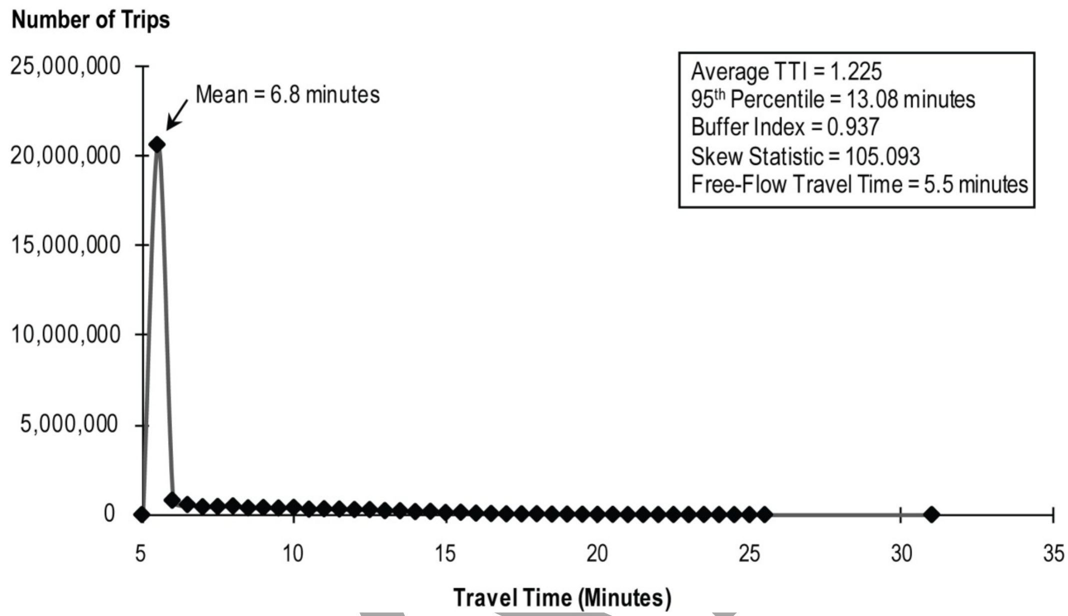
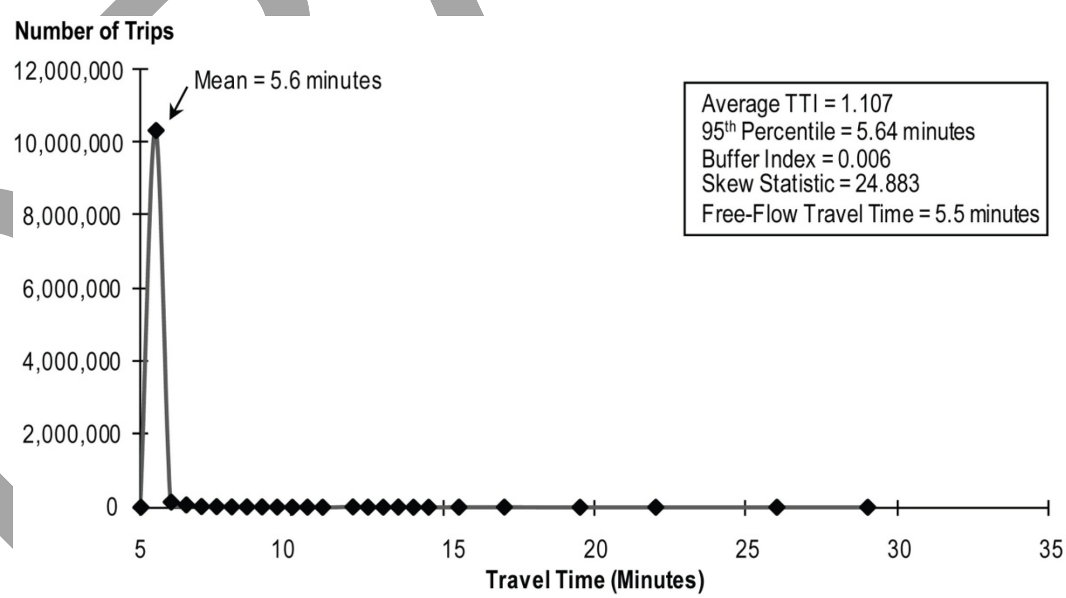


Figure 4.8 Weekend/Holiday Travel-Time Distribution, Atlanta, I-75 NB, I-285 to SR 120
2007



4.4 Data Requirements for Establishing Reliability: How Much Data Is Enough?

In order to allow the myriad of events that can occur (e.g., incidents, bad weather) to have an effect on travel times, reliability requires a fairly long history of travel times. The question is: how much data is needed in order to make a reasonable estimate of a section's reliability? The study team has been working with the assumption that a year's worth of data is desirable.

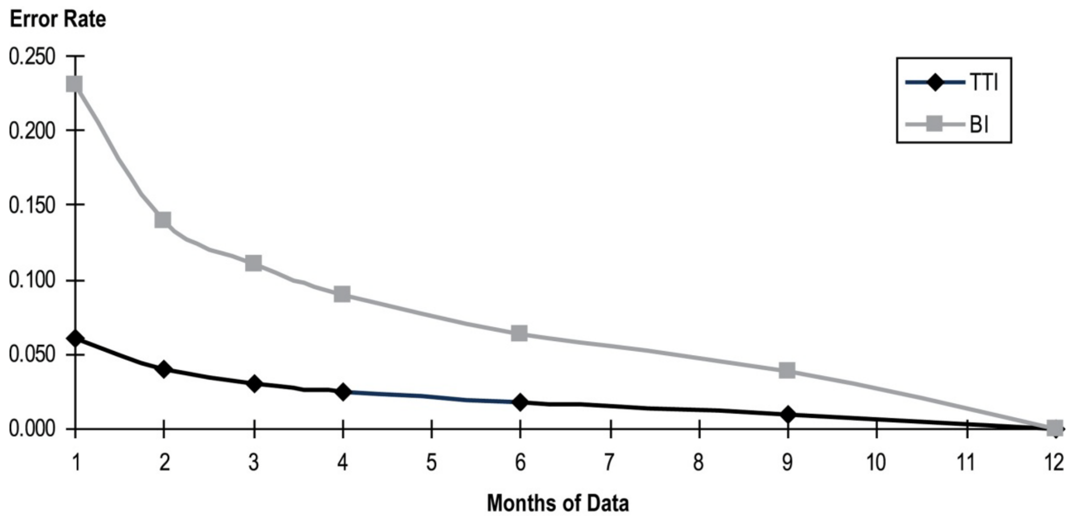
The Research Team conducted tests with urban freeway (detector-based) data from Atlanta and the Bay Area. The tests were conducted by selecting multiple samples based on several time durations, computing the Travel Time Index and Buffer Index for the samples, comparing them to the annual value, and noting the error. Table 4.5 shows the results of using 2007 freeway data from Atlanta for the peak period on each section. It is apparent from these results that a month's worth of data provides reasonable estimates of average travel time but is insufficient to establish reliability.

Longer time periods also were tested and the results for the Buffer Index appear in Figure 4.9. For this analysis, we tested all possible month combinations for each sampling rate. With six months of data, the error rate for the Buffer Index is about the same as it is with one month of data for estimating the Travel Time Index.

Table 4.5 Error Rates for Using One Month of Data to Estimate Annual Average Travel Time and Reliability
Peak Periods, Atlanta, 2006

Section	Mean Absolute Error	
	Travel Time	Buffer Index
I-285 Eastbound from GA 400 to I-75	8.1%	25.4%
I-285 Eastbound from GA 400 to I-85	7.0%	24.9%
I-285 Westbound from GA 400 to I-75	5.8%	26.9%
I-285 Westbound from GA 400 to I-85	5.1%	26.4%
I-75 Northbound from I-20 to Brookwood	4.0%	46.2%
I-75 Northbound from I-285 to Roswell Road	7.1%	26.1%
I-75 Northbound from Roswell Road to Barrett Parkway	4.3%	42.1%
I-75 Southbound from I-20 to Brookwood	6.0%	33.5%
I-75 Southbound from I-285 to Roswell Road	5.2%	25.0%
I-75 Southbound from Roswell Road to Barrett Parkway	8.2%	19.3%
Overall	6.1%	23.1%

Figure 4.9 Error Rates for Samples to Estimate the Travel Time and Buffer Indices
Peak Period, Atlanta Study Sections, 2008



Incidents are relatively infrequent in terms of the number of minutes each year that they are present on a facility. (See Table 4.6 of annual incident-minutes for an 11-mile stretch of U.S. 101 southbound in California). All incidents of any type were present only 17 percent of the time on U.S. 101 southbound. One must, therefore, simulate a relatively long time in order to hope to be able to capture a single incident.

Table 4.6 Annual Incident-Minutes on Marin CA-101
Southbound

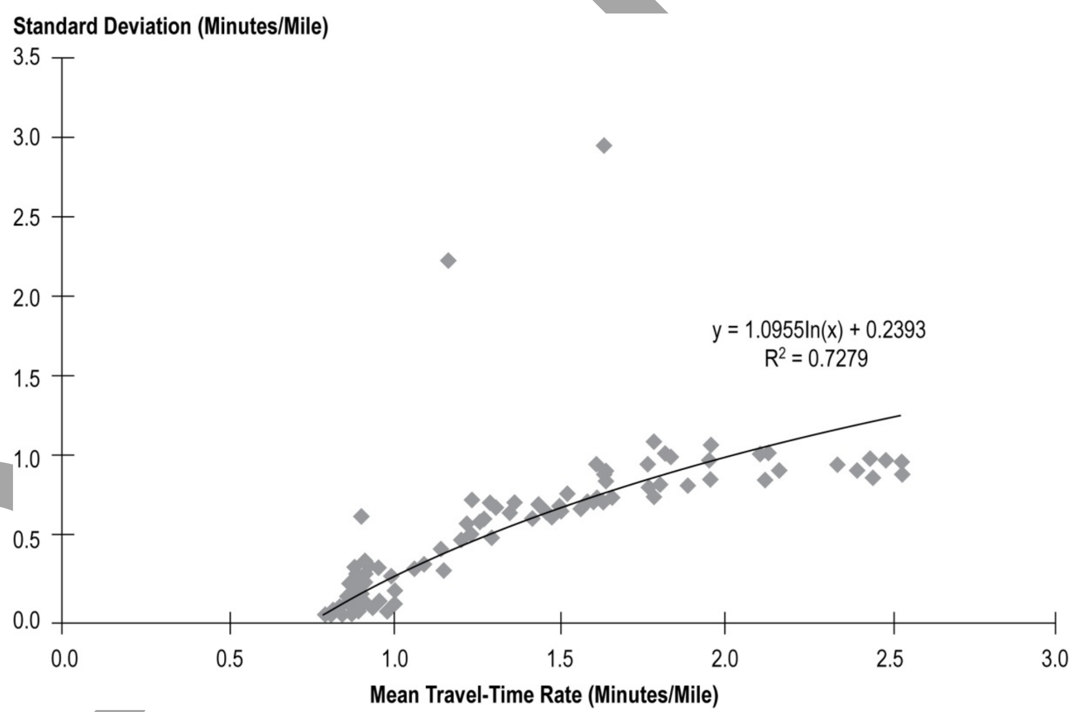
Incident Type	Logged Incidents	Estimated Percent Logged	Estimated Number Incidents	Duration (Minutes) Mean	Duration (Minutes) Standard Deviation	Total Incident-Minutes	Annual Probability
Accident, Injury	19	100%	19	42.8	40.3	813	0.87%
Accident, Noninjury	84	99%	85	22.6	22.2	1,915	2.05%
Accident, Other	76	99%	77	19.7	17.0	1,513	1.62%
Breakdown	88	60%	147	17.9	19.8	2,620	2.80%
Other	15	60%	25	32.5	73.4	812	0.87%
Traffic Hazard	274	60%	457	19.0	14.9	8,662	9.25%
Subtotal Incidents	556	69%	809	20.2	22.2	16,335	17.45%
Nonincidents	N/A	N/A	N/A	N/A	N/A	77,265	82.55%
Total Year	N/A	N/A	N/A	N/A	N/A	93,600	100.00%

N/A = Not Applicable. "Estimated Percent Logged" accounts for the typical under reporting of less severe incidents.

Our exploratory research also has found that the travel-time variance and the mean travel time for any facility are **highly** correlated (Figure 4.5, which shows how the standard deviation of the travel-time rate for U.S. 101 southbound varies according to the mean travel-time rate). As also exhibited by the Atlanta data above, many fewer samples are required to estimate the mean travel time than its variance (or standard deviation).

We conclude from these analyses that a minimum of six months of data is required to estimate travel-time reliability. In areas where snow and ice are frequent events, we would expect this requirement to increase to a full year. It may be possible in winter weather-affected locations to use six months of data if the data represent every other month. Therefore, we are moving forward with the idea that a year's worth of data will provide more sound results and we will strive to achieve the one-year minimum.

Figure 4.10 Standard Deviation
Minutes per Mile



4.5 TRENDS IN RELIABILITY

An examination of congestion and reliability trends from 2006 to 2008 on the 10 Atlanta study sections was undertaken. We had heard anecdotally that congestion had decreased in 2008, based on a spike in gas prices midyear and the economic downturn. Table 4.7 presents the results for the peak period. Note that the peak period was fixed and was determined using the procedure given in

Section 4.6 using 2006 data. On all 10 sections, the TTI increased between 2006 and 2007 and decreased between 2007 and 2008. In 9 cases, the 2008 TTIs are below those of 2006. Note that 8 of the 10 sections had ramp meters installed in 2008.

Table 4.7 Trends in Reliability, Atlanta Freeways
2006 to 2008

	Year		
	2006	2007	2008
SHRP Section I-75 Northbound from I-285 to Roswell Road[a]			
Travel Time Index	2.046	2.026	1.665
Average Travel Time	11.271	11.162	9.177
95th Percentile Travel Time	16.934	17.507	14.800
Buffer Index	0.502	0.568	0.613
80th Percentile Travel Time	13.974	14.191	11.458
Skew Statistic	0.942	1.087	1.514
Daily VMT	691,399	689,628	N/A
SHRP Section I-75 Southbound from I-285 to Roswell Road[a]			
Travel Time Index	1.312	1.369	1.293
Average Travel Time	7.665	7.994	7.552
95th Percentile Travel Time	10.139	10.517	9.868
Buffer Index	0.323	0.316	0.307
80th Percentile Travel Time	8.353	8.719	8.306
Skew Statistic	1.524	1.515	1.461
Daily VMT	691,399	689,628	N/A
SHRP Section I-75 Northbound from I-20 to Brookwood			
Travel Time Index	1.350	1.542	1.339
Average Travel Time	6.710	7.664	6.656
95th Percentile Travel Time	8.120	10.755	8.031
Buffer Index	0.210	0.403	0.207
80th Percentile Travel Time	7.097	8.112	7.015
Skew Statistic	1.283	1.923	0.771
Daily VMT	616,038	620,959	595,034
SHRP Section I-75 Southbound from I-20 to Brookwood			
Travel Time Index	2.052	2.171	2.067
Average Travel Time	9.336	9.877	9.404
95th Percentile Travel Time	13.110	14.270	12.389
Buffer Index	0.404	0.445	0.317
80th Percentile Travel Time	10.805	11.416	11.042
Skew Statistic	1.324	1.120	0.956
Daily VMT	616,038	620,959	595,034

	Year		
	2006	2007	2008
SHRP Section I-285 Eastbound from GA 400 to I-75[b]			
Travel Time Index	1.359	1.481	1.380
Average Travel Time	9.322	10.162	9.469
95th Percentile Travel Time	12.548	13.150	12.493
Buffer Index	0.346	0.294	0.319
80th Percentile Travel Time	10.505	11.382	10.849
Skew Statistic	1.148	0.996	1.070
Daily VMT	584,487	588,442	572,211
SHRP Section I-285 Westbound from GA 400 to I-75[b]			
Travel Time Index	1.826	1.893	1.672
Average Travel Time	12.564	13.026	11.504
95th Percentile Travel Time	19.053	19.754	19.543
Buffer Index	0.517	0.516	0.699
80th Percentile Travel Time	15.632	16.140	14.699
Skew Statistic	1.202	1.043	1.779
Daily VMT	584,487	588,442	572,211
SHRP Section I-285 Eastbound from GA 400 to I-85[b]			
Travel Time Index	2.247	2.314	1.797
Average Travel Time	14.495	14.926	11.593
95th Percentile Travel Time	23.353	24.724	21.084
Buffer Index	0.611	0.656	0.819
80th Percentile Travel Time	19.336	19.945	15.256
Skew Statistic	1.285	1.248	2.347
Daily VMT	588,597	580,629	567,497
SHRP Section I-285 Westbound from GA 400 to I-85[b]			
Travel Time Index	1.621	1.681	1.511
Average Travel Time	10.424	10.809	9.713
95th Percentile Travel Time	13.740	13.707	12.612
Buffer Index	0.318	0.268	0.299
80th Percentile Travel Time	11.622	11.957	11.082
Skew Statistic	0.790	0.763	0.656
Daily VMT	588,597	580,629	567,497
SHRP Section I-75 Northbound from Roswell Road to Barrett Parkway[a]			
Travel Time Index	1.579	1.652	1.514
Average Travel Time	8.762	9.170	8.405
95th Percentile Travel Time	11.827	12.823	12.357
Buffer Index	0.350	0.398	0.470
80th Percentile Travel Time	10.206	10.560	9.656
Skew Statistic	1.513	1.348	1.586
Daily VMT	669,568	675,274	N/A

	Year		
	2006	2007	2008
SHRP Section I-75 Southbound from Roswell Road to Barrett Parkway[a]			
Travel Time Index	1.809	1.872	1.614
Average Travel Time	9.785	10.129	8.730
95th Percentile Travel Time	13.835	14.301	12.791
Buffer Index	0.414	0.412	0.465
80th Percentile Travel Time	11.208	11.575	10.529
Skew Statistic	0.849	0.920	0.945
Daily VMT	669,568	675,274	N/A
All Sections			
Travel Time Index	1.720	1.800	1.585
Average Travel Time	10.033	10.492	9.220
95th Percentile Travel Time	14.266	15.151	13.597
Buffer Index	0.399	0.428	0.451
80th Percentile Travel Time	11.874	12.400	10.989
Skew Statistic	1.186	1.196	1.308
Daily VMT	3,150,088	3,154,932	2,878,074
Daily VMT without I-75 (I-285 to Barrett Pkwy)	1,789,122	1,790,030	1,734,742

Note: VMT was calculated for both directions combined, then divided by two for each directional section.

[a] Ramp meters turned on mid-October 2008.

[b] Ramp meters turned on July 1, 2008.

We observe that on 7 of the 10 study sections, the Buffer Index actually increased in 2008 over 2007 levels, yet overall congestion was better (i.e., the Travel Time Index went down). Looking at the two components of the Buffer Index – the 95th percentile and the mean travel time – both decreased in all cases. However, where the Buffer Index increased, it can be seen that the drop in the 95th percentile was proportionately lower than the drop in the mean travel time, leading to a higher index value. The 80th percentile travel time decreased in 2008 on all sections, while the Skew Statistic exhibits a similar pattern as the Buffer Index. (The Planning Time Index exhibits the same characteristics as the 95th percentile since its base is free-flow speed, which does not change.)

Figures 4.11 and 4.12 show the travel-time distributions for two of the sections where the Buffer Index and Skew Statistic increased:

- The I-75 section had ramp meters turned on in mid-October 2008 and saw a decrease in demand of 5.5 percent from 2007 to 2008; and
- The I-285 section had ramp meters turned on by July 1, 2008 and saw a decrease in demand of 1.8 percent.

Note that for the same fixed peak period, there was more free-flow travel in 2008 on both sections. On the I-75 section the increase in free-flow travel was due primarily to the decrease in demand while on the I-85 section the improved flow was probably due to a combination of reduced demand and ramp meters. (Both the Buffer Index and the Skew Statistic indicate there is more "spread" in the distribution, but the worst travel times (the 80th and 95th percentiles) have been decreased.)

What can be concluded from these seemingly conflicting results on the seven segments about reliability trends? In other words, does reliability get better or worse at these locations? Both the Buffer Index and the Skew Statistic indicate there is more "spread" in the distribution, but the worst travel times (the 80th and 95th percentiles) have been decreased. That the drop in the 95th percentile was not as great as the drop in the mean indicates that while base (typical) conditions have improved, the variation around the new base is higher (as indicated by the Buffer Index and Skew Statistic). So, as a traveler in 2008, my worse days are better than they were in 2007, but compared to my typical trip, the worse days are proportionately worse. Whether reliability got better or worse depends on how I perceive the extra time – in absolute or relative terms. In absolute terms, the buffer time (95th percentile minus the mean) improved in 2008.

Figure 4.11 I-285 Eastbound
GA 400 to I-85, Peak Period

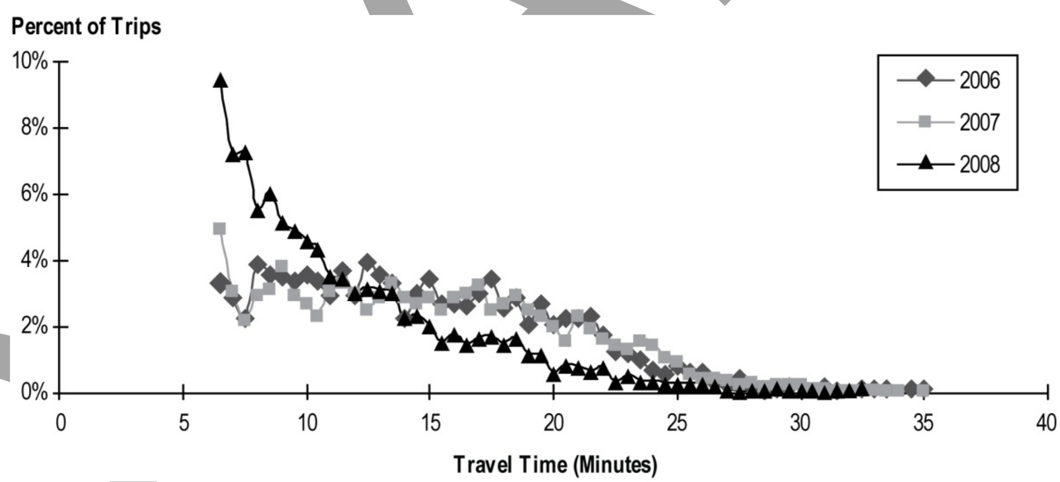
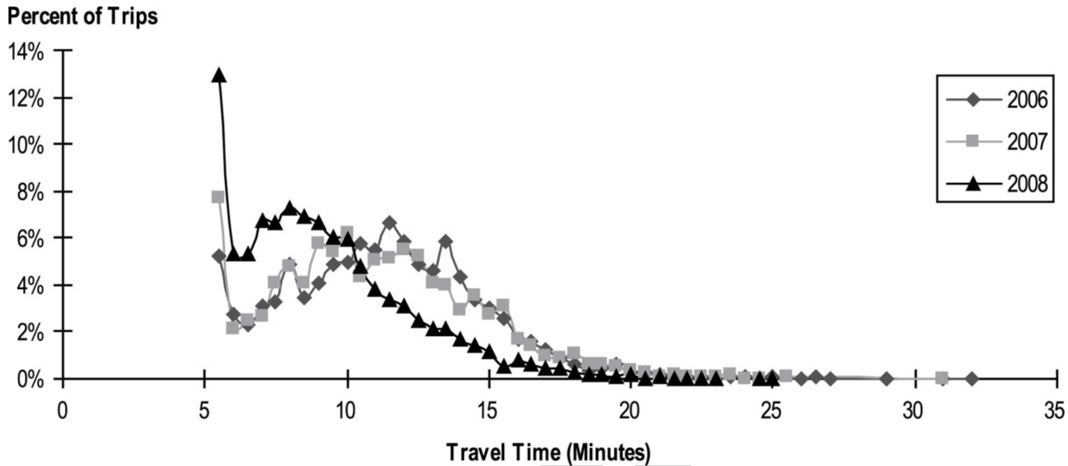


Figure 4.12 I-75 Northbound
I-285 to Roswell Road, Peak Period



Assume for the moment that the decreases in the metrics are due solely to the decreased demand in 2008, thereby reducing base (recurring) congestion. Also assume that the worst travel times are influenced by roadway events such as incidents. The fact that the 80th and 95th percentiles decreased in 2008 are another indication of the interaction between base congestion and events – assuming event characteristics are equivalent, less base congestion leads to lower event-related congestion. However, the lessened impact is somewhat marginal in nature – the drop in the worst travel times was not as big as for base congestion.

There are two implications of these results for both future research and existing practice. First, the Buffer Index may not be the most appropriate metric for tracking trends. In the Atlanta analysis, it can be seen that the mean travel times had a proportionately higher decrease than the 95th percentile. Presumably, this is because the major factor was decreased demand, which would tend to decrease **all** travel times, and not primarily affect the extremes as some operational treatments do. So, because of the way the Buffer Index is normalized by the mean, it can produce a counterintuitive result, i.e., worsened reliability while average congestion decreased. However, while it might not be the best metric for measuring trends because of this nuance, it still tells us something useful about conditions. In the "new reality" of 2008, the size of the buffer did indeed increase, even if it is largely due to a large decrease in the mean travel time.

The second implication is the significant effect that demand can have on both average congestion level and reliability. As shown back in Figure 2.2, conceptually, demand and base capacity interact with events to produce total congestion patterns. This analysis shows just how important volume is to the congestion and reliability pictures when capacity is fixed.

4.6 Defining the Peak Hour and Peak Period

There are two ways to define the length of peak times for conducting congestion and reliability analyses: 1) determine fixed times for all locations, based on subjective local knowledge; 2) or determine the start and end times empirically. The Research Team previously had decided on the latter method. The definitions developed for use in the research are as follows:

- **Peak Hour –** The peak hour is defined as a continuous 60-minute period where the space mean speed is less than 45 mph. As this period can be much longer than an hour, the selection of the actual peak hour within this period is based on examining alternative 60-minute periods based on three criteria:
  - Low space mean speed;
  - High vehicle-hours of travel; and
  - High vehicle-miles of travel.

  The analyst must decide which 60-minute period is the actual peak hour based on comparing this information with local knowledge. Note that for routinely congested sections, the highest VMT will occur either right before the actual peak (high flow right before breakdown conditions) or after the peak (high flow during queue release.)
- **Peak Period –** The peak period is simply defined as a continuous time period at least 75 minutes long where the space mean speed is less than 45 mph.

The peaks for the urban freeway study sections are shown in Table 4.8.

Table 4.8 Peak Hour and Peak Period Definitions, L03 Study Sections

City	SHRP Section	Peak-Hour Start	Peak Period Start	Peak Period End	Peak Period Length
Houston	1	6:20	6:00	8:15	2:15
	2	6:35	6:15	8:40	2:25
	3	7:35	6:40	9:20	2:40
	4	16:40	15:15	18:55	3:40
	5	16:50	16:20	19:10	2:50
	6	16:50	16:20	19:10	2:50
	7	6:05	6:15	7:50	1:35
	8	6:45	6:15	9:10	2:55
	9	6:45	6:15	9:10	2:55
	10	7:00	7:20	8:55	1:35
	11	16:35	16:15	18:30	2:15
	12	16:50	16:40	18:30	1:50
	13	16:55	16:45	19:00	2:15
Minneapolis	14	7:00	6:25	8:55	2:30
	15	15:19	15:10	17:35	2:25
	16	16:35	15:10	18:05	2:55
	17	16:20	16:20	18:10	1:50
	18	16:05	15:05	18:25	3:20
	19	16:15	16:15	18:20	2:05

City	SHRP Section	Peak-Hour Start	Peak Period		
			Start	End	Length
	20	7:55	7:55	9:25	1:30
	21	16:15	16:15	17:55	1:40
	22	16:10	14:45	17:55	3:10
	23	7:00	7:00	8:35	1:35
	24	16:20	16:10	18:20	2:10
	25	6:55	6:55	8:55	2:00
	26	16:00	15:25	17:55	2:30
	27	16:15	16:15	18:05	1:50
	28	7:05	7:05	8:55	1:50
	29	16:20	16:20	18:15	1:55
Los Angeles	30	7:10	6:45	9:30	2:45
	31	7:15	6:35	9:00	2:25
	32	16:45	16:50	19:00	2:10
San Francisco	35	16:25	15:45	18:50	3:05
San Diego	37	15:45	15:25	18:40	3:15
	38	16:55	16:55	18:30	1:35
	39	6:45	6:45	8:20	1:35
	40	16:40	15:00	19:05	4:05
	41	16:25	15:45	18:25	2:40
	42	6:30	6:25	8:55	2:30
Atlanta	43	17:00	16:30	18:30	2:00
	44	7:45	7:15	8:30	1:15
	45	17:15	7:15	9:00	1:45
	46	17:00	15:30	18:30	3:00
	47	7:15	7:15	8:45	1:30
	48	17:15	16:30	18:30	2:00
	49	17:00	16:00	18:30	2:30
	50	7:45	7:15	9:00	1:45
	51	17:00	16:30	18:30	2:00
	52	7:30	7:15	9:00	1:45
Jacksonville	74	7:30	7:15	8:40	1:25
	75	17:00	16:45	18:10	1:25
	76	7:25	7:10	8:30	1:20
	77	17:00	16:45	18:10	1:25
	78	17:00	16:45	18:10	1:25
	79	7:20	7:10	8:35	1:25
	80	17:00	16:45	18:10	1:25
	81	16:45	16:35	17:55	1:20

Notes: SHRP Section is keyed to Table 3.2.

4.7 ESTIMATING DEMAND IN OVERSATURATED (CONGESTED) CONDITIONS ON FREEWAYS

When traffic flow breaks down on freeways, the observed volume of vehicles moving past a point drops due to slower speeds and the onset of queuing. Roadway detectors count only volume (the number of vehicles physically able to pass a given point) not demand (the number of vehicles that want to pass the point). The simultaneous volume/speed plots in Figures 4.13 and 4.14 are very typical of congested freeways everywhere. This loss in capacity after flow has broken down is often referred to as "lost productivity" or "lost efficiency" because it means that under such conditions, throughput is actually lost.

Figure 4.13 Volume Drop After the Onset of Congestion – Example 1

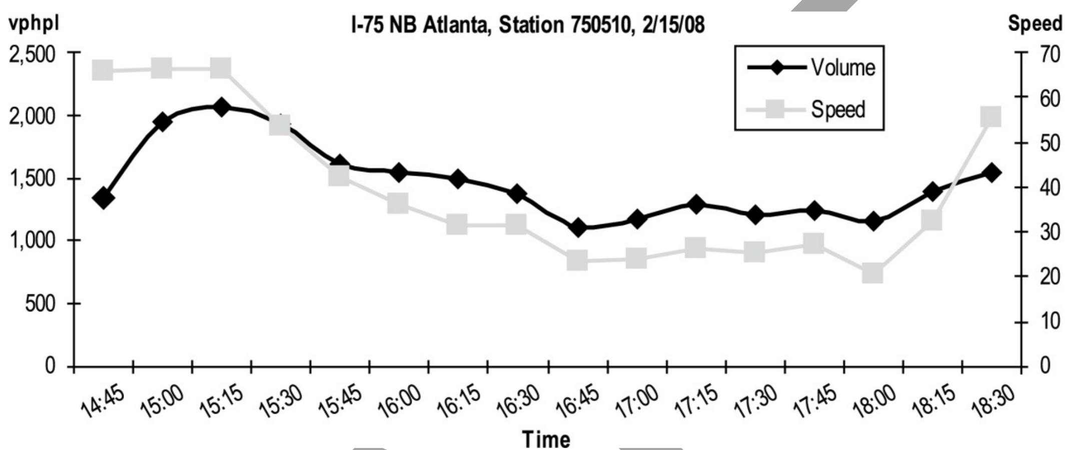
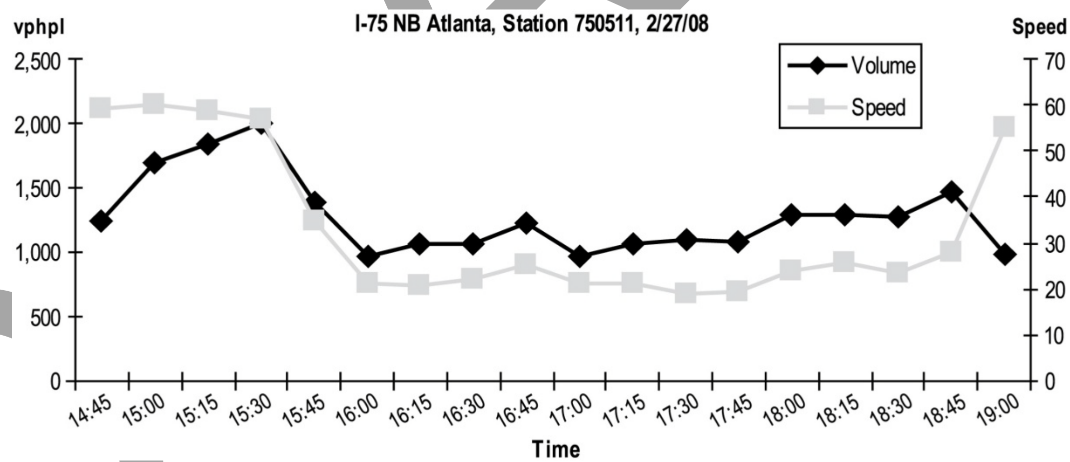


Figure 4.14 Volume Drop after the Onset of Congestion – Example 2



The actual demand that wants to pass the point is stored upstream in the queue. The applications that are likely to use the L03 results (e.g., the *Highway Capacity Manual*, travel forecasting and simulation models) need to know the demand in order to predict traffic conditions. To address this method, the Research Team developed a procedure for allocating queued demand to the time period when that demand was trying to use a section of highway. The steps are as follows.

1. A congestion threshold speed is set by the analyst, between 35 mph and 45 mph (40 mph is used in the examples presented here). For each five-minute observation:

   a. If the mean observed speed is 40 mph or greater, then the observed volume is equal to the demand.

   b. If the mean speed is less than 40 mph, then the observed volume is NOT demand and a demand estimate is required.

2. The "Congested Period" is then the set of consecutive five-minute observations with speeds <40 mph. If a single five-minute period is uncongested and it is surrounded by congested five-minute observations, this single five-minute observation is considered to be congested as well.

3. The Congested Period is split into two halves. The queue is assumed to be building during the first half. The queue is assumed to be dissipating during the second half of the Congested Period.

4. The cumulative demand is computed for about half an hour before the onset of congestion and for half an hour after the termination of congestion.

   a. During the first half of the congested period, the demand rate (vehicles per five-minute period) is assumed to be equal to the average of the demands observed in the last two five-minute periods just before the onset of congestion. This demand rate is assumed to be fixed for the first half of the congested period, and is used to compute the cumulative demand for this half of the congested period.

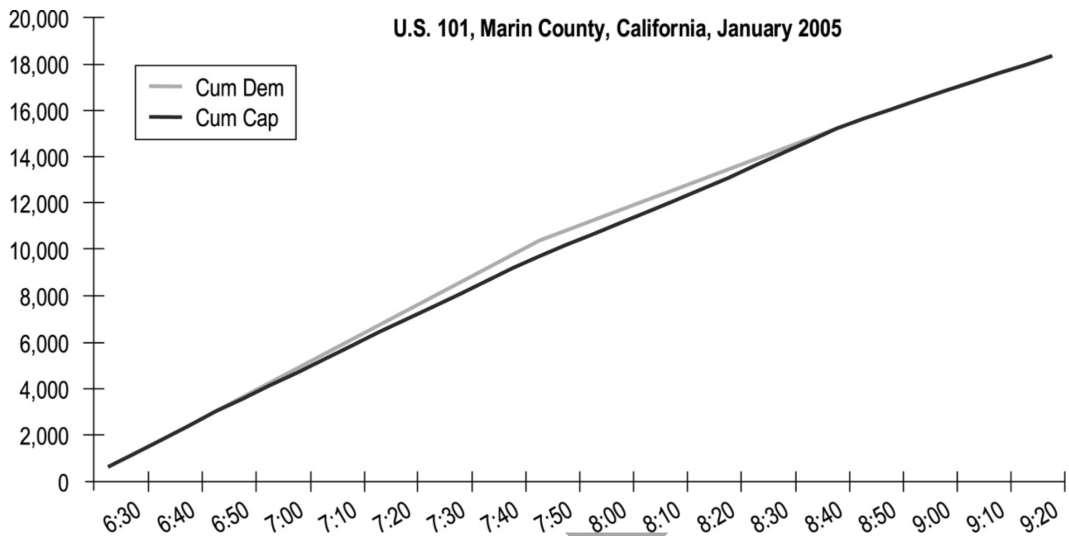
   b. Once the cumulative demand at the midpoint of the congested period is computed, then the analyst calculates a second demand rate to be used during the second half of the congested period. This second demand rate is set so that the cumulative demand will equal the cumulative observed volume by the end of the Congested Period.

   c. The second half demand rate then is added to the cumulative demand at the midpoint of the Congested Period until the end of the Congested Period is reached, at which point the estimated demand should be equal to the observed cumulative volume.

   d. Check the next two, five-minute periods after the termination of the congested period to see if the estimated demand curve smoothly fits to the observed cumulative volume curve. (The observed five-minute volume for the first five-minute period following the end of the Congested Period should not be sharply higher than the estimated demand rate for the second half of the Congested Period). It is sometimes necessary to smooth out the transition by assuming the congested period extends one more five-minute period.

Figure 4.15 illustrates the application of this approach to a congested period for U.S. 101 in Marin County, California.

Figure 4.15 Estimating Demand During Oversaturated Conditions: Example



4.8 RELIABILITY BREAKPOINTS ON FREEWAYS

After reviewing urban freeway data, it became apparent to the Research Team that the data could be used in creative ways to answer basic questions about reliability and to provide insight into the complex statistical modeling ahead. One of these questions is: at what volume (demand) levels does reliability radically change? This is similar to establishing basic capacity values for when flow breakdown occurs. But here we are concerned with the volume level that causes reliability to rapidly deteriorate. A complete description of this effort is provided in the Phase 2 Report; a summary is provided below.

Various measures of travel-time reliability were investigated and the standard deviation of the measured travel-time rate per mile was selected as an appropriate indicator of travel-time reliability for the purpose of establishing reliability breakpoints. We chose the standard deviation because we wanted to examine both sides of the mean volume that leads to breakdown.

Two methods for measuring the standard deviation in the travel-time rate were evaluated. The first computed the standard deviation directly from the 5-minute data. The second computed the standard deviation from the hourly summaries. The second method was chosen as the most appropriate and is used in the analysis presented here. Loop detectors provide excellent temporal coverage but for limited geographic locations, while vehicle probes provide excellent geographic coverage of the facility but for limited time periods. A method was developed for calibrating loop detector estimates of travel-time reliability to probe vehicle measurements of travel-time reliability so that the annual travel-time reliability for the freeway could be estimated.

A year's worth of loop detector station data for four stations (located on two different freeways in the San Francisco Bay Area) then was evaluated to determine how traffic volumes and incidents affected the observed travel-time reliability on a freeway for the morning peak, afternoon peak, and off-peak periods over the course of a year. In this case rather than spatially mix several detectors in one plot, data for a longer period of time (one year) was sought, but only for one detector at a time. Comparing the two sets of figures (Figures 4.16 and 4.17 with Figures 4.18, and 4.19) shows the effect of spatially lumping several detector stations into one reliability data set. The single station data show much more pronounced verticality in performance when volumes exceed breakdown.

Three weeks of travel-time rate data was evaluated from 13 loop detector stations on eastbound I-580. The mean and standard deviation of the travel-time rate (minutes per mile) was computed for each of three time periods (A.M. peak, P.M. peak, off-peak) for each day of the week. Each data point is the average or standard deviation of the travel time rate (miles per minute) measured for each weekday (Sun-Sat) period (AM, PM, or off peak). Thus, since there are 7 days in a week, and three peak periods are evaluated for each weekday, we get 21 observations possible. These observations include the effects of holidays. The AM peak is defined as 6:30-10 AM, The PM peak is defined as 15:00-19:00. Off peak is the remainder of the 24 hours in the day.As shown in Figure 4.16, both the mean travel-time rate and the standard deviation are relatively constant until the counted mean volume (across all detectors) for a peak period reaches between 1,250 and 1,350 vehicles per hour per lane. Somewhere in this range, the mean and standard deviation of the travel-time rate starts to soar almost vertically. This figure also shows how spatially mixing multiple loop detectors tends to the mask the vertical breakpoint shown later. The breakdown portion of the curve is sloped, rather than vertical. Three weeks of data from 5 loop detectors applies to I-580 WB (Figure 4-17).

This "breaking point" when there are strong indications of congestion on the freeway is quite a bit lower than the theoretical 2,000 vehicles per hour per lane capacity of the freeway (after converting from passenger car capacity to mixed flow capacity). But note that the volumes in the figure are the average across the peak period. Peak 15-minute demands within the peak period may be significantly higher than the average volume across the entire peak period.

Figure 4.16 Volume and Reliability – I-580 Eastbound at Multiple Detectors

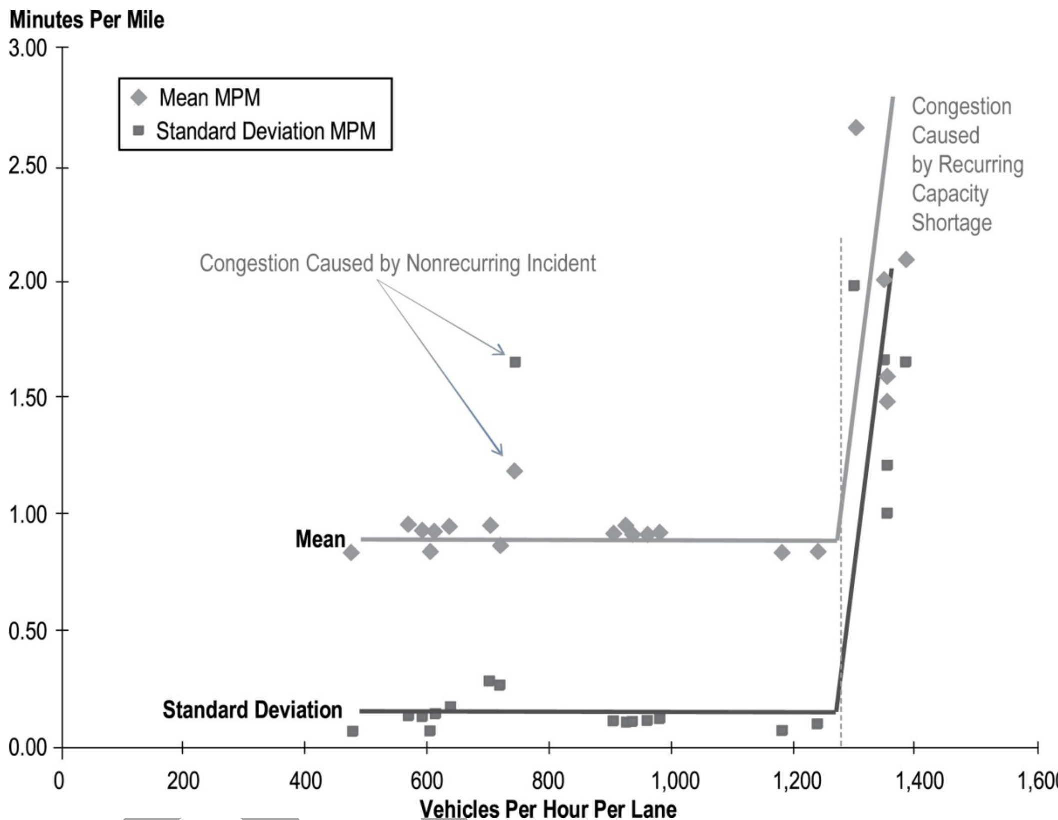
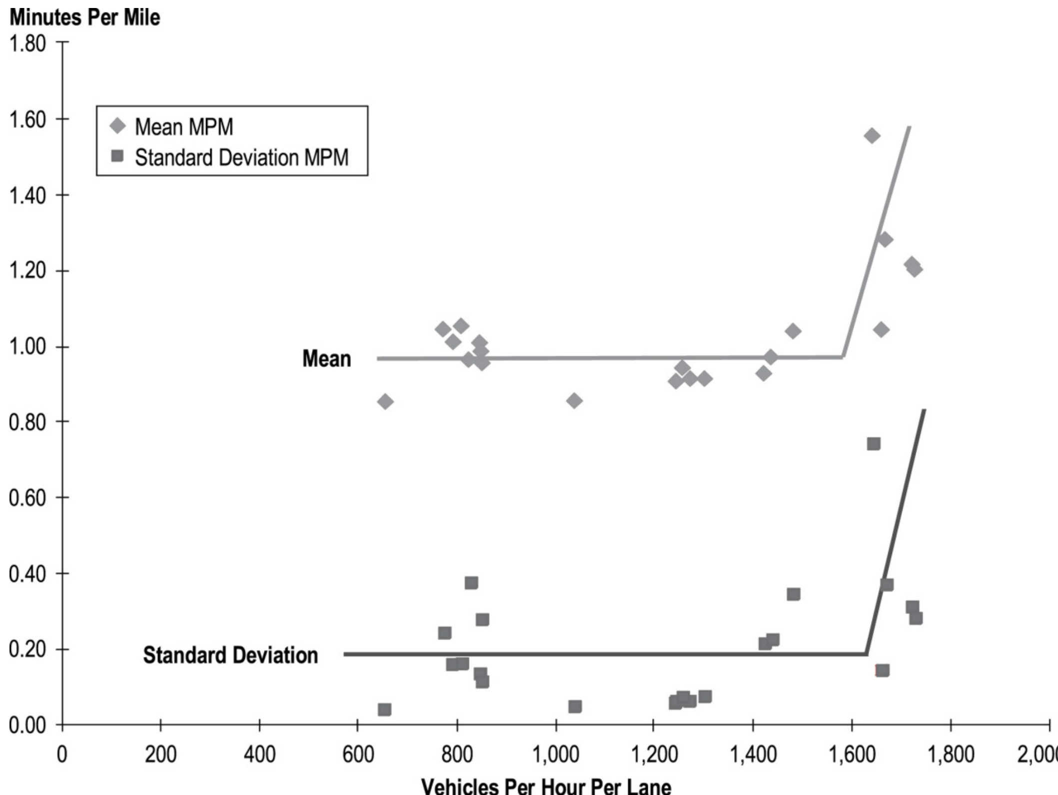


Figure 4.17 shows similar computations and results for the five detectors in the westbound direction of I-580. Both the mean and the standard deviation in the travel-time rate for each peak period tends to rise almost (if not exactly) vertically in the range of 1,600 to 1,700 vehicles per hour per lane averaged across the peak period.

The breakpoint volumes for freeway reliability vary by detector location, even for the same facility.

Figure 4.17 Volume and Reliability – I-580 Westbound at Multiple Detectors



Figures 4.18 and 4.19 show the volume to reliability relationships for one year's worth of peak and off-peak time periods for a single detector in each direction on I-580. The breakpoint volume for this detector is in the 1,200 to 1,300 vphpl range for eastbound and 1,100 to 1,200 vphpl for the westbound direction. For the eastbound direction, the relationship appears to be precisely vertical once the breakpoint volume is reached for the peak period. The westbound direction appears to have a couple of nonrecurrent incidents that caused some reliability problems prior to the breakpoint volume is reached.

Figure 4.20, computed from a year's worth of loop detector data for U.S. 101 Southbound shows that a similar flat relationship between mean volume and standard deviation of travel time exists on this freeway until the breakpoint volume of between 1,050 and 1,150 vphpl is reached. Then both the mean and the standard deviation of the travel-time rate increases steeply, but not precisely vertically.

Figure 4.18 Volume and Reliability – Single Detector I-580 Eastbound

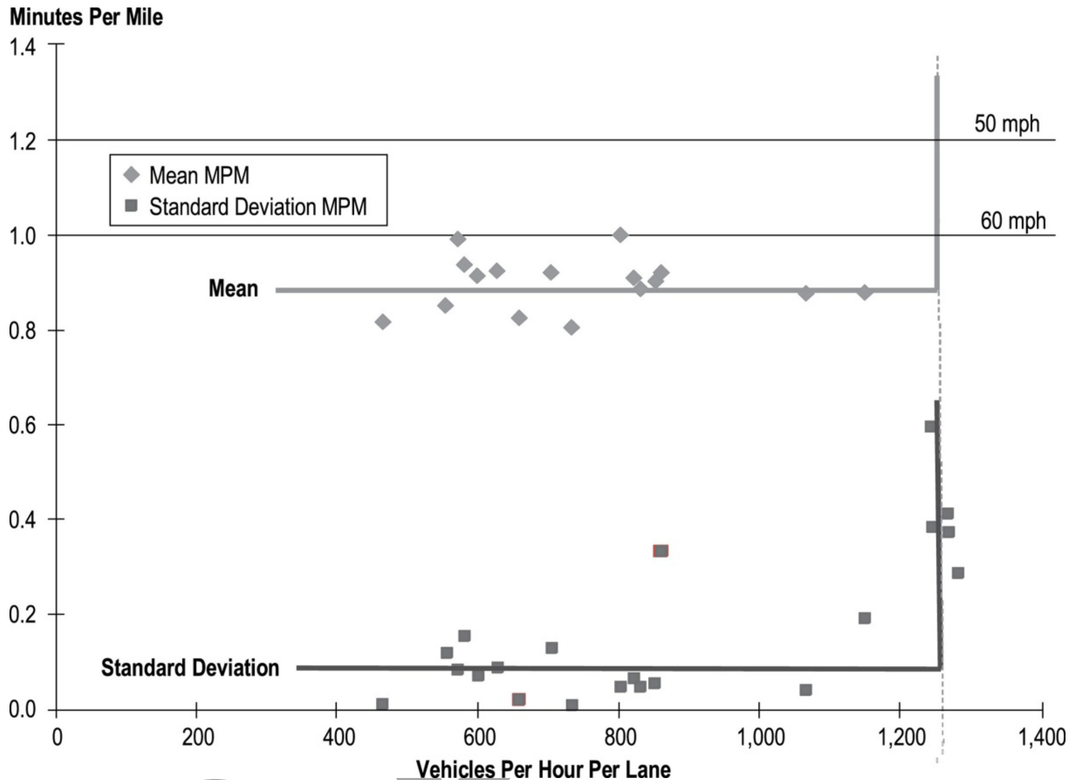


Figure 4.19 Volume and Reliability – Single Detector I-580 Westbound

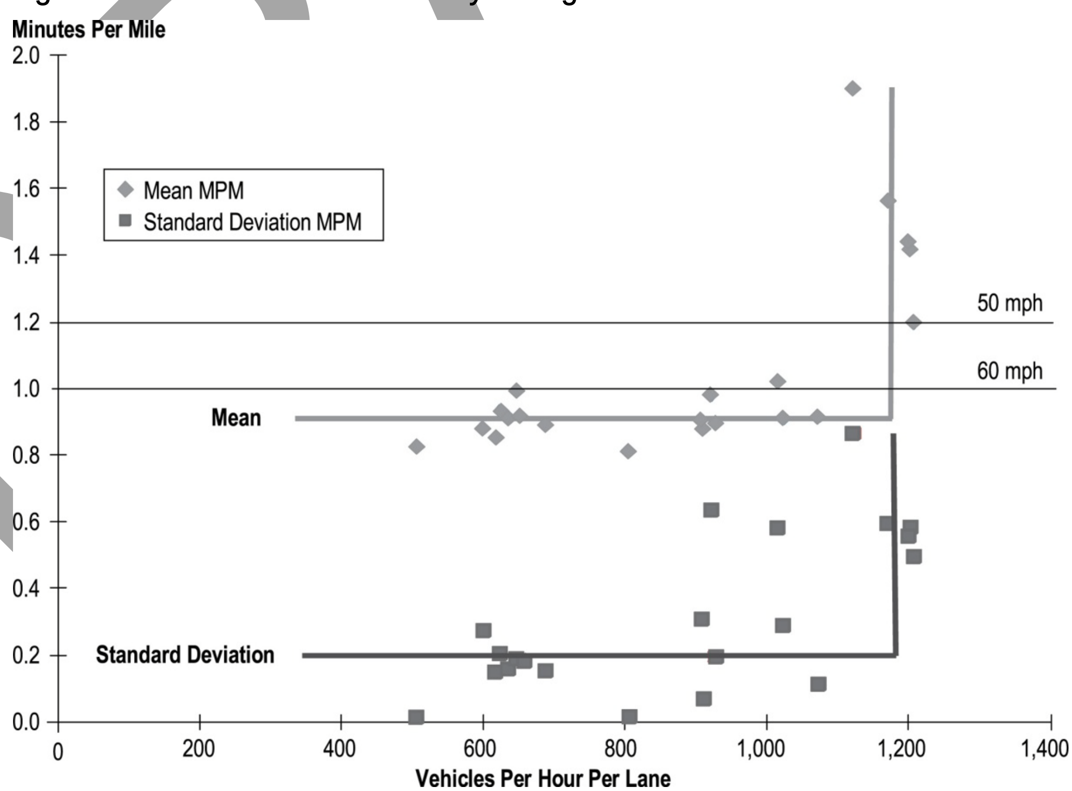
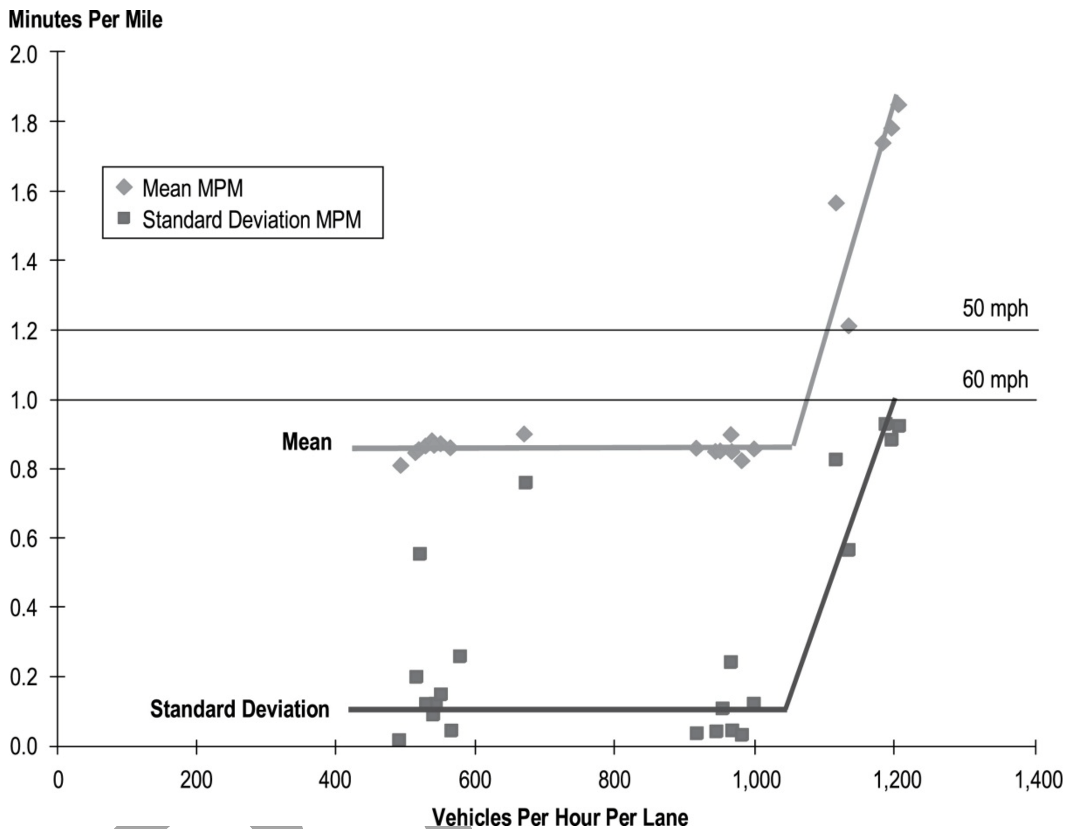


Figure 4.20 Volume and Reliability – U.S. 101 Southbound



Note that in Figures 4.16 through 4.19 , the lines showing the relationships were visually drawn to illustrate the phenomenon. Piece-wise linear regression was not used. Indeed, a strict regression analysis would not have consistently produced the lines drawn. In some cases, the observed volumes were not high enough to achieve breakdown. In others, there is enough noise in the data (due to non-recurrent incidents) to hide the relationship.

The above analysis has shown that travel-time reliability on a freeway is NOT a function of counted traffic volumes until a "breakpoint volume" is reached. At that breakpoint, the travel-time reliability decreases abruptly. Once the breakpoint volume is exceeded, the decrease in travel-time reliability (increase in the variance) is so extreme and abrupt as to suggest it is asymptotic, with a nonsingular relationship to further volume increases.

The breakpoint volume varies significantly between facilities and even within the same freeway facility (by location and direction of travel on the same facility). The breakpoint volume does not appear to be a fixed ratio of the theoretical capacity of the subject section of the facility.

The breakpoint in reliability generally occurs at a counted volume significantly lower than the theoretical capacity of the facility computed per the Highway Capacity Manual (HCM). This is partly because the breakpoint volume computed in this analysis is the average hourly volume counted over a peak period and not the peak 15-minute demand as used in the HCM capacity.

But this peaking effect does not entirely explain the difference. Part of the reason that the breakpoint volume is significantly lower than the theoretical capacity is because most sections of freeway are upstream of a bottleneck and, thus, are impacted by downstream congestion backing up into the subject section long before the subject section's HCM capacity is reached. Further, the effect of traffic-influencing events, especially incidents, effectively lower capacity when they occur and over time, cause reliability to degrade. This effect manifests itself in lower breakpoint volumes than for capacity related strictly to physical features. Finally, even for bottlenecks, the data suggests that the reliability breakpoint occurs long before the theoretical HCM capacity of the bottleneck is reached.

4.9 Sustainable Service Rates on Freeways

The concepts presented in the last section can be extended to the idea of sustainable (or sustained) service rates: "Sustained service rate" (SSR) is defined as the highest flow rate that can be sustained over a peak demand period with a low probability of breakdown. Werner Brilon (*1*) proposed to call this broader capacity the whole year capacity of the facility. Brilon focused on capacity just prior to breakdown, while we will want to quantify the probability of breakdown for different flow rates.

An analysis was undertaken using data from L03 study sections in Seattle and Atlanta. For comparison with HCM terminology, we defined SSR in terms of vehicles per hour per lane (vphpl).

- Data were available at 5-minute intervals in the two locations, so the first step was to aggregate to 15-minute time intervals.
- For each 15-minute interval, an estimate of the corresponding vphpl value was made by multiplying the 15-minute volume by four and applying a peak-hour factor of 0.95. (A more sophisticated version of this method would compute the peak-hour factor directly from the data.)
- The data for a detector location was scanned over in time sequence, looking for points where flow broke down, i.e., congestion (queuing) began. (Speeds less than 45 mph was used in this analysis.) When two consecutive 15-minute periods registered speeds less than the threshold, the flow that occurred immediately before breakdown was assigned as the SSR.

The results are shown in Table 4.9. The results are in vphpl, which includes both automobiles and trucks. One way to look at the results is that they represent how capacity varies over the course of a year. The theoretical maximum capacity is probably somewhere close to the 99th percentile, allowing for the fact the actual maximum SSR may be an outlier.

Table 4.9 Distribution of Sustainable Service Rates at Selected Locations
2007

		Sustainable Service Rates (VPHPL)										
Route	Station	Mean	Standard Deviation	Maximum	P99	P95	P90	P75	Median	P10	P5	P1
Atlanta												
I-75 Northbound, Northside	10068	1,390	482	1,975	1,921	1,848	1,739	1,663	1,560	543	132	87
I-75 Northbound, Northside	10070	1,922	288	2,407	2,386	2,236	2,125	2,050	1,967	1,750	1,430	621
I-75 Northbound, Northside	750510	1,825	264	2,561	2,449	2,295	2,157	1,954	1,809	1,579	1,357	985
I-75 Northbound, Downtown Connector	10026	1,631	357	2,169	2,169	2,082	2,036	1,900	1,654	1,205	929	316
I-75 Northbound, Downtown Connector	10033	1,597	475	2,245	2,240	2,170	2,121	1,944	1,686	915	684	174
I-75 Northbound, Downtown Connector	10037	1,581	366	2,553	2,199	2,016	1,936	1,806	1,682	1,152	840	287
I-75 Northbound, Downtown Connector	10038	1,567	367	2,412	2,153	1,961	1,879	1,804	1,696	1,058	892	272
I-75 Southbound, Downtown Connector	10130	1,270	306	2,110	1,776	1,658	1,599	1,493	1,295	902	575	291
I-75 Southbound, Downtown Connector	10131	1,666	334	2,381	2,181	2,017	1,955	1,853	1,733	1,321	1,031	305
I-285 Eastbound, North Arc	2850010	1,675	328	2,091	2,082	1,984	1,950	1,889	1,789	1,174	966	536
I-285 Eastbound, North Arc	2850014	1,843	457	2,444	2,434	2,360	2,305	2,206	1,933	1,248	838	448
I-285 Eastbound, North Arc	2850017	1,347	495	2,175	2,130	1,905	1,852	1,721	1,419	507	209	42
I-285 Westbound, North Arc	2851033	1,634	307	2,230	2,126	1,917	1,849	1,797	1,728	1,306	911	527
Seattle												
I-405	614DN	1,668	202	1,991	1,953	1,904	1,851	1,782	1,708	1,463	1,326	817
I-405	614DS	1,766	233	2,212	2,082	2,018	1,976	1,896	1,809	1,562	1,265	680
I-405	672DN	1,749	348	2,101	2,094	2,041	2,018	1,953	1,854	1,250	775	486
I-405	677DN	2,145	358	2,595	2,557	2,493	2,462	2,371	2,219	1,790	1,649	574
I-405	678DN	1,839	315	2,265	2,253	2,151	2,105	2,044	1,910	1,497	1,117	650
I-405	678DS	1,554	268	1,976	1,961	1,881	1,839	1,725	1,596	1,250	1,072	547
I-405	681RS	2,027	266	2,398	2,356	2,291	2,240	2,170	2,081	1,826	1,687	635
I-405	684DN	1,687	169	2,094	2,044	1,896	1,862	1,782	1,706	1,505	1,429	1,197
I-405	684DS	1,616	198	1,961	1,896	1,828	1,775	1,725	1,659	1,433	1,303	673
I-405	687RN	1,531	200	1,961	1,832	1,775	1,729	1,649	1,558	1,341	1,227	597
I-405	689RS	1,516	173	1,961	1,786	1,718	1,664	1,611	1,543	1,334	1,224	836
I-405	693RN	1,599	167	1,961	1,851	1,794	1,767	1,702	1,630	1,417	1,349	992
I-405	694RN	1,574	178	1,961	1,889	1,820	1,763	1,687	1,596	1,368	1,296	961
I-405	696DN	1,927	48	1,961	1,961	1,961	1,961	1,961	1,927	1,892	1,892	1,892
I-405	696DS	1,615	221	1,961	1,953	1,866	1,835	1,769	1,674	1,349	1,186	920
I-405	698DN	1,586	151	1,961	1,961	1,805	1,771	1,693	1,571	1,414	1,349	1,091
I-405	698DS	1,607	185	1,999	1,938	1,866	1,813	1,721	1,630	1,383	1,292	1,087
I-405	704DN	2,032	276	2,398	2,383	2,337	2,272	2,204	2,105	1,714	1,497	992

Route	Station	Mean	Standard Deviation	Maximum	P99	P95	P90	P75	Median	P10	P5	P1
		Sustainable Service Rates (VPHPL)										
I-405	706DN	1,615	541	1,961	1,961	1,961	1,961	1,961	1,892	992	992	992
I-405	708DN	1,811	175	2,124	2,105	2,010	1,995	1,919	1,843	1,630	1,467	1,201
I-405	708DS	1,788	222	2,117	2,094	2,048	2,003	1,934	1,839	1,528	1,440	954
I-405	709DN	1,930	222	2,322	2,208	2,158	2,139	2,060	1,961	1,740	1,550	866
I-405	709DS	1,933	293	2,379	2,364	2,223	2,174	2,117	1,995	1,588	1,307	783
I-405	710RN	1,778	229	2,132	2,086	1,999	1,961	1,904	1,824	1,592	1,292	714
I-405	710RS	1,926	239	2,318	2,288	2,177	2,124	2,056	1,951	1,786	1,600	673
I-405	711RN	1,776	179	2,060	1,999	1,959	1,934	1,877	1,820	1,617	1,427	946
I-405	711RS	1,877	427	2,504	2,402	2,310	2,250	2,174	2,048	1,205	920	688
I-405	716RN	1,891	256	2,291	2,227	2,139	2,098	2,041	1,930	1,661	1,349	817
I-405	716RS	1,979	291	2,409	2,345	2,280	2,200	2,128	2,025	1,775	1,455	509
I-405	717RN	1,830	246	2,284	2,124	2,067	2,041	1,972	1,877	1,581	1,330	692
I-405	717RS	1,940	215	2,333	2,307	2,236	2,147	2,060	1,959	1,754	1,653	1,068
I-405	720DS	1,498	272	1,961	1,923	1,820	1,775	1,695	1,554	1,180	984	540
I-405	722DS	1,512	209	1,961	1,892	1,744	1,710	1,642	1,539	1,296	1,060	817
I-405	726RS	1,629	334	2,333	2,291	2,128	2,029	1,900	1,585	1,345	1,007	638
I-405	730RN	1,572	313	2,044	2,044	1,961	1,923	1,843	1,568	1,243	882	585
I-405	730RS	1,641	218	1,961	1,961	1,892	1,851	1,744	1,661	1,490	1,258	570
I-405	731RN	1,564	309	1,972	1,972	1,921	1,870	1,816	1,695	1,094	1,056	654
I-405	731RS	1,459	220	1,961	1,961	1,824	1,718	1,623	1,482	1,224	1,140	654
I-405	734DN	1,781	251	2,200	2,200	2,071	2,006	1,921	1,832	1,493	1,224	654
I-405	734DS	1,736	281	2,170	2,170	2,105	2,067	1,955	1,721	1,493	1,391	570
I-405	736DN	1,951	248	2,470	2,345	2,253	2,181	2,092	1,982	1,752	1,391	897
I-405	736DS	1,942	285	2,424	2,333	2,242	2,212	2,117	2,006	1,634	1,455	654
I-405	738DN	1,888	255	2,223	2,200	2,139	2,094	2,014	1,934	1,733	1,486	665
I-405	738DS	1,894	265	2,409	2,265	2,200	2,155	2,056	1,946	1,596	1,509	752
I-405	739DN	1,816	240	2,147	2,120	2,037	2,003	1,946	1,858	1,661	1,277	718
I-405	739DS	1,790	238	2,272	2,196	2,120	2,048	1,915	1,813	1,566	1,440	654
I-405	740RN	1,772	251	2,101	2,075	2,014	1,987	1,927	1,835	1,471	1,307	673
I-405	740RS	1,846	227	2,379	2,307	2,139	2,075	2,003	1,866	1,611	1,497	1,037
I-405	741RN	1,624	386	2,082	2,044	1,984	1,946	1,873	1,790	950	756	498
I-405	741RS	1,795	214	2,307	2,212	2,143	2,014	1,904	1,801	1,626	1,566	965
I-405	742DN	1,783	281	2,120	2,098	2,044	2,016	1,949	1,877	1,429	1,144	661
I-405	742DS	1,606	556	1,961	1,961	1,961	1,961	1,961	1,892	965	965	965
I-405	763DS	1,644	226	2,044	2,003	1,927	1,873	1,794	1,695	1,372	1,262	806
I-405	764DS	1,927	48	1,961	1,961	1,961	1,961	1,961	1,927	1,892	1,892	1,892

Note: P99 = 99th percentile, etc.

Further examination of the shape of the SSR distributions revealed some interesting results. Two distinct patterns emerged: a unimodal and a bimodal distribution. The unimodal SSR distribution is exhibited in Figures 4.21 and 4.22. As with travel times, the distribution is skewed, but to the left as opposed to the right.

Figure 4.21 Distribution of SSR, I-405, Seattle, Station 651DN

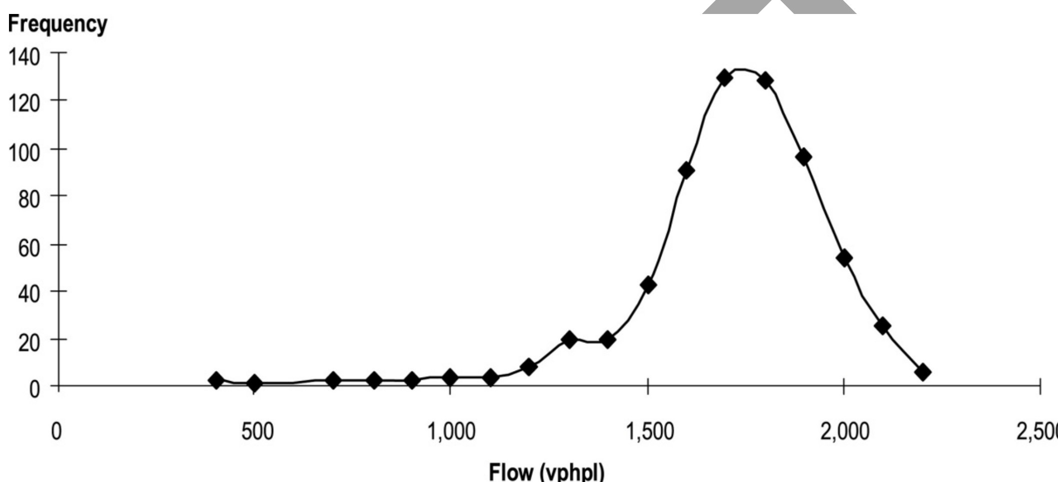
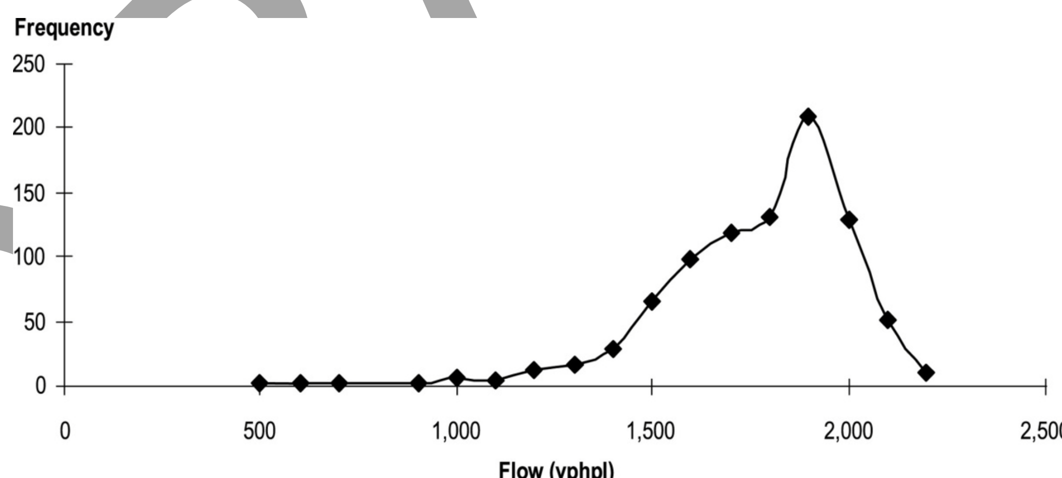
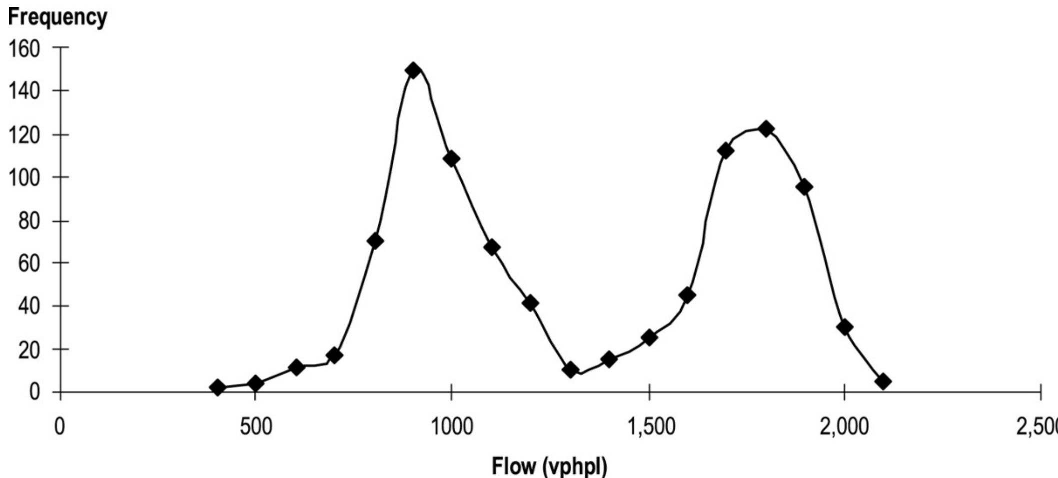


Figure 4.22 Distribution of SSR, I-405, Seattle, Station 708DS



A typical bimodal distribution is shown in Figure 4.23. A crude analysis of congestion level at the locations indicates that the unimodal distribution is most common on slightly to moderately congested sites while the bimodal is more characteristic of highly congested locations.

Figure 4.23 Distribution of SSR, I-405, Seattle, Station 612DN



A possible explanation for the two distribution types is that the bimodal distribution is showing both a recurring (close to 2,000 vphpl) and a nonrecurring SSR (around 1,000 vphpl). The reason may be, as we already have seen, that locations with high base congestion are more vulnerable to traffic-influencing events such incidents, and this sensitivity shows up in the SSRs. These locations also may be more prone to lane-blocking incidents because of higher incident rates, lack of shoulders, or both. For less congested locations, incidents have less of an effect as there is more excess capacity to buffer their effect, thus the long tail to the left but no second peak for nonrecurring events.

Another possible reason is that the bimodal sites may be upstream of a bottleneck. Thus, flow will be observed to "breakdown" under low volume conditions when actually it is queue spillback from the downstream bottleneck.

4.10 Reliability of Signalized Arterials

Data from the Orlando signalized arterial study sections were analyzed, after undergoing the QC checks discussed in Section 3.0. Figures 4.24 to Figure 4.29 show the travel-time distributions and selected performance measures. (These are the first *continuous* travel-time distributions for signalized arterials that we have seen.) As with urban freeway travel-time distributions, the distribution is skewed to the right (i.e., toward higher travel times, but the extent of the skew does not appear to be as great, possibly because incidents do not have the same effect as on freeways). That is, midblock flows of signalized arterials are largely controlled by the metering of upstream signals. Thus, the flows are well below what the midblock capacity would be absent the signals. This excess capacity absorbs the effect of single lane and shoulder blockages at midblock locations. However, if the incident occurs at the signal, where capacity already is restricted, there will be a major impact on traffic flow. But the fact that some midblock incidents have little or no effect does not produce as many extreme travel times as on freeways.

Figure 4.24 Orlando, Section 3, A.M. Peak

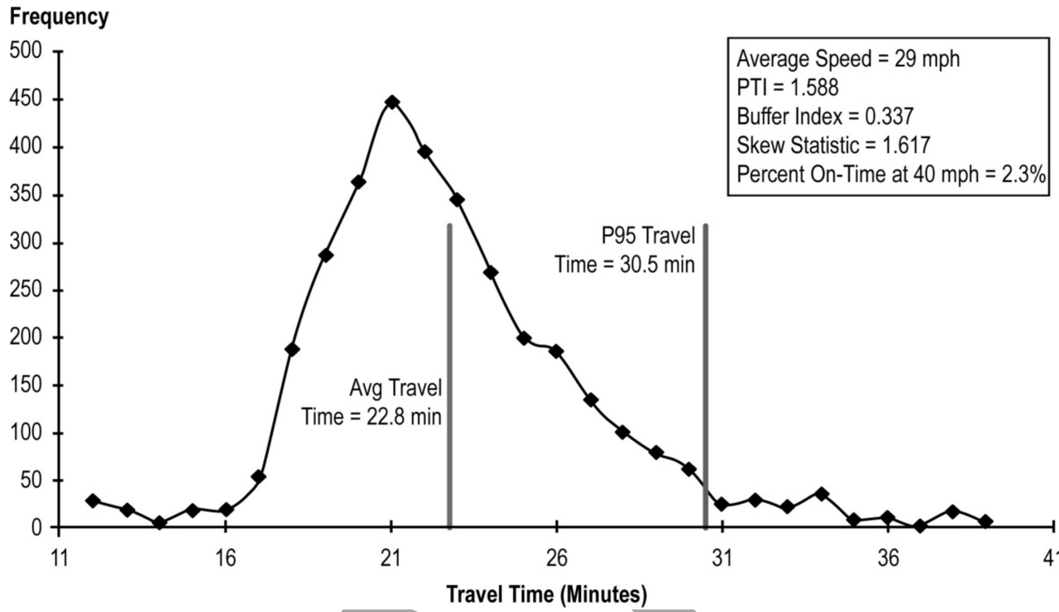


Figure 4.25 Orlando, Section 3, P.M. Peak

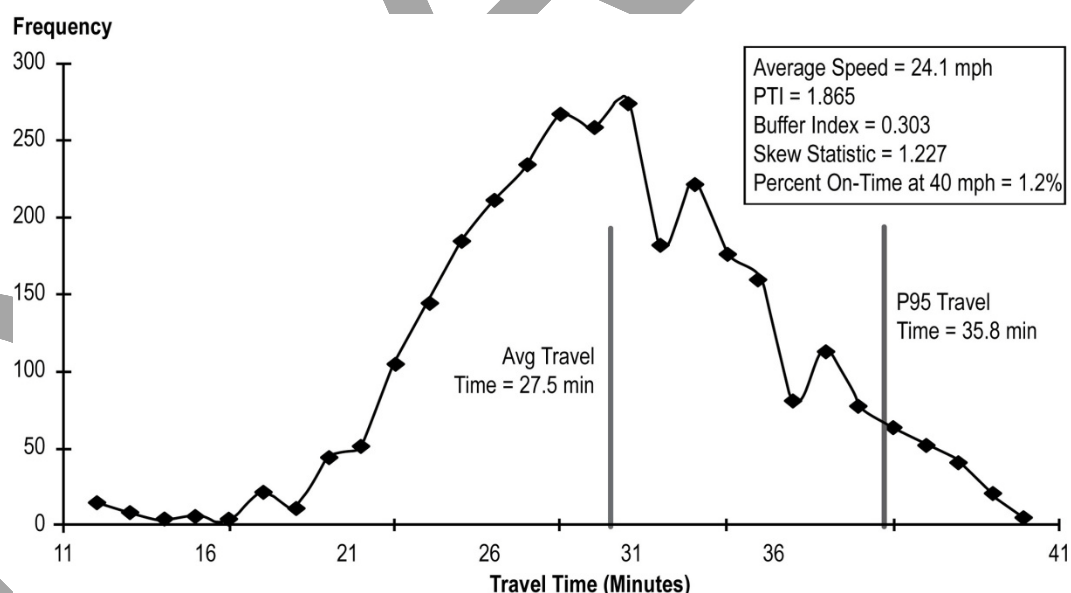


Figure 4.26 Orlando, Section 4, A.M. Peak

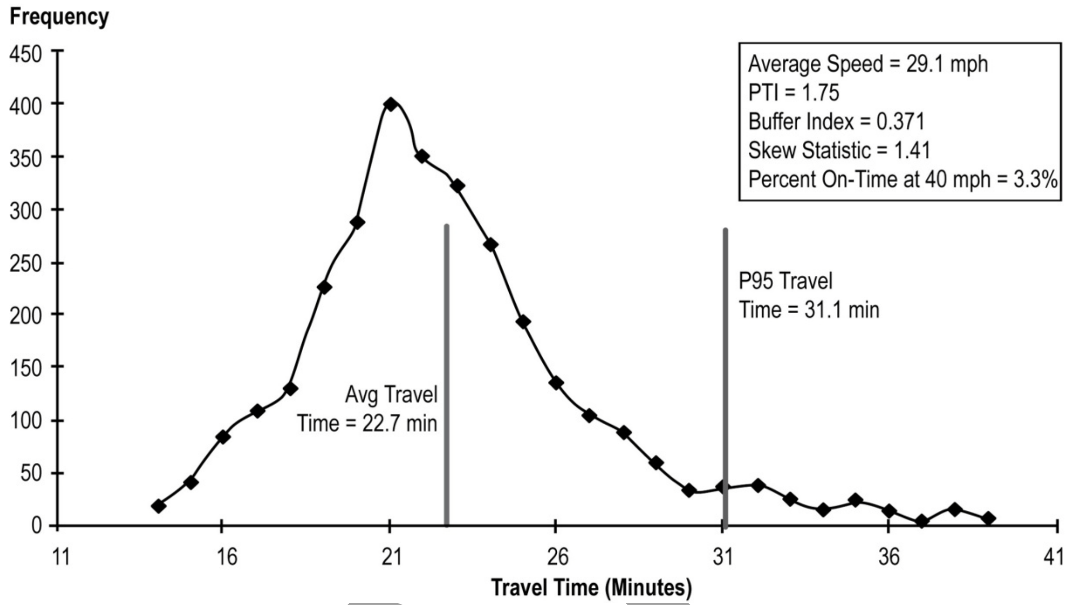


Figure 4.27 Orlando, Section 4, P.M. Peak

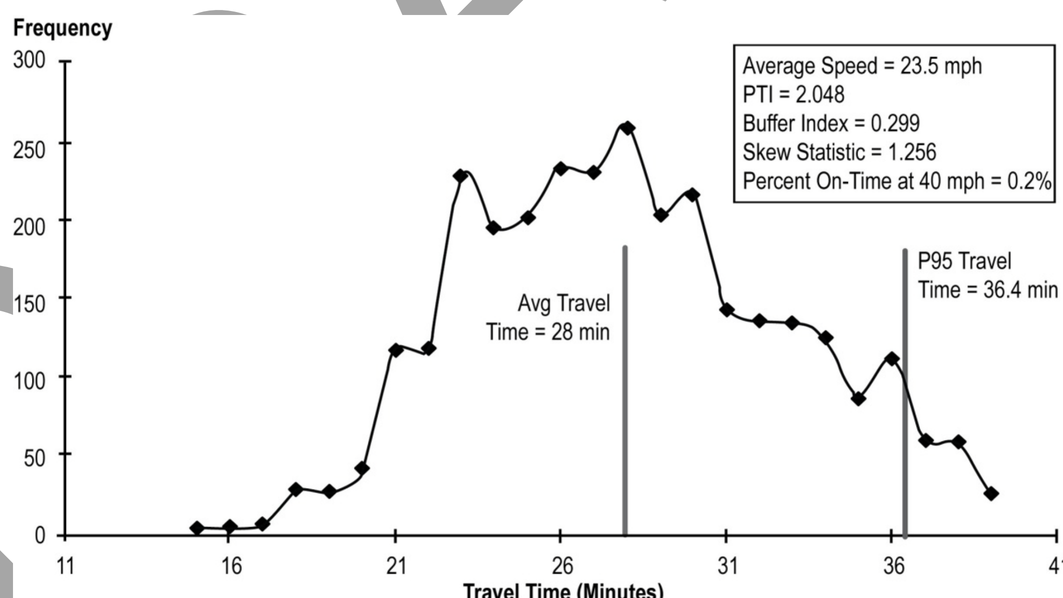


Figure 4.28 Orlando, Section 5, A.M. Peak

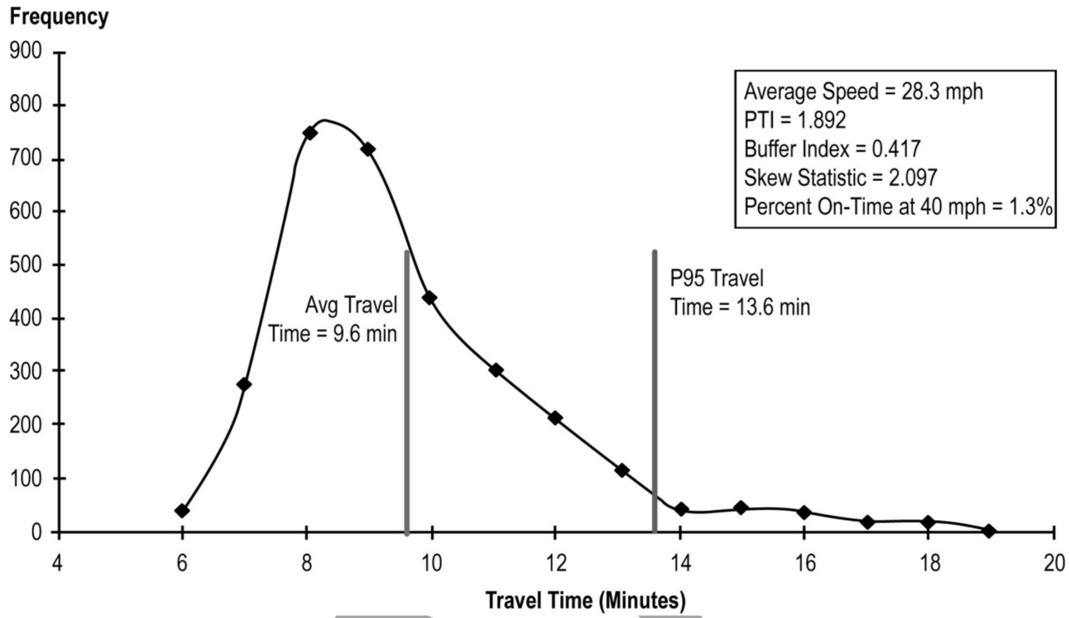
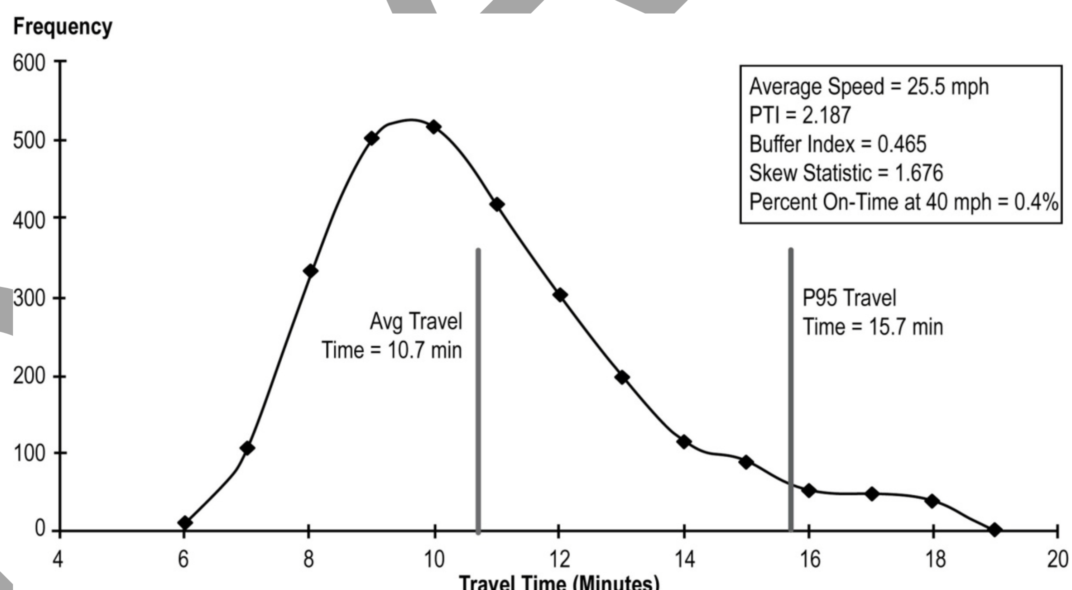


Figure 4.29 Orlando, Section 5, P.M. Peak



Another observation of the distributions is that the morning distributions appear to be more compact and peaked than the afternoon distributions, which tend to be broader. This may be a function of a higher-congestion level in the afternoon; we have noticed a similar pattern on congested urban freeways.

4.11 RELIABILITY OF RURAL FREEWAY TRIPS

Figures 4.30 through 4.33 show the reliability of trips on the two study sections for 2006 and 2007 combined. The plots show the distribution of the actual travel times. However, in calculating the TTI and associated statistics, travel times faster than the free-flow travel time have been set to the free-flow travel time, to be consistent with how these statistics are calculated on urban freeways.

Figure 4.30 I-45, Texas, Northbound
Length = 61.4 miles

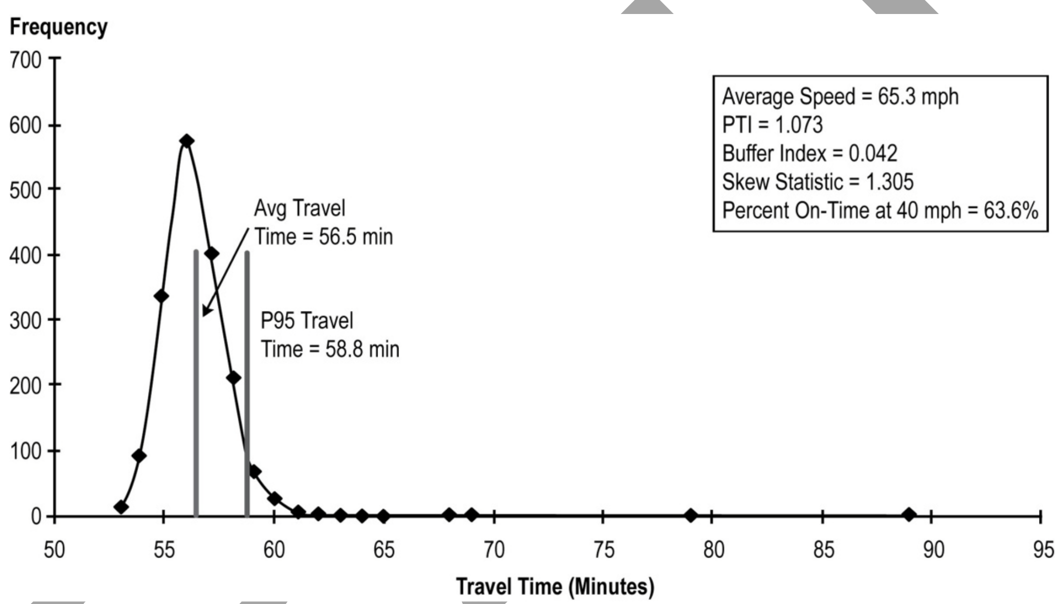


Figure 4.31 I-45, Texas, Southbound
Length = 60.0 miles

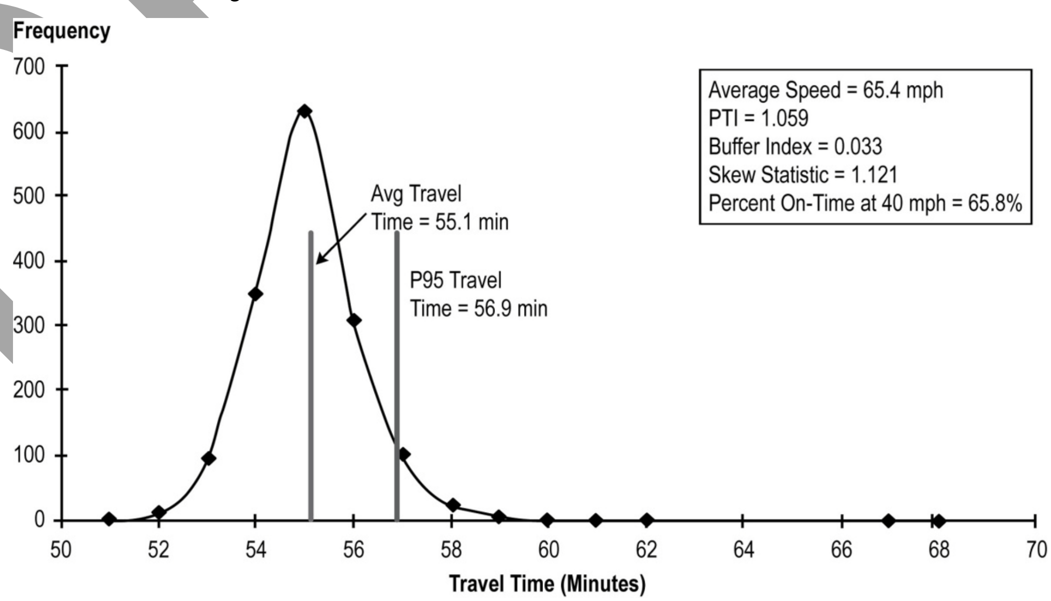


Figure 4.32 I-95, South Carolina, Northbound
Length = 33.1 miles

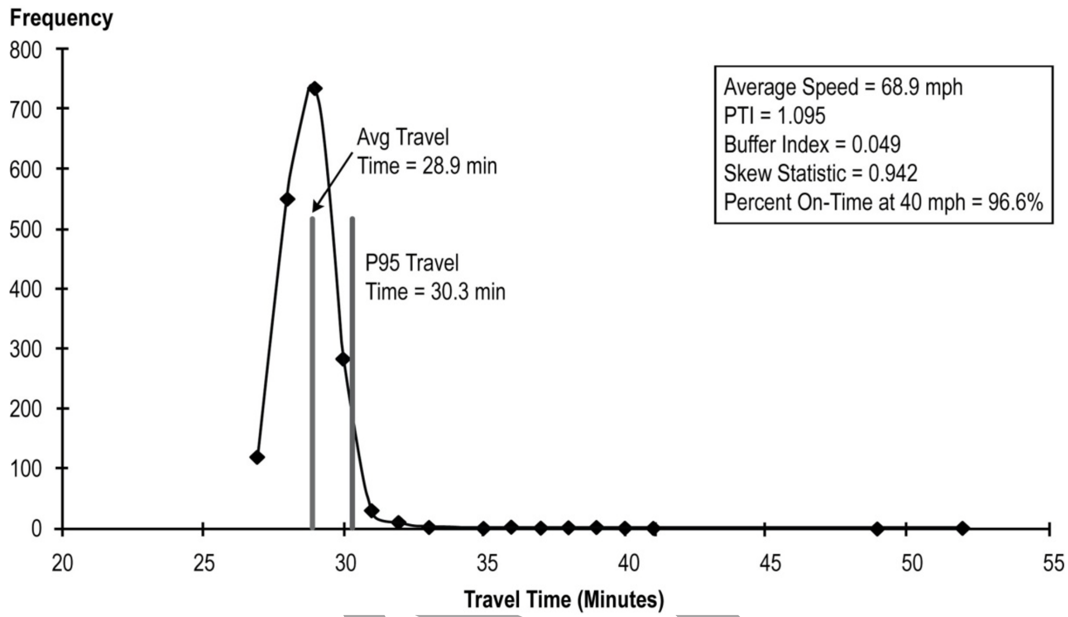
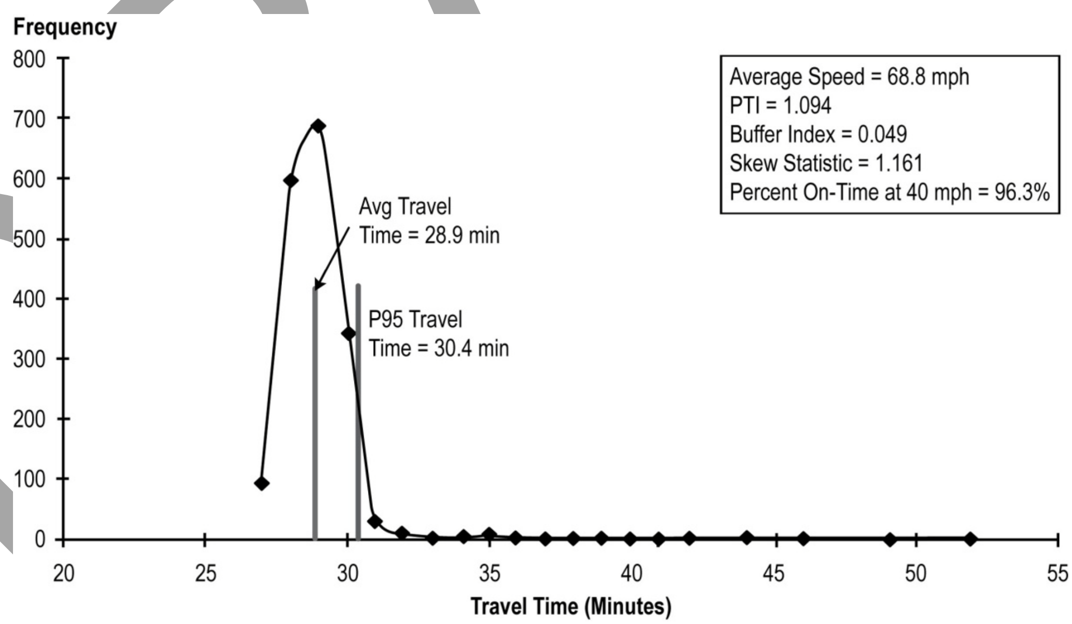


Figure 4.33 I-95, South Carolina, Southbound
Length = 33.1 miles



4.12 VULNERABILITY TO FLOW BREAKDOWN

An alternative way to view travel-time reliability is in terms of the vulnerability or susceptibility to disruptions that lead to congestion. That is, in the absence of recurring congestion, there is a likelihood that a disruption (e.g., an incident) may cause congestion to form. Whether or not congestion will materialize is a function of how severe the disruption is and how much traffic volume is present.

An analysis was undertaken to understand this effect using data from Atlanta. Figure 4.34 shows volumes and TTIs for individual stations (detectors in all lanes at a roadway location) measured at five-minute intervals for weekdays, nonholidays. In Figure 4.34, the transition from uncongested mid-day conditions to "prepeak" conditions can be seen around 2:50 p.m. Volumes start to turn up quickly at about this time and the 95th percentile TTI turns up even more sharply. However, average TTI stays almost unchanged until after 3:15 p.m. The point at which the 95th percentile and average TTIs diverge (i.e., 2:50 p.m.) can be thought of as the point where the facility begins to be highly vulnerable to breakdown. On average days, there is little noticeable congestion, but on the worst days, congestion builds rapidly. This period between "TTI divergence" and the uptick in average congestion is therefore extremely important to concentrate on from a traffic management standpoint.

Figure 4.34 Beginning of Weekday Peak, I-75 Atlanta, Station 750502
2008

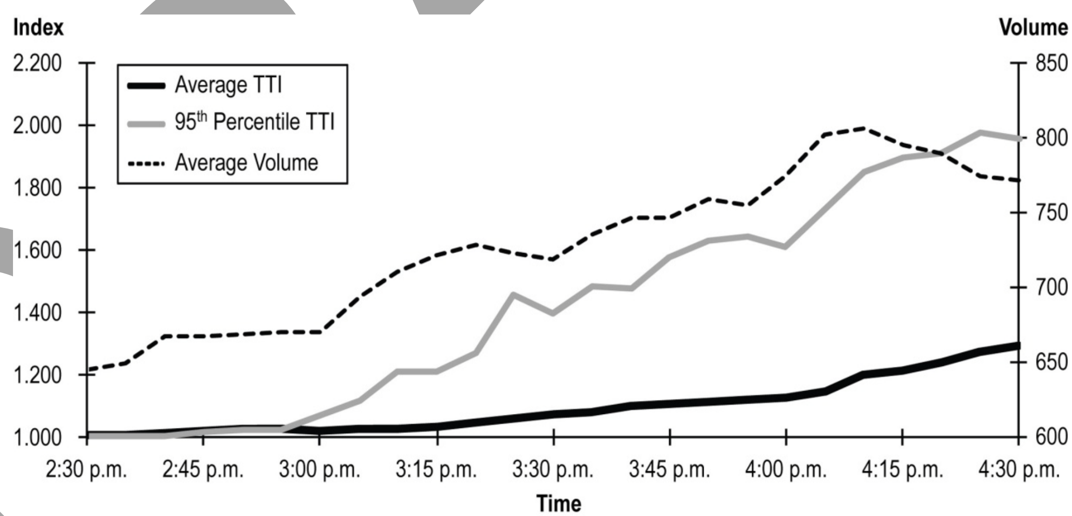


Figure 4.35 shows the corresponding probability of congestion (where speeds are less than 50 mph, the approximate point of breakdown flow according to the *Highway Capacity Manual*)) for this location entire afternoon time period for the same location as above. Figure 4.36 shows two characteristics of congestion at point locations. First, there appears to be a nonlinear relationship between average TTI and the 95th percentile TTI, as seen in the steeper growth of the curves up to the peak. Second, average volume peaks early (around 4:10 p.m.)

stays relatively flat throughout the peak, indicating that congestion is suppressing volumes, as discussed n Section 4.7.

Figure 4.35 I-75 Atlanta, Station 750502
2008

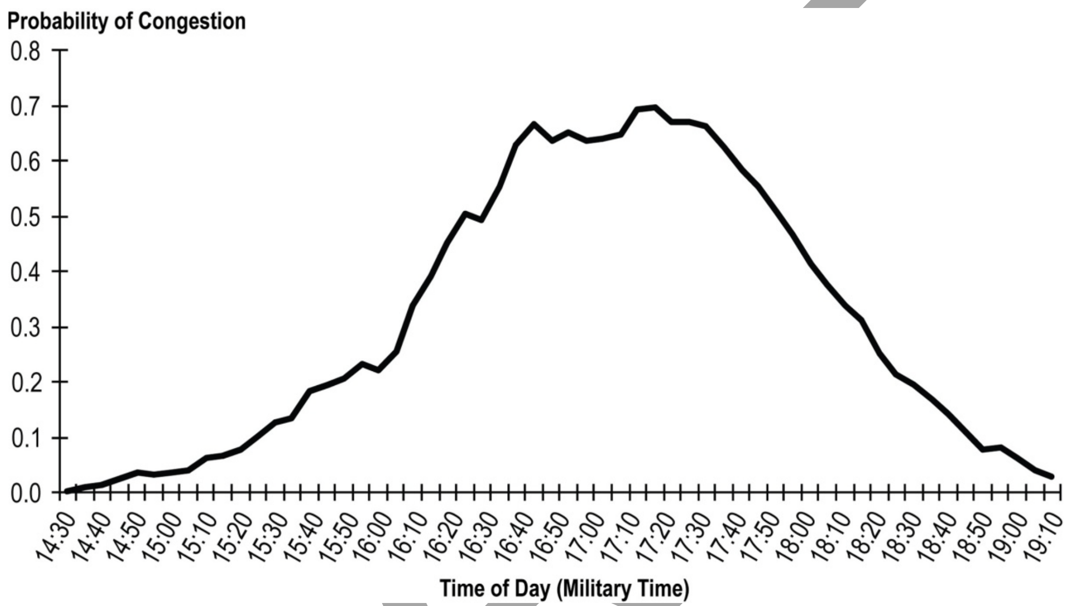
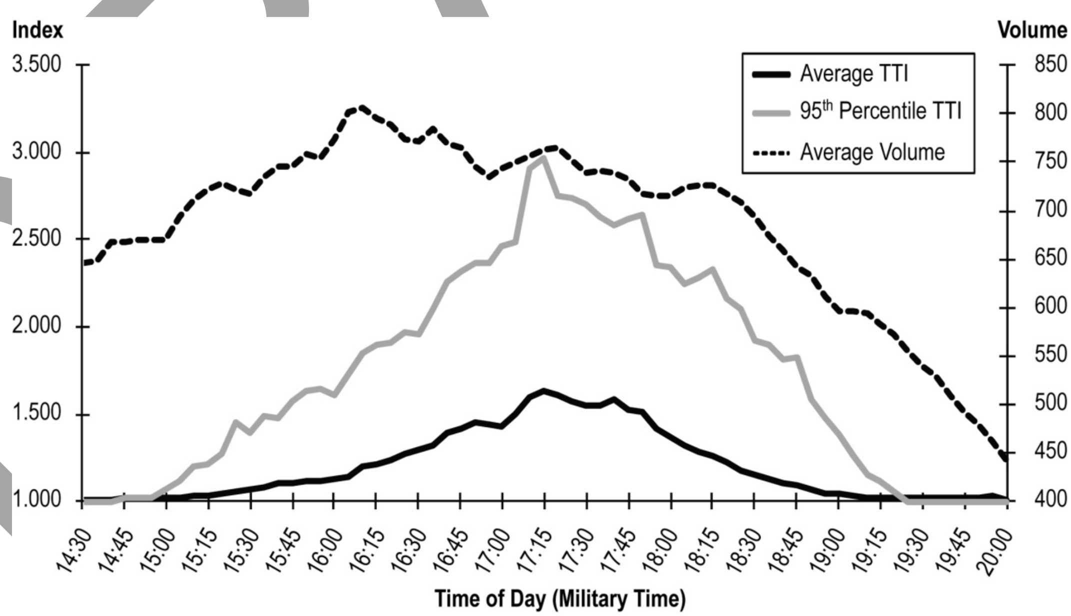


Figure 4.36 Complete Weekday Peak, I-75 Atlanta, Station 750502
2008



4.13 RELIABILITY OF URBAN TRIPS BASED ON THE RELIABILITY OF LINKS

The approach taken in this research for urban conditions is to define travel-time reliability over a relatively homogenous (in terms of geometric and traffic conditions) section of highway, typically 4-5 miles in length. In many transportation modeling applications, it is desirable know the travel time of entire trips, and by extension, the reliability of trips. The data sources used in this study precluded studying entire trips (from origin to destination) because they are collected at the roadway level.

However, we conducted an experiment with urban freeway data in Atlanta in an attempt to develop trip-base reliability. Specifically, we were interested in seeing if the reliability of a trip can be predicted from the reliability of the individual links comprising the trip. Here we use the term "trip" to occur solely on the freeway, as we did not have data for the access and egress from the freeway for the trip. "Links" refer to stations (detectors for all lanes at a specific location)

From the Atlanta section data, we developed extended sections by combining two adjacent sections. This resulting in four one-way trips (one in each direction) for:

- I-75 North, from I-285 to Barrett Parkway (12.53 miles):
  - 25 links northbound; and
  - 20 links southbound.
- I-285 Northern Arc, from I-75 to I-85 (10.37 miles):
  - 36 links eastbound; and
  - 34 links westbound.

Note that the number of links is different for the directions because of station placement. For each directional section, morning and afternoon peak times were considered. The analysis proceeded as follows.

First, reliability metrics for the individual links were calculated for each direction and time slice. Then, reliability for the entire trip was calculated. A simple method of combining the link reliability metrics was then used: average all the metrics for the links and see if it was correlated with the trip metrics. Figures 4.37 and 4.38 demonstrate that the metrics are very highly correlated. Simple nonlinear functions were then fit to the data: (All coefficients are significant at an alpha level of 0.001, most at an alpha level of 0.0001. and RMSE = Root Mean Squared Error; used as a measure of goodness of fit when no intercept term is specified in regression analyses.)

$$95^{th}\ percentile\ TTI_{trip} = X_1^{0.8014}\ \text{(RMSE=0.032)} \quad [1]$$

$$80^{th}\ percentile\ TTI_{trip} = X_2^{0.8702}\ \text{(RMSE=0.018)} \quad [2]$$

$$MeanTTI_{trip} = X_3^{0.9020}\ \text{(RMSE=0.001)} \quad [3]$$

$MedianTTI_{trip} = X_4^{1.0600}$ (RMSE = 0.026) [4]

$StandardDeviation_{trip} = 0.6195*X_5^{1.1163}$ (RMSE=0.133 percent, R^2=0.976) [5]

Where:

- X_1 = *average of the 95th percentile TTIs for all the links in the trip.*
- X_2 = *average of the 80th percentile TTIs for all the links in the trip.*
- X_3 = *average of the mean TTIs for all the links in the trip.*
- X_4 = *average of median TTIs for all the links in the trip.*
- X_5 = *average of the standard deviations of the TTIs for all the links in the trip.*

It should be pointed out that the strong correlation is probably due to the fact that the trip-based measures use the travel times from the individual links. However, in travel demand forecasting models, trip travel times are calculated this way. While the analysis was restricted to freeway sections only, we do not see why nonfreeway links could not be added to the trip, and their reliability metrics treated in the same way, i.e., combined with the freeway links' reliability statistics. Finally, the trips used here are still relatively short, even for urban conditions. Longer trips may run into the same time dependency noted for long distance trips in Section 4.11.

Figure 4.37 Trip versus Link-Derived Reliability
Mean TTI

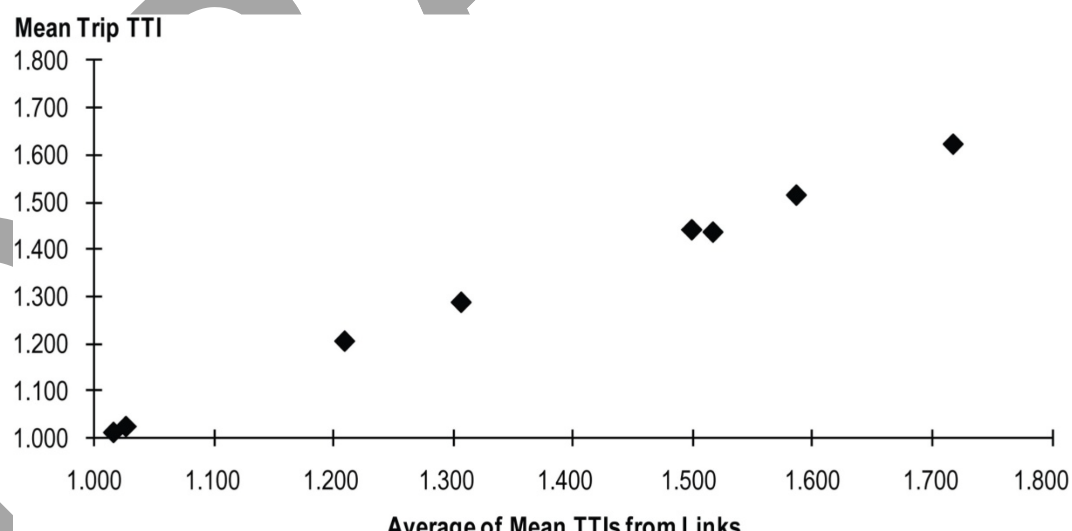


Figure 4.38 Trip versus Link Reliability
Standard Deviation

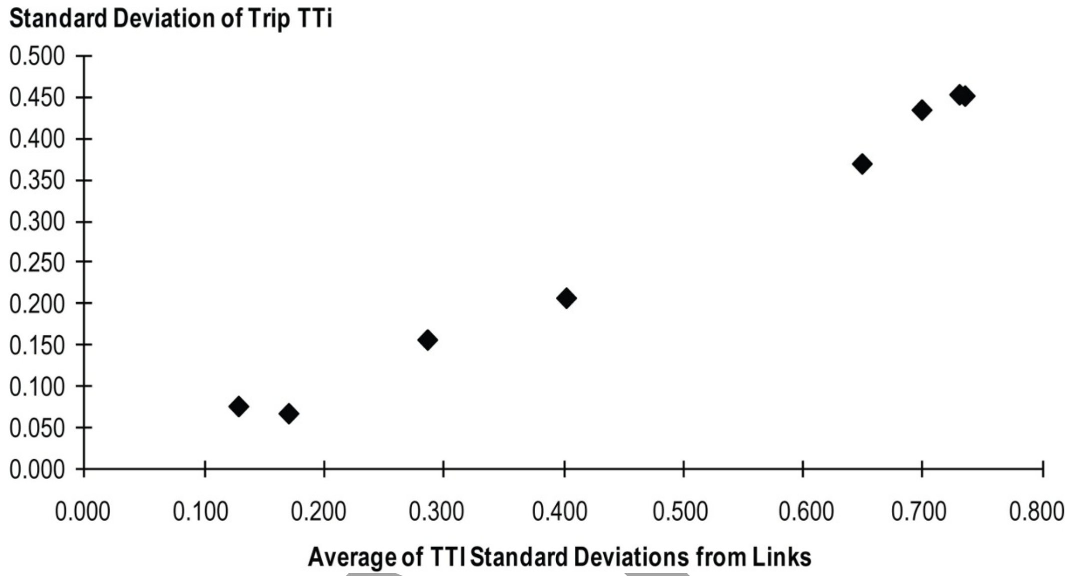
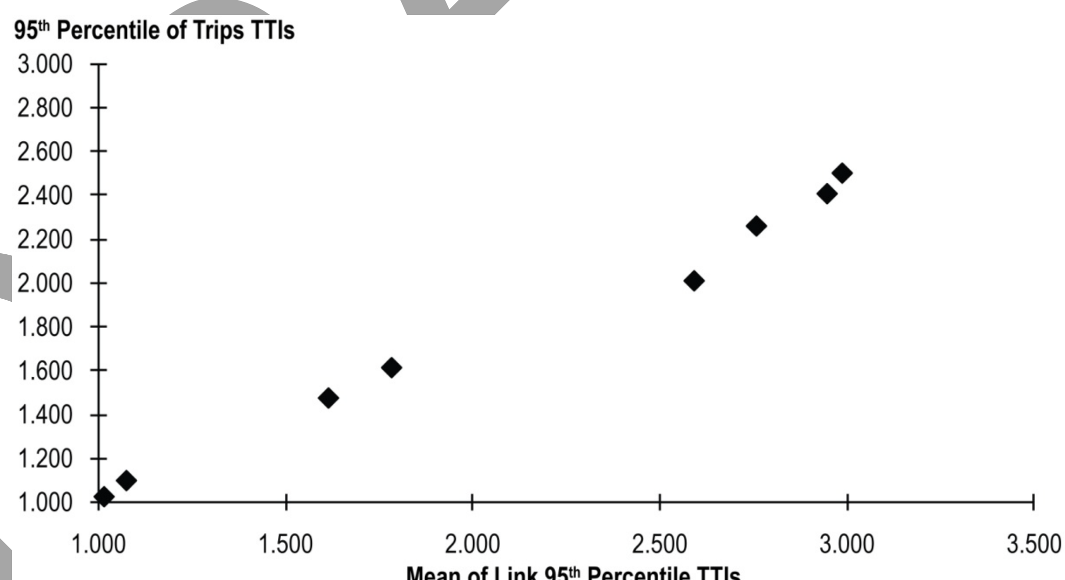


Figure 4.39 Trip versus Link Reliability
95th Percentile TTI



References

1. Brilon, Werner, Geistefeldt, Justin, and Zurlinden, Hendrik, *Implementing the Concept of Reliability for Highway Capacity Analysis*, Transportation Research Board Annual Meeting 2007 Paper #07-295, Washington, D.C. (2007).

5.0 Estimating Congestion by Source: The Cause of Congestion

5.1 INTRODUCTION

The objective of this section is to describe in more detail the factors that cause congestion to form, with the specific intent of helping agencies respond cost-effectively in ways that reduce the formation of congestion.

This document discusses the results of a series of analyses that examine the causes of congestion on freeways, first in Atlanta, then in greater detail in the Seattle metropolitan region. The analyses were based on an entire years worth of freeway operations data, covering a significant portion of freeways in the regions. The freeway performance information was combined with data that described when incidents, accidents, and construction activity occurred, as well as tracked the effects of weather. The effects of a variety of special events also were tracked in Seattle. The analyses did not include an examination of ramp delays, either entering (ramp meters) or exiting (queuing due to inadequate ramp intersection capacity) the roadway.

A large number of analyses have been performed over the years to examine the causes of roadway delay (refer back to Table 2.9). Traditionally those studies have been based on: 1) queuing analysis of specific incidents; 2) simulation of specific roadway corridors, given a limited set of volume conditions and incident/nonincident conditions; and 3) national scale estimates based on base roadway volumes and reported incident/crash rates.

5.2 A PRELIMINARY LOOK AT CONGESTION-BY-SOURCE: ATLANTA

A simple analysis was undertaken in Atlanta to develop a point of comparison for the detailed Seattle analysis. For the Atlanta study sections for their peak periods, the times and locations of incidents and weather conditions were merged with the traffic data. Incidents that occurred just prior to the start of the peak were assumed to have influence on traffic flow: any incident that started 15 minutes prior to the peak-start or lane-blocking incidents that started an hour prior to the peak start were counted. Each peak period then was assigned an influencing "cause": incidents, weather, or both. No attempt was made to track incident-caused queues in time and space; if an incident occurred at any time or location during the peak, the entire peak was assigned as incident-influenced. This assumption will overstate the importance of incidents as a contributor to total congestion.

Overall, the recurring/nonrecurring split is roughly 50/50 (Table 5.1). A more detailed breakdown of "nonrecurring" appears in Table 5.2 where the significance of incidents is clear, roughly a third of the congestion occurred on days when incidents occurred.

Table 5.1 Recurring versus Nonrecurring Congestion, Peak Period, Atlanta *2008*

	Congestion Type			
	Nonrecurring Peak Periods		Recurring Peak Periods	
SHRP Section	Number	Percent	Number	Percent
I-75 Northbound from I-285 to Roswell Road	128	52.0%	118	48.0%
I-75 Southbound from I-285 to Roswell Road	81	41.8%	113	58.2%
I-285 Eastbound from GA 400 to I-75	89	46.8%	101	53.2%
I-285 Westbound from GA 400 to I-75	126	56.5%	97	43.5%
I-285 Eastbound from GA 400 to I-85	159	64.6%	87	35.4%
I-285 Westbound from GA 400 to I-85	134	56.5%	103	43.5%
I-75 Northbound from Roswell Road to Barrett Parkway	121	49.2%	125	50.8%
I-75 Southbound from Roswell Road to Barrett Parkway	100	42.3%	136	57.6%
Total		51.6%		48.4%

Table 5.2 Congestion by Source, Peak Period, Atlanta *2008*

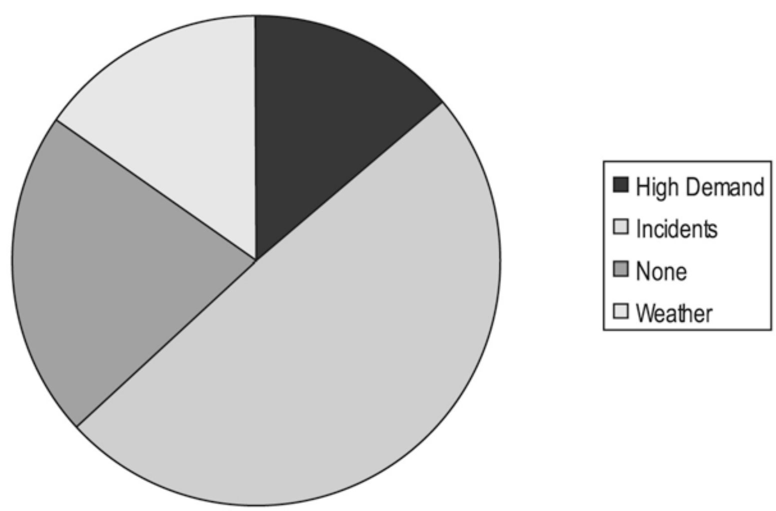
Source	Percentage
Recurring (Bottleneck)	48.4%
Incidents	32.8%
Weather	11.1%
Incidents and Weather	7.7%

Figure 5.1 examines congestion causes for the 50 worst congestion peak periods on these sections, i.e., those with the highest TTI. Another potential source of congestion was added here – high demand – which is defined as days with

demand volumes higher than the average, plus five percent. For simplicity, only one source was assigned responsibility in a hierarchy: incident, weather, or high volume, in that order. For example, if a day had both at least one incident and high volumes, the cause was assigned as "incident." Even allowing for this extra source, there are still 21 percent of the days that could not be assigned to a source. There are several potential other sources that may explain these conditions:

- Congestion that forms "off section" and spills back onto the study section, which could be from a downstream section or an exit ramp to either a surface street of an intersecting freeway.
- Minor perturbations in traffic flow at a microlevel, which could be brief surges in demand or variations in driver behavior that cause flow breakdown when volumes are operating very near to physical capacity.

Figure 5.1 Congestion Causes for the 50 Worst Congested Peak Periods
Atlanta, 2008



5.3 A Closer Look at Congestion-by-Source: Seattle

5.3.1 Background

Analysis Overview

To examine some of the issues raised in the preliminary Atlanta, analysis, a detailed analysis was conducted using data from Seattle. The work performed by the L03 research team with the Seattle data differs from these efforts in several key ways. The most significant difference is in the data used in the analyses. This effort uses measured roadway performance data (volumes and travel times taken every five minutes) for an entire year, on just under 120 center-line miles of urban freeway. It includes all crashes which occurred on those roadway segments, as well as all noncrash incidents to which Washington State Department of Transportation (WSDOT) personnel responded, and the National Oceanic and Atmospheric Administration weather data for the region. Based on these data, the analysis then examined how a wide variety of factors effected travel times experienced by travelers on different freeway sections throughout the metropolitan region. Unlike traditional queuing analysis, use of segment-based travel times over defined roadway segments as the dependent variable allows the research team to explore both upstream and downstream impacts of a wide variety of disruptions, as well as examining the effect of those disruptions on travel-time reliability.

The primary intent of this report is to explore the causes of congestion on the instrumented Seattle freeway system, and summarize those findings in a generalized manner so that the results are applicable elsewhere.

Factors Affecting Congestion

Congestion obviously occurs where there is too much volume and too little roadway capacity. Thus, it can be said that all congestion is caused by having too much traffic volume. In some cases, "too much volume" is associated with routine temporal fluctuations in demand, such as peak period commute congestion in urban areas. In other cases, it is associated with demand associated with special events, such as sports or cultural activities. In other cases, analysis suggests that microscale variations in demand during periods of already high demand can cause congestion even when hourly volumes would not indicate that "capacity" has been reached.

However, traffic engineers also know that roadway capacity is not a constant. A variety of factors reduce effective or operational roadway capacity from the "normal" capacity figures that are computed with Highway Capacity Manual procedures. These are the factors that cause congestion to occur even when volumes are "lower" than "normal, theoretical" roadway capacity.

It is commonly accepted that there are a limited number of basic factors that cause congestion to form. They are commonly referred to as "the seven sources of congestion":

1. Traffic incidents;
2. Weather;
3. Work zones;
4. Fluctuations in demand;
5. Special events;

6. Traffic control devices; and
7. Bottlenecks/inadequate base capacity.

Traffic incidents (including crashes, debris on the roadway, and other types of incidents) decrease effective capacity either by physically blocking lanes or by producing visual distractions that cause motorists to slow, resulting in lowered roadway throughput.

Weather has similar effects on effective roadway capacity. Poor weather causes drivers to drive more cautiously, slowing down and leaving more space between vehicles in order to maintain safety – thus reducing effective roadway throughput.

Work zones narrow lanes or reduce the total number of lanes available. They also can reduce speed limits and frequently include right/left lane shifts. All of these physical changes decrease available or effective roadway capacity.

Fluctuations in demand cause congestion because demand that exceeds roadway capacity causes queuing to occur, and that queuing reduces effective vehicle throughput. Thus, the arrival rates (timing) with which vehicles use a roadway segment is another cause of congestion. In a simple example, a two-lane (one direction) freeway has a capacity of 4,000 vehicles per hour (vph). In a three-hour period, 11,000 vehicles need to use that facility. If that demand is uniformly distributed, no congestion occurs, as volume never exceeds 4,000 vph. However, if demand arrives at the roadway section in the form of 2,200 vehicles in the first hour, 5,000 in the second hour, and 3,800 in the last hour, congestion will occur in the second hour. That congestion will cause queuing that further reduces effectively roadway capacity, creating delays even in the last hour, despite the fact that demand is then lower than theoretical capacity.

Special events cause congestion because they create significant fluctuations in demand. The starting and ending times of major events create surges in traffic demand that overwhelm roadway capacity near the event venue, causing congestion.

Traffic control devices (e.g., traffic signals) delay some vehicles in order to allow other vehicles to move safely. Therefore, by definition, traffic control devices create delay (control delay). When optimally timed, traffic control delays minimize congestion. When not optimally timed, traffic control devices create unnecessary delays to vehicles.

Inadequate base capacity and bottlenecks create delay in the same way that traffic volume fluctuations cause delay. "Inadequate base capacity" (i.e., not enough roadway capacity for "normal" traffic flows) most frequently manifests itself at points along a segment of roadway where effective capacity is "routinely" lowest – a bottleneck. Bottlenecks are a decrease in effective roadway capacity that occurs as a result of some physical change in roadway geometry or environment (e.g., a lane drop, a weaving section). That geographic location becomes the initial point where traffic demand first exceeds effective capacity, causing queuing, which further decreases effective capacity.

As can be seen from the above discussion, two of the causes of congestion (Fluctuations in demand and special events) influence the demand side of the volume/capacity relationship which ultimately determines formation of congestion, while the other five influence the actual volume carrying capacity of the roadway. The "cause" of congestion has significance to transportation agencies, in part, because it describes the level of control the agency has over that measure – and thus the level to which it can anticipate and therefore mitigate congestion formation. For example, the agency has no control over weather. It can only react to weather events. On the other hand, the agency can directly influence other causes, such as the operation of traffic control devices or the design and timing of work zones.

5.3.2 Data Description

Traffic Incidents

Data on traffic incidents were obtained from two sources, the Washington State Department of Transportation's (WSDOT) incident response program resource management system database (WITS), and the State of Washington's accident reports.

The more detailed and useful data source is the WSDOT WITS database. This database was created to track the work performed by WSDOT's freeway service patrol personnel. Key variables for each task performed by WITS field staff are recorded. As a result, WSDOT has a record of when an incident is reported (used as an estimate of when that event occurs), as well as when the incident respondent declares the site of the incident cleared. The location (route, milepost, and direction) of the incident also is reported, as are whether a lane of traffic is blocked by the incident. While these data allow detailed analysis of different incident types, the analysis for this project limited the analysis to: 1) when and where an incident occurred; 2) how long that incident lasted (in seconds); and 3) whether that incident closed a lane. Note that for the year 2006 incident data for weekends and night are not reported within WITS.

Accident records were used to supplement the WITS data. Accident records should be present for all significant accidents that occurred within the study area. During peak periods, accident records generally match with WITS records, as WITS members are usually called to the scene of accidents when they are on duty. (There were a number of instances in which accident records and WITS records appeared to reference the same event but listed slightly different starting times. This project did not try to identify which of these times were "correct," but kept both, and used the time related to a particular kind of event. That is, for an analysis of crash effects, the time from the accident record was used. If the analysis concerned the effects of all incidents, then the time noted in the WITS database was used.

Weather

The weather data used for these analyses were obtained from publicly available records collected from the National Oceanic and Atmospheric Administration (NOAA) weather station at Sea-Tac International Airport. The analytical database created for this study tracked the major statistics reported by NOAA, including the following:

- Visibility:
  - Up to 10 miles.
- Temperature:
  - Dry bulb.
- Wind speed:
  - Average speed; and
  - Gust speed (highest gust speed that hour).
- Precipitation:
  - Inches.
- Weather type:
  - Rain;
  - Mist;
  - Thunderstorm;
  - Drizzle;
  - Haze;
  - Snow;
  - Freezing;
  - Small hail;
  - Hail;
  - Ice pellets;
  - Squall; and
  - Fog.

These data were too detailed for the basic analyses intended for this study. Consequently, the project team performed a considerable amount of analysis to determine the types of summary weather statistics that would effectively indicate whether weather conditions contributed to congestion. A summary of these tests is given in Appendix E. Findings from the most important of these tests are presented under the subsection "Effects of Weather" later in this chapter. The outcome of those tests was to define the indicator of "bad weather" as any time period in which any measurable precipitation had fallen at some time in the previous hour. Importantly, the use of this indicator discounts several weather effects: wind, fog, snow, and rainfall intensity.

An analysis of the effects of wind on roadway performance indicated that on the two roadway that cross Lake Washington on floating bridges (I-90 and SR 520), high winds (wind gusts above 20 mph) had an observable effect in moderate volume conditions, especially eastbound when the winds caused waves to crash against the bridge, creating significant spray. (Winds are generally from the south, so the spray affects the eastbound traffic more than westbound traffic). However, wind appeared to have little observable effect on all other freeway corridors in the region.

The analysis of the effects of fog was problematic, as fog tends to be very localized. Thus, while the airport could be very foggy (to the point that landings and take-offs are restricted for lack of visibility), at the same time I-5, passing within two miles of SeaTac, could have clear visibility. As a result, “fog” variable was not useful in identifying specific fog-related delays.

The examination of fog as a weather variable did highlight the problems associated with using weather data from a single point to represent weather experienced around a fairly large geographic region. That is, while the Sea-Tac weather records accurately reflect conditions at the airport, the weather experienced simultaneously in other areas of the metropolitan region can be different. For example, a storm moving south to north that affects SeaTac at 5:00 p.m. will have occurred in the southernmost roadway sections before 5:00 p.m. and in the northern part of the city some time later than 5:00 p.m. In addition, that storm may have dropped exactly 0.25 inches of rain at the airport, but it may have deposited only 0.1 inch south of the airport, and 0.5 inches in areas north of the airport. Therefore, although the rain data are a reasonable estimate of weather conditions, they cannot be used as a precise, highly accurate measure of the actual weather occurring on any given segment of roadway during a specific five-minute time interval.

In addition to the basic time and geographic problems noted above, the snow and rainfall intensity variables presented a second problem. That is that many of the effects of heavy rain (that is, heavy rain short of very intense thundershowers, which rarely happen in Seattle) occur after the precipitation has fallen. This is especially true for snowfall, as the effects of the snow falling are not nearly as significant as the effects from snow accumulations on the ground, depending on the amount remaining on the roadway. For example, snow flurries actively falling have little effect on driving, but four inches of snow on the ground two hours after the snow has stopped falling have a major impact on roadway performance.

Another issue associated with snowfall in the Seattle area was caused by a combination of how rarely snow falls in the region and how travel times are computed. When snow falls (and sticks), Seattleites tend to avoid driving whenever possible. (The region does not use salt; agencies do not clear snow as effectively as those in regions of the country that routinely experience snowfall; and snow is frequently turned into sheet ice on the roadways by cars that do travel, making the area's hilly terrain dangerous. The result is that a large percentage of travelers simply avoid going out). Therefore, after snow falls, volume and lane occupancy are frequently low on the freeways despite the slow speed of those cars that are left. However, the loop detector system only sees low volumes and occupancy values, and can thus overestimate the speeds at which the vehicles are moving. Luckily for this study, the number of days on which snow fell during the analysis year was small.

Work Zones

To identify work zones, Variable Messages Sign (VMS) logs were examined. From the VMS logs, it was possible to identify where, when, and for what period these messages were posted. It also was possible to determine from the logs when lanes were closed, but the number of lanes closed for a given construction lane closure was not incorporated into the analysis database. (Note that the closures recorded on the VMS logs are "approximate" times, e.g., "9:00 p.m. until 5:00 a.m.," and do not represent the exact time when lanes were actually closed and/or open to traffic).

What are not included in the VMS database are "long-term" construction changes, such as narrowed lanes during lengthy construction projects or the presence of construction barrels on shoulders in and approaching the work zone, which are likely to also cause minor disruptions in "normal" traffic flows.

Because the freeways examined were major urban highways, all work zones had nighttime and weekend closures. No lanes were closed during normal weekday business hours.

Fluctuations in Demand

Volume data for the study were obtained from the WSDOT Northwest Region's traffic management center database system (FLOW). All traffic volume data used in the study were collected with permanent inductive loops that are part of that system. Loops are located roughly every half-mile on the freeways analyzed in this study. Each loop reports total volume every five minutes, as well as average lane occupancy for that location.

Because five minutes is the basic WSDOT data reporting period, the analyses for this report were based on these five-minute periods. Traffic volumes were available every five minutes, for every roadway study segment, for all 365 days for 2006. (However, some corridors were missing specific days/times of data because of equipment malfunction).

Because volumes varied over the course of the roadway study segments, several volume statistics were used to describe each five-minute period for each roadway segment. These are:

- The maximum volume observed for the roadway segment in that five-minute interval;
- The minimum volume observed for the roadway segment in that five-minute interval;
- The average volume over the length of the segment;
- The vehicle miles traveled (VMT) for the segment; and
- The vehicle hours traveled (VAT) for the segment.

Volumes were reported in units of vehicles per hour.

Special Events

Some special event data were collected by manually reviewing calendars for major regional venues. (For example, looking up the Seattle Mariners' game schedule allowed the researchers to identify the days on which Mariner baseball games took place in 2006 and when those games started). However, it quickly became apparent that it was not possible to collect uniform "special event" data for this study. In part, this is because there is no uniform definition of how big an event must be to be classified as a "special event." Major league baseball games with 30,000 people attending undoubtedly qualify, but do major college basketball games with 8,000 people attending? What about games with 2,500 people? While all major sporting events have known start times, many (e.g., baseball) do not have consistent durations and, therefore, their ending times are not easily determined. This complicates the analysis of the "after the event" traffic, in many cases beyond what could be addressed in this project.

While there is little argument that major sporting events are special events, what about community events? Large events such as July 4 fireworks displays are obviously special events from a traffic perspective, but what about parades or conventions? Not only are the sizes of these events difficult to obtain, but their start and end times are far less consistent, especially in terms of when traffic volumes going to and from with those events affect roadway performance.

A final consideration in developing the analysis dataset was that special event traffic generally only affects roadway performance near the event venue. That is, when a major college/professional football game takes place, traffic near the stadium is bad, but traffic farther from the stadium is often light (because a large percentage of the population is at the game or watching it on television). Previous work for WSDOT showed that while special event (professional baseball and basketball) traffic had statistically significant effects on major freeways leading to the event locations, roadway performance in the opposite direction before the game began was generally not statistically significantly different (*1*).

Consequently, "Special Event" data need to be applied on a site-specific basis and, therefore, require not only descriptive information (time, location, and size) but also local knowledge of the likely routes of travel affected by the event. This made attempting to analyze 21 roadway corridors on 5 different freeways covering over 120 centerline miles of roadway problematic. In the end, the project team decided to simply use the volume data from the freeway and to analyze the effects of special events as case studies to illustrate the relative size and significance of their impacts.

Traffic Control Devices

This study did not collect data on traffic control devices. All sections of freeway under study operate under ramp metering control. The fuzzy, neutral ramp metering algorithm used by WSDOT changes ramp metering rates dynamically in response to a combination of inputs, including mainline volumes and lane occupancy values at the ramp, upstream of the ramp, and downstream from the ramp, as well as the presence of ramp queues, and the determination of whether those queues are long enough to affect arterial operations.

Ramps are metered whenever congestion routinely forms. This includes all commute periods and most weekend afternoons for freeways near the downtown core areas. Metering is only applied in the direction in which congestion is (or has) formed.

Because only one year of data was analyzed in this study, it was not possible within this analysis to determine the effects of the ramp metering algorithm on congestion. A case study is presented in Section 5.0 that describes the benefits obtained from meters. Other than that case study, traffic control devices are not examined in this report.

Bottlenecks/Inadequate Base Capacity

No specific data were collected relative to the base capacity of the roadways being studied. Several major bottlenecks are represented in the dataset. In most cases, bottlenecks are located at the ends of study sections. One type of bottleneck is a ramp terminal at the end of a roadway. Two examples of this occur: the eastern end of SR 520 (affecting SR 520 Redmond eastbound), and the western end of I-90 (affecting I-90 Seattle westbound). A second type of bottleneck is a freeway to freeway ramp interchange, where ramp volumes overwhelm the interchange capacity. One example is the interchange between northbound SR 167 and I-405 (both directions). This bottleneck affects SR 167 Renton northbound, I-405 Kennydale southbound, and I-405 South northbound. Other freeway to freeway ramps also contribute to congestion, usually because the mainlines to which they lead experience routine back-ups. While these may not be “classic bottlenecks,” ramp queues can cause congestion. Freeway to freeway ramps that exhibit these conditions fairly frequently include SR 520 Redmond going westbound to I-405 Kirkland northbound and I-405 Bellevue CBD southbound, SR 520 Seattle westbound to I-5 Seattle North northbound, and I-5 Seattle CBD southbound. Both the northbound Seattle CBD and southbound Seattle North sections of I-5 can be affected by queues extending from the eastbound SR 520 Seattle study section. Similarly both directions of the I-5 Seattle CBD sections of I-5 are affected by queues on westbound I-90s Seattle section. Finally, the I-90/I-405 ramps cause delays primarily to four movements: to westbound I-90 from the northbound (Eastgate) and southbound (Bellevue CBD) sections of I-405, and to westbound I-90 from northbound I-405. (The ramp to southbound I-405 also backs up, but the queues to that ramp rarely affect I-90 performance because of the storage available on the ramps).

The I-5 Seattle CBD sections (both north and southbound) actually contain several bottlenecks. In addition to the freeway interchanges, this section of freeway is affected by several C-class weaving movements, a variety of lane drops/adds, and the northbound entrance/southbound exit from the I-5 Express lanes. (The performances of the I-90 and I-5 Express Lanes were not included in this study). The southbound entrance/exit to the Express lanes also affects traffic on I-5 southbound on the North King County study section and northbound on the Seattle North section. The I-90 express-lane entrances/exits have less of an impact (the westbound on-ramp modestly affects the I-90 bridge section in both directions).

The other major bottlenecks of special significance are the two Lake Washington floating bridges (SR 520 and I-90). The entrances to the SR 520 Bridge, in particular, are major bottlenecks, as they both involve a combination of narrow lanes, strong visual impacts, and ramp entrances. In both cases, the bridge bottlenecks exist in the middle of the study section. The affected sections are the two Seattle sections of SR 520 and the two bridge sections of I-90.

No attempt was made to quantify the specific capacity reductions caused by these bottlenecks. However, as will be seen in the results presented later in this report, these sections all experience considerably more delay than nonbottleneck freeway sections.

Computed Variables Used for Tracking the "Influence" of Disruptions on Travel Times and Delays

The interaction of all of the factors discussed above is very complex. All analytical methodologies have limitations when trying to determine how each of these factors affects the delays experienced by a traveler using the roadway system. As a result, this study developed a number of additional variables used to help associate travel times, and delays with specific disruptions. To understand the need for these variables, consider the following example incident.

A major traffic accident occurs early in the morning, before the start of the morning commute on the outer extent of the metropolitan region. The accident blocks most of the freeway and lasts two hours, forming a significant queue despite the early hour. Because traffic from the outlying areas is blocked, inbound commute travel times downstream of the accident start off better than normal. The accident is cleared after the morning commute peak begins. Once the accident has been cleared, a major "pulse" of traffic flows downstream from the accident location because the roadway clearance releases the large queue of vehicles stored upstream of the accident scene. That pulse of traffic nearly equals roadway capacity. When normal on-ramp volumes are added to that flow, congestion forms in unusual locations. ***The result is significant travel-time delay continuing to occur well after the accident has been cleared from the roadway, with the congestion occurring well downstream of the accident location.***

If a queuing analysis is performed for the accident location, only the delay computed upstream of the accident location is attributed to the accident, as the downstream congestion occurs both after the accident has been cleared and at locations that are geographically removed from the accident site. Thus, the delays "associated with the accident" are computed to be smaller than the real congestion "caused" by the accident, which should include the delays occurring downstream of the accident site.

At the same time, some of that congestion should rightly be attributed to the fact that peak-period morning traffic will cause congestion anyway. Therefore, not all of the delays in the corridor should be attributed to the accident. The delays are "influenced" by the accident, but high volumes also contribute to the measured delay.

With the above scenario in mind, the project team developed a set of variables to help relate the measured performance of the roadway (travel times, volumes, and delays) to known disruptions. A value was assigned for each of these new, computed "variables for every five-minute time interval in the analysis dataset (i.e., all of 2006). These additional variables included the following:

- Travel delays were computed by corridor segment so that all delay (any travel less than 60 mph, in units of vehicle-seconds) was computed.
- The times when potential disruptions took place were identified for each type of disruption event, and variables identifying that a disruption was "active" or "not present" were created for each five-minute interval for the year.
- Binary "influence" variables were computed for which "influence" was defined as occurring when either: 1) the potential disruption event was active during a given five-minute period; or 2) travel times for the corridor were observed to be slower than any observed during the observed disruption. (This definition of "influence" essentially means that slow-downs occurring in the corridor during the period of active "disruption" are *at least partially caused* by that disruption. That is, travel times are "influenced" by a given disruption. In the analysis, the binary "influence" tag stays "on" until travel times in the corridor return to values equal to or faster than the fastest travel time observed during the duration of event itself. This means that if a crash or incident occurs at the beginning shoulder of a peak period, and some congestion forms (even if the majority of that congestion is caused by the increasing peak period volumes), the "influence" tag will likely stay "on" until after the peak-period congestion eases. This is an intended outcome. It

signals that the disruption (crash/incident) may have caused congestion to be worse and last longer than it otherwise would have. The influence tag is turned "off" once travel times return to "predisruption" levels, indicating that any queues present in the corridor are no larger than those that existed before the effects of the disruption. A more complete discussion of the "influence" variables is found in the Appendix D.)

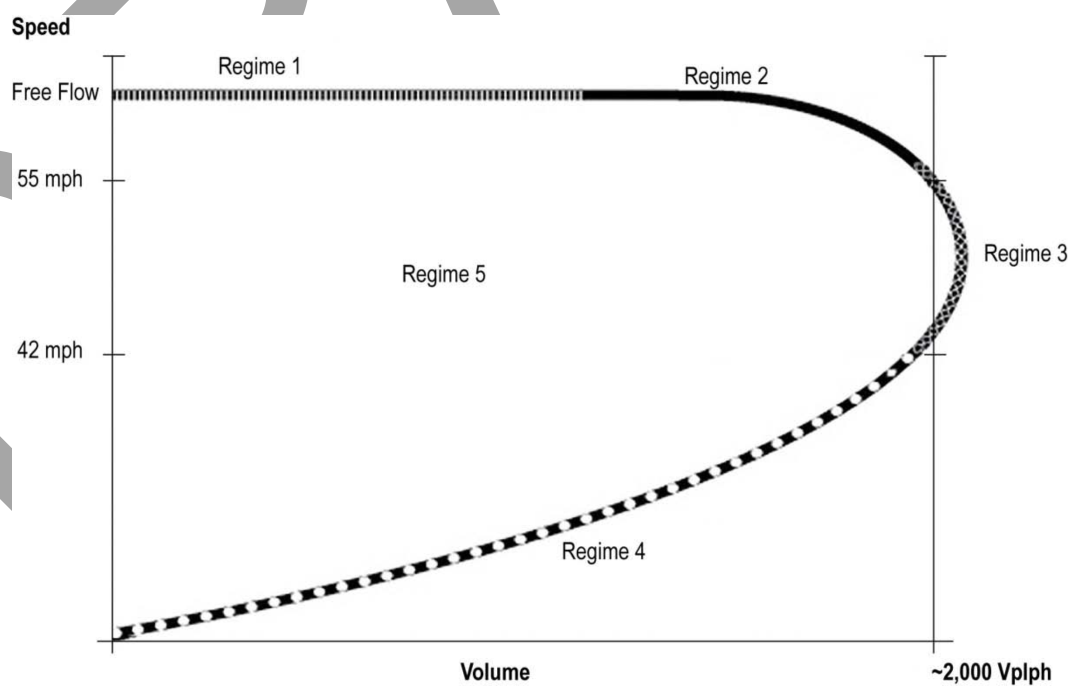
- "Influence" variables were computed for: 1) all incidents; 2) only those incidents that involved lane closures; 3) vehicle crashes; 4) active construction events; 5) bad weather; and 6) rubbernecking, where rubbernecking was defined as a time during which a crash or incident was active on the roadway section being studied, but in the opposite direction of travel. (A variety of "influence" variable calculations were computed and tested. A more complete discussion of these variables is given in Appendix D.)

- Variables were developed that would allow "off-segment" congestion influences to be related to the segment under study. (A detailed description of the variable codes (categories) used to indicate influence on congestion from off-study segments to the study section of interest is found in Appendix C – Variable Definitions.) These variables were activated when the first detector (mainline or ramp) downstream of the study section had an occupancy value of greater than 35 percent for the five-minute period of interest. When that occurred, these variables were set to a categorical value that described the "influences" on the congestion of that downstream segment. Variables were created for the downstream mainline roadway sections, for freeway-to-freeway ramps known to experience back-ups, and for major off-ramps known to spill back on the mainline roadway during peak commute periods. These variables were designed to allow transfer of the effects of a downstream disruption to an upstream roadway study segment when queues from that disruption extended off the end of the downstream segment. (For example, if a crash on the roadway section just north of the CBD caused a queue on I-5 northbound, when that queue reached the detector just downstream of the northbound CDB roadway study section, the variable representing the mainline roadway section downstream of the CBD section would be set to "Crash Influenced Congestion" so that analyses of the CBD roadway section would include the fact that an off-segment crash was influencing the performance of the roadway segment).

- A variable called "Regime" was developed to describe the "worst" condition found in the test segment during each five-minute interval. (A detailed description of the regime variable is found in Appendix C .) "Regime" is a categorical variable in which 1 = free-flow traffic, low volumes, 2 = free-flow traffic, less than one lane of capacity remains, 3 = constrained flow, very high volumes, 4 = congestion exists, and 5 = recovery. Regime was used to define the basic operating condition of the roadway study section. (Regime is illustrated in Figure 5.2).

- Six binary variables were defined to indicate whether a roadway section moved from a free-flowing regime to a congested regime within a given timeframe. This allowed an estimate of the probability that a specific event resulted in congestion formation when the period was compared to similar time periods on other days when operating conditions were similar. Three binary variables described whether roadway operation moved from Regime 2 to Regime 4 within 5, 10, or 15 minutes. Three more variables described whether roadway operation moved from Regime 3 to Regime 4 within 5, 10, or 15 minutes.
- The time "when congestion ends" was computed for both the A.M. and P.M. peak periods. This was defined as the first five-minute time period after the start of the peak period (7:00 a.m. or 4:00 p.m.) when travel times were at least faster than five percent above travel at the speed limit. (For example, if travel at the speed limit required 300 seconds, "congestion ended" for the peak period on any given day when four consecutive travel times were observed to be below 315 seconds. A more complete discussion of this variable is included in Appendix C. On 11 of the 42 study sections, this definition created mean "congestion ending" times for the A.M. peak period that were later than noon due to various volume and bottleneck conditions which cause mid-day traffic to routinely travel below the speed limit. For some specific analyses, congestion was defined **on these sections only** as being when travel time dropped to within 10 or 20 percent of travel at speed limit).

Figure 5.2 Illustrations of Roadway Operating "Regimes"



5.3.3 Findings from Seattle

This section is divided into four major subsections:

1. Congestion by source;
2. The effect of weather;
3. The effects of crashes and incidents on travel times; and
4. The effects of crashes and noncrash incidents on the extent of congestion.

The first subsection examines, at an aggregated annual level, how delay changes given different types of disruptions to the fixed infrastructure. Congestion sources examined include weather, crashes, other noncrash incidents, and construction activities.

The second subsection looks specifically at how weather, and primarily rain, affects travel times and congestion formation.

The third subsection examines how travel times change given the occurrence of incidents and the queues that result from those disruptions. As part of this analysis, the specific effects of vehicle crashes are examined, both independent of noncrash incidents and in combination with noncrash incidents.

The fourth subsection examines how the duration of peak-period-related congestion changes as a result of crashes and noncrash incidents. The intent of this analysis is to put into context how crashes and incidents change the travel experiences of commuters in a congested urban area.

Congestion by Source

This analysis examined how different types of disruptions influence the formation of congestion and the degree of delay experienced by travelers. It covered only general purpose travel lanes (no HOV or HOT lanes) and used units of vehicle-hours of delay, not person-hours, as the available data did not account for changes in vehicle occupancy during different days of the week, times of day, or types of facilities (e.g., weekends having much higher vehicle occupancy rates than weekdays, commute hours having generally higher occupancy rates than the middle of the day on weekdays, and HOV lanes having much higher occupancy rates than general purpose lanes). The analysis covered only urban freeways in the Seattle metropolitan region. The analysis did not attempt to differentiate among relative causes when two or more causative factors were present. (That is, when a crash happened in the rain during the peak period in the peak direction, the analysis did not attempt to determine how much of the delay was caused by the crash, how much was caused by rain, and how much was caused by high peak-period volumes.)

Methodology

The congestion by source analysis computed delay per five-minute period for all five-minute periods in the year (2006) and assigned that delay on the basis of the "influence" variables associated with each of those five-minute periods. (See Appendix C for a description of the influence variables.) Delay was computed with the following equation:

(Actual Travel Time – Travel Time at the Speed Limit) * (Roadway Segment Volume) where Roadway Segment Volume was chosen to be the maximum volume observed in the study section for that five-minute period. (This slightly overstated delay in lower volume periods but better estimated the number of vehicles actually in the roadway section during times of peak congestion. This is because actual volume counts tend to underestimate the number of vehicles queued within a section during times of heavy congestion.) Where study section travel times were faster than the speed limit, conditions were assumed to be operating at the speed limit.

A categorical variable was developed that allowed any combination of "influences" to be maintained simultaneously. The following influences were tracked:

- No cause indicated;
- Only incident-influenced queues are present;
- Only crash-influenced queues are present;
- Only rain is present;
- Both a crash and an incident have influenced queues that are present;
- Both rain and an incident have influenced queues that are present;
- Both rain and a crash have influenced queues that are present;
- Rain, a crash, and an incident have influenced queues that are present;
- Queues from a ramp have influenced mainline queues, but the ramp delays have no identified influence factor;
- Construction activity has influenced queues;
- Construction and queues from a ramp – cause unknown – have influenced mainline queues;
- Construction and an incident have influenced queues present;
- Construction and a crash have influenced queues present;
- Construction and rain have influenced queues;
- Construction, a crash, and an incident have influenced queues that are present;
- Construction, rain, and an incident have influenced queues that are present;

- Construction, rain, and a crash have influenced queues that are present; and
- Construction, rain, a crash, and an incident have influenced queues that are present.

Delay statistics were then aggregated by type of "influence" present. Traffic volume, whether it was "routine" volume or an unusual surge in volume associated with something like a special event, was not explicitly tracked in this analysis. "Unexplained congestion" was assumed to be caused exclusively by the presence of too much traffic volume.

Results

Table 5.3 summarizes the amount of delay influenced by each type of disruption tracked in this study. "Percentage of delay" was computed by totaling all vehicle hours of delay in the region associated with each of the types of disruptions, and then dividing by the sum of all measured delays. This computation automatically weighted the delays experienced by each roadway on the basis of the relative amount of VHT occurring within that roadway section. (In Table 5.3, delays that occurred when more than one type of disruption influenced the size and scope of that delay are counted in each of the categories of disruption and, therefore, the percentages total to more than 100 percent.)

Table 5.3 Percentage of Delay by Type of Disruption Influencing Congestion

Causes of Congestion Ongoing Disruptions that Influence Congestion Duration and Severity	Percentage of Delay[a]
Incidents	38.5%
Crashes	19.5%
Bad Weather (Rain)	17.7%
Construction[b]	1.2%
No Cause Indicated (mostly volume)	42.2%

[a] Delays that occurred when more than one type of disruption influenced the size and scope of that delay were counted in each of the categories of disruption and, therefore, the percentages total to more than 100 percent.

[b] "Construction delays" do not include any delays caused because general roadway capacity was reduced as a result of temporarily narrowed or reconfigured lanes. It was computed only when construction activity actively took place along the roadway.

Of interest is the fact that rain had almost as much influence over congestion as vehicle crashes. Not surprisingly, construction (defined as lane closures during active construction or maintenance activity) had the least influence on congestion formation. The number associated with construction is small in large part because construction closures are only allowed to occur on urban area freeways during the late night hours, when volumes are low. Thus, even when congestion (measured in terms of either the queue length or the amount of time an individual spends in that queue) is significant as a result of construction lane closures, total vehicle delay (vehicle-hours) is small relative to the amount of delay experienced in the peak periods, when volumes are high.

One type of construction delay **not** included in Table 5.3 is delay caused by the temporary geometric changes (narrowed lane widths, lane shifts) that are commonly required during many urban freeway construction activities. These geometric restrictions are likely to cause congestion to form earlier and last longer than it would with the roadway's normal geometry. The project team did not attempt to establish when these semi-permanent geometric conditions were implemented, nor did we attempt to associate delays with these changes during nonclosure hours (e.g., A.M. and P.M. peak periods).

The "no cause" in Table 5.3 means that no cause of congestion was reported other than high traffic volume levels. The project team examined a number of these conditions as case studies. It was clear from that review that a variety of disruptions occur that affect traffic flow but that are not recorded within conventional traffic operations databases. Many of these disruptions are visual distractions (e.g., boats on the lake, sunshine slowdowns) that cause measurable delays only when traffic volumes are relatively high. In some of the case study investigations, traffic volumes on the study corridor were abnormally high because of disruptions on parallel roadways. This analysis did not attempt to track route diversion onto parallel roadways and, therefore, was not able to associate congestion on one roadway with disruptions occurring on a second roadway. This subject is discussed in more detail later in this section.

Table 5.4 shows a more disaggregated version of Table 5.3 in that it tracks multiple disruptions occurring at the same time. Table 5.4 also illustrates the wide variation among the 42 study sections in the percentage of delay influenced by any given cause (e.g., incident-influenced queues may have been much more prevalent at one study site than at another) by presenting the maximum and minimum values observed for each combination of delay causes.

Table 5.4 Percentage of Delay by Type of Disruption Influencing that Congestion

Causes of Congestion Ongoing Disruptions that Influence Congestion Duration and Severity	Percentage of Delay	Maximum Percent Within a Corridor	Minimum Percent Within a Corridor
No cause indicated	37.1%	74.2%	14.3%
Incident-influenced queues are present	23.9%	48.2%	1.0%
Crash-influenced queues are present	6.0%	25.3%	1.7%
Rain is present	8.4%	25.8%	2.0%
Both a crash and an incident have influenced queues that are present	9.2%	23.9%	0.5%
Both rain and an incident have influenced queues that are present	5.0%	8.9%	0.0%
Both rain and a crash have influenced queues that are present	1.6%	8.7%	0.2%
Rain, a crash, and an incident have influenced queues that are present	2.4%	13.6%	0.0%
Queues from a ramp – cause unknown – have influenced mainline queues	5.1%	37.3%	0.0%
Construction activity has influenced queues	0.6%	16.2%	0.0%
Construction and queues from a ramp – cause unknown – have influenced mainline queues	0.0%	0.2%	0.0%
Construction and an incident have influenced queues present	0.2%	2.6%	0.0%
Construction and a crash have influenced queues present	0.1%	1.4%	0.0%
Construction and rain have influenced queues	0.1%	4.6%	0.0%
A crash and an incident and construction have influenced queues that are present	0.1%	1.2%	0.0%
Construction, rain and an incident have influenced queues that are present	0.0%	0.5%	0.0%
Construction, rain and a crash have influenced queues that are present	0.0%	0.7%	0.0%

Table 5.5 shows the total amount of vehicle-hours of delay measured. (Note that the northbound I-405 data sets were missing about 1.5 months of data (most from November and December), while other corridors periodically missed days or weeks of data as a result of a variety of data quality/availability issues. This means that the total measured delay was not the true annual delay for the region's freeways. However, the missing data should have only a marginal effect on the percentages of delay associated with different types of disruptions.) In the test database for each of the 42 corridors examined and the percentage of that delay not associated with an identified traffic disruption (crash, reported incident, or bad weather). In general, the roadway corridors with the highest percentage of delay attributed to "unknown causes" tended to be those roadway

sections with the least absolute vehicle delay. That is, 9 of the 10 sections with the highest percentage of delay not caused, at least in part, by a known traffic disruption were among the 13 sections with the lowest total vehicle-delay for the year.

The converse of this statement was not true. While the two test sections with the most vehicle-hours of delay did have fairly low percentages of delay not associated with known disruptions, only half of the 10 test sections with the highest vehicle-delay were among the 10 sections with the lowest percentage of congestion influenced by an unspecified disruption. The sections with very large amounts of total vehicle delay and large amounts of delay caused by unknown disruptions were all segments where frequent, significant peak-period delays occurred. The westbound segment of the SR 520 Seattle bridge has a large bottleneck at the eastern end of the two-mile-long floating bridge. Both SR 520 and I-405 Kennydale (both directions for both corridors) operate near or above capacity for 10 to 14 hours per day. The two I-5 sections (the South section northbound and North King County section southbound) experience routine a.m. peak congestion. Consequently, it is reasonable to assume that large amounts of the delay in these corridors is simply caused by too much peak-period volume.

The percentage of delay occurring with no reported disruption also was compared with the A.M. and P.M. peak-period travel rates (a.m. and p.m. peak period travel rates are defined as the mean travel time for the peak period converted to units of minutes per mile.) for each corridor. No correlation between these values was apparent.

Table 5.5 Hours of Delay versus Percentage of Delay without a Known Type of Disruption

Corridor	Vehicle-Hours of Delay	Percentage of Delay Not Associated with a Disruption
I-5 Seattle CBD Northbound	28,689,099	14.3%
I-5 Seattle North Southbound	19,828,935	23.1%
I-5 South Southbound	14,063,546	27.7%
I-5 Seattle CBD Southbound	12,997,924	21.5%
SR 520 Seattle-Bridge Westbound	12,901,102	43.3%
I-405 Kennydale Northbound	11,531,897	55.3%
I-405 Bellevue Southbound	11,345,712	20.8%
I-405 Kennydale Southbound	11,077,760	56.9%
I-5 North King County Southbound	10,782,330	45.2%
I-5 South Northbound	10,441,430	41.6%
I-405 Kirkland Southbound	9,655,929	34.0%
I-405 Kirkland Northbound	9,651,791	24.4%
I-405 North Southbound	9,116,178	44.2%
I-5 Lynnwood Southbound	8,517,553	39.8%
I-5 Lynnwood Northbound	7,733,702	53.5%
SR 520 Seattle-Bridge Eastbound	6,445,475	29.6%

I-5 North King Northbound	6,020,659	22.6%
I-5 Tukwila Northbound	5,997,528	42.5%
I-90 Bridge Westbound	5,310,825	57.3%
SR 167 Renton Northbound	4,980,431	28.0%
SR 167 Renton Southbound	4,582,608	58.3%
I-5 Seattle North Northbound	4,399,711	35.9%
I-405 North Northbound	4,327,382	56.4%
I-405 South Northbound	4,091,618	61.8%
I-5 Tukwila Southbound	3,863,679	45.1%
I-5 Everett Northbound	3,838,909	33.0%
I-405 Bellevue Northbound	3,773,393	52.0%
I-90 Bridge Eastbound	3,744,002	17.2%
SR 520 Redmond Eastbound	3,307,029	36.2%
SR 167 Auburn Southbound	3,305,901	59.9%
I-90 Issaquah Westbound	3,229,088	73.4%
I-405 Eastgate Southbound	2,861,851	64.8%
I-405 South Southbound	2,740,581	74.2%
SR 167 Auburn Northbound	2,167,614	73.0%
I-90 Seattle Eastbound	1,738,429	65.6%
I-405 Eastgate Northbound	1,715,306	64.4%
I-90 Bellevue Westbound	1,705,939	30.6%
SR 520 Redmond Westbound	1,399,767	19.7%
I-5 Everett Southbound	915,200	41.2%
I-90 Bellevue Eastbound	519,902	66.1%
I-90 Seattle Westbound	454,026	40.8%
I-90 Issaquah Eastbound	256,341	63.5%

This lack of correlation between different measures of congestion and the amount of delay without a known disruption was not expected at the outset of this analysis. It had been assumed that most of the delay without an observable cause was primarily due to too much traffic volume. The expectation was that highly congested locations, especially those with well known geographic bottlenecks, would have the most delay with unspecified causes because the congestion would be caused by a combination of volume and roadway geometry-based capacity limitations. Test sections with lower levels of routine delay were expected to have higher percentages of delays with identified disruptions, as delay would exist on those road segments primarily when unusual events occurred.

Instead of simple volume/capacity issues being the primary cause of high levels of delay unrelated to observable disruptions, further analysis of the study corridors identified at least three major reasons for delay occurring without disruptions being present:

1. Operating agencies simply do not record many of the disruptions that occur, especially on less congested corridors and during less congested periods (weekends, at night);

2. In several cases, the research team's analytical approaches did not adequately track all of the disruptions that occurred, given the data available to indicate when and where those disruptions actually happened; and
3. Even on Seattle's less congested urban freeway segments that do not have major geometric bottlenecks, volume is frequently sufficient to cause at least modest amounts of delay.

Where total delay values are small, these types of "no cause" delays can represent a fairly high percentage of total annual delay.

These conclusions were supported by several case study examinations of the various study corridors.

One such case study was performed on the I-90 Issaquah Eastbound roadway section. This roadway segment had the lowest measured annual delay of all 42 segments studied for this project. Only 256,000 vehicle-hours of delay were measured in 2006, and 63.5 percent of that delay was not associated with an identified disruption.

The roadway segment experienced two major delay-causing events in November 2006 that were not identified by the analysis methods described earlier in this report. One of those events was a snow storm. The second was a major truck accident. A special analysis of the snow event determined that roughly 5.9 percent of all delay measured for the year – for this section of roadway – occurred during that event. Yet because the snow stopped falling (at least at the weather station from which data were obtained) several hours before congestion started on this freeway segment, the congestion delays recorded were not associated with that weather phenomenon. (A review of newspaper stories published the next morning confirmed that massive problems occurred that night on that roadway section and that they were snow-related. Additional discussion of the difficulty in analyzing snow-related delays is presented later in this report.)

On a second day in November, an accident involving a truck killed the driver of a passenger car on I-90. That accident was not listed in either the state accident database or the WSDOT WITS database. **(**The newspaper indicated that the crash occurred in the **westbound** lanes of I-90 at 10:38 in the morning west of Front Street. That is on the eastern end (but within the boundaries) of the I-90 Issaquah test section. While the crash occurred in the direction opposite of the I-90 Issaquah eastbound roadway section examined in the case study, the eastbound section reported far larger delays than the westbound section after 10:30 in the morning. This may have been due to the location of the crash, which likely caused much of the westbound queue to form east of the monitored portion of the roadway. In addition, the eastbound delays were likely primarily "rubbernecking" delays, although some response equipment may have been parked on the eastbound section of the roadway.) It is not clear why. (Again, information on the accident was obtained from newspaper reports.) It is clear from the database that travel times were significantly affected, as would be expected with both an accident involving a truck and with the time and lane closures required to investigate a fatal accident. While some delays on that day were associated with rain, the majority of delay was not associated with any disruption. Thus, another 5.1 percent of all annual delay (8.1 percent of delay not associated with a disruption) was erroneously attributed to no cause other than volume.

Consequently, for this roadway section, of the 63.5 percent of delay "not associated with a disruption," 11.0 percent was actually associated with just two events, leaving at most 53 percent caused only by too much traffic volume.

Similar case study analyses of significant but unexplained delays were undertaken on more congested road segments. One of the most congested segments in the region is the westbound section of SR 520 as it crosses Lake Washington from Bellevue to Seattle. This segment experiences over 50 times the annual delay experienced on the I-90 Issaquah section discussed above. The SR 520 bridge operates near or over capacity for 13 to 14 hours every weekday. It is parallel to another cross-lake bridge (the I-90 bridge, located to the south of SR 520), which is close enough so that motorists can easily divert between the two when one of them experiences heavy congestion.

Each August, a major hydroplane race takes place on Lake Washington, south of the I-90 bridge. During the weekend when the race takes place, the Navy's Blue Angels flying team also performs an air show in between hydroplane race heats. The Blue Angels practice their routine, during the day, on the Thursday and Friday preceding the air show. During the times when the Blue Angels are practicing or performing their show, the I-90 bridge is closed to traffic.

Not surprisingly, considerable delay occurs that week crossing the two bridges. Much of that delay is caused by the visual distraction of pleasure boats on the lake going to and from the race course, and by airplanes flying low overhead. In addition, because the I-90 bridge is closed to traffic during the Blue Angel flights, considerable traffic diverts to the SR 520 bridge. This results in the "perfect storm" for creating congestion on SR 520, much of which is not related to a specific disruption **on** SR 520. The "disruption" (as noted in variable message sign records) is on I-90.

In 2006, on the Thursday prior to the hydroplane races, westbound SR 520 did not experience any major disruptions (i.e., recorded construction, lane closures, crashes, or rain). However, it did experience 117,000 vehicle-hours of delay (roughly **half the total annual delay of the I-90 Issaquah Eastbound test section**). About half of that delay was not associated with a disruption in the analysis database, and that value was over 2.5 times the usual "uninfluenced" Thursday delay. It is obvious from a manual review of the data that these delays were caused by excessive demand due to the 2-hour closure of the I-90 bridge combined with a high level of visual distraction for motorists crossing the lake. However, because the delays routinely experienced on this section of roadway are so high, this "very bad day" for travel on this section of roadway only contributed 0.9 percent of the total annual delay for this test section, and thus the large "not influenced" delay for that day was less than 0.5 percent of the annual total.

Taken together, these case studies illustrate that a large percentage of the congestion in the analysis data set without a "cause" can be traced back to some type of unusual occurrence. However, because of limitations in both the analysis data set and the methodology used to associate delays to specific events this analysis is not able to reliably identify all of these congestion sources. Consequently, three conclusions are drawn from the above examples:

1. The statistics presented in this report should be assumed to be a very conservative estimate of the amount of delay caused by the various types of disruptions;
2. The percentage of delay caused by any given factor can be a misleading statistic about the importance of that factor, since it is highly correlated to the total amount of delay on a given roadway; and
3. In the presence of moderately heavy volumes, a large number of factors that are not tracked by operating agencies may be the cause of congestion.

The Effects of Weather

The case study of delays on I-90 when snow fell illustrates the difficulties in determining the effects of weather on roadway performance. In the case study, the largest roadway performance effects caused by the snowfall did not occur while the snow was falling at the weather station. Instead, they occurred as a result of accumulation of snow on the roadway and the conversion of that snow into sheet ice on some roadway sections. The latter of these events took place well after the snow had stopped falling at the weather station.

In addition, the analysis of that case study reveals that delays did not happen similarly on all roadway sections that evening (although the newspaper reported long delays on several corridors). In fact, the eastbound and westbound sections of I-90 (presumed to experience the same level of snowfall) experienced very different roadway performance (delay) conditions during and after the snow storm. While the westbound direction showed modest delays in the evening, with moderate delays occurring between 6:00 and 9:00 p.m., the eastbound section experienced an unusually heavy day of congestion prior to the snowfall, and then a major additional pulse of congestion starting at 8:00 p.m. and lasting well into the morning hours. Exacerbating the eastbound congestion was the traffic volume added because of a professional football game that occurred that night in downtown Seattle. (The Seahawks played the Packers on Monday Night football, adding 65,000 fans, divided across multiple freeways, to the outbound traffic beginning at about 8:30 p.m.)

Methodology

The snowfall case study revealed a number of the analytical problems associated with an analysis of the effects of bad weather. The first major problem is defining, in analytical terms, "bad weather." As discussed previously the key regionwide weather variable used to indicate bad weather was whether measurable rain had fallen in the past hour. This variable was then used as an independent variable to predict the probability that any given roadway section was operating in a given "Regime" (essentially, level of service).

The analysis computed the probability that a given test section of roadway was operating in each regime for each time slice of a day. These probabilities were computed for days when rain occurred within the last hour and were then compared with probabilities on days when the same roadway was dry at that same time of day. The mean, median, 80th percentile, and 95th percentile travel times for each corridor and time period also could be computed for "wet" and "dry" conditions.

One limitation with the travel-time analysis is best explained with an example. Rain falls between 3:00 and 4:00 p.m. The time periods between 3:00 and 5:00 p.m. are assumed to be "rain affected" (within one hour of when measurable rain has fallen). Travel times occurring at 4:55 that day are "rain affected," whereas travel times at 5:05 are considered "dry" trips. The limitation with this analysis is that the rain may have created a queue that affects the 5:05 dry trip. For the analysis results in the discussion below, we ignored that possibility, thus slightly underestimating the potential impacts of rain on travel time.

Sensitivity tests were performed with various definitions of rain (e.g., requiring different fractions of an inch of rain falling within an hour before pavement was considered wet) and with different time periods within which rain had to have fallen (e.g., within the last hour, two hours, four hours, or eight hours for the pavement to be considered wet) to test how sensitive the results were, given different definitions of "wet." In general, any measurable rain falling within the last hour had the greatest effect on congestion formation and the resulting travel time. Other values showed slightly lower effects.

The effects of wind on roadway performance were analyzed differently than the effects of rain. This is partly because – other than the lasting effects of any queues being formed – wind does not have a lasting effect similar to that of rain. (Once wind stops, its direct effects stop. That is, wind does not have a lasting effect equivalent to spray from wet roadways caused by rain.) The lack of this effect also limited our confidence in the use of the available NOAA wind data for specific roadway sections.

As a consequence, we did not use the "wind gust" variable produced by NOAA. The project team had little confidence that this variable was effectively applicable to geographically removed locations. Similarly, the "wind speed" variable that was used was assumed to be only a reasonable surrogate for "windy conditions," rather than a definitive statistic indicating the precise wind speed at which travel might be affected.

To test the effects of wind on travel times, the data set was divided into "wind affected" and "not wind affected" groups on the basis of the wind speed variable present in each five-minute time slice. The travel times for these two groups were them compared within specific time intervals with both traditional t-tests, which assumed normally distributed travel times within those time periods, and nonparametric tests of the sample means. Tests were performed only for nonholiday Tuesdays, Wednesdays, and Thursdays (combined).

Sensitivity tests were performed with different values of the wind speed variable to determine the sensitivity of the analysis results to the breakpoint selected for identifying "windy" versus "not windy" conditions. The performance of different roadway corridors was found to be sensitive to different wind speeds. The authors believe that this is due in part to differences between actual wind speeds within the study corridor and those measured at the airport, and in part to the way that site-specific roadway geometry affects how drivers respond to wind. (That is, travel times over the SR 520 floating bridge, which has narrow lanes, no shoulders, and physically moves when struck by wind-blown waves, are affected at much lower wind speeds than travel times on I-5 in the northern reaches of the metropolitan region, where lanes are wider, full-width shoulders exist, and wind does not cause the roadway to move. In the end, sustained wind speeds of 16 mph were used as the primary split between "windy" and "not windy" conditions. Adopting a different definition would marginally change the travel times associated with windy and not windy conditions for some corridors but would not change the ultimate conclusions of the study.

Results

Not surprisingly, the results uniformly showed that the occurrence of rain leads to a statistically significant increase in the amount of congestion, but only during periods of moderately high traffic volume. That is, rain does not cause congestion uniformly throughout the day. The probability of congestion forming as a result of rain is a function of the underlying level of vehicular demand. And given the time series nature of traffic flow, time of day and day of week can be used as surrogates for vehicular demand when estimating the probability of congestion forming.

Rain causes the roadway to operate just a little less efficiently than it would otherwise (*2*, pp. 1-14), (*3*, pp. 8-18). The result, as observed in our data set, is that given a normal commute period, the roadway is likely to break down a little earlier than it would otherwise under conditions of similar demand but dry roadways. (The amount of rainfall likely determines the degree to which roadway efficiency declines, but an analysis confirming this has not been completed for this study.) Because the roadway breaks down earlier than it would if rain had not occurred, the queues grow larger than they otherwise would, and consequently last longer. The moderate rate at which rain falls in

Seattle (or more accurately, the region's frequently wet roadways) does not *cause* congestion; it simply lowers the amount of traffic volume that can a given roadway can handle before it becomes congested. Therefore, the roadway breaks down earlier in the commute period than it would otherwise.

Figure 5.3 illustrates this trend for SR 520 Seattle westbound crossing the Lake Washington floating bridge. The grey line shows the probability of a traveler experiencing congestion on this corridor on a dry day. The black line illustrates the probability of being in congestion if rain has fallen within the last hour. State Route 520 westbound into Seattle is one of the more congested roadway segments in the region. It experiences congestion during both the A.M. and P.M. peaks, as well as periodically in the middle of the day.

Figure 5.4 shows one of the less congested roadway sections in the region. In this case, only one peak period (the a.m.) routinely experiences congestion. Therefore, in the morning when volumes are high, if rain falls, the probability of congestion forming in the next hour increases. However, after the peak period ends, the fact that rain has fallen has no discernible impact on the formation of congestion. Yes, falling rain may increase accident rates during off-peak times (see a later discussion on accident rates and the presence of rain), but congestion caused by that increase in accident rates is no more likely to occur than congestion from other sources.

Figure 5.3 The Probability of Being in Congestion: Rain versus No Rain
SR 520 Westbound from Bellevue to Seattle

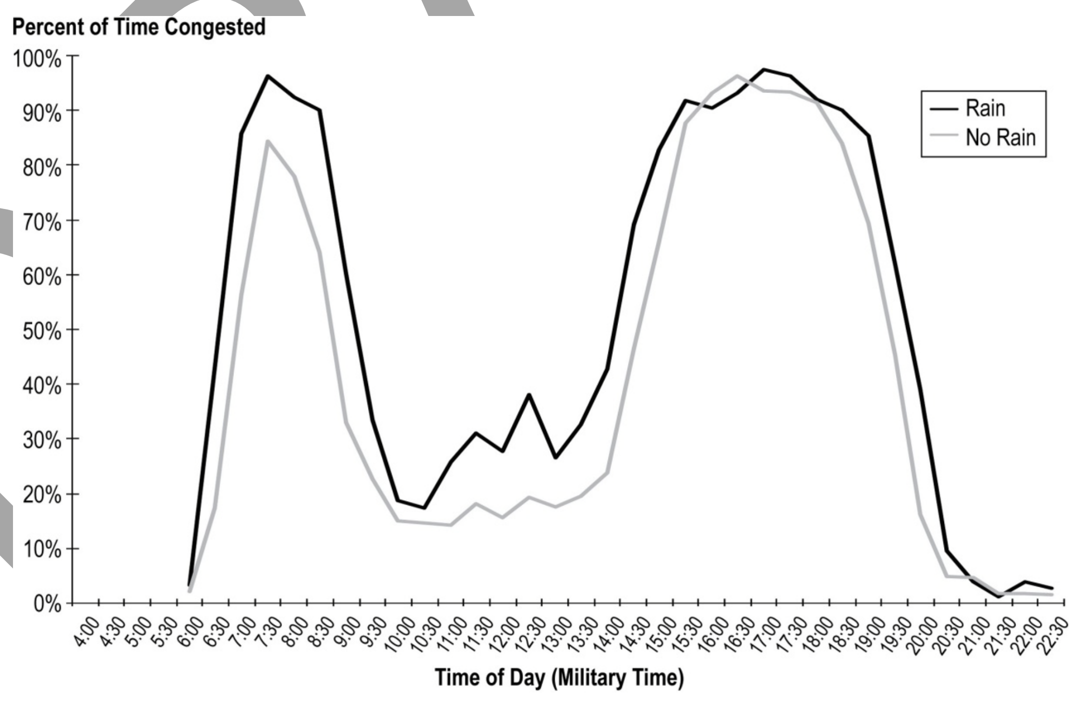
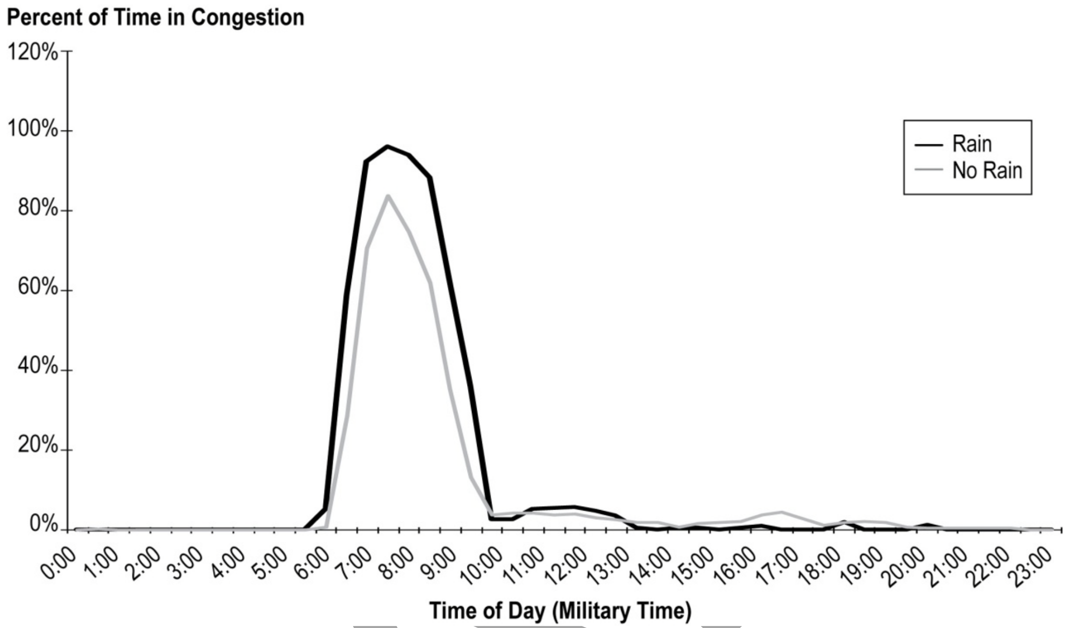
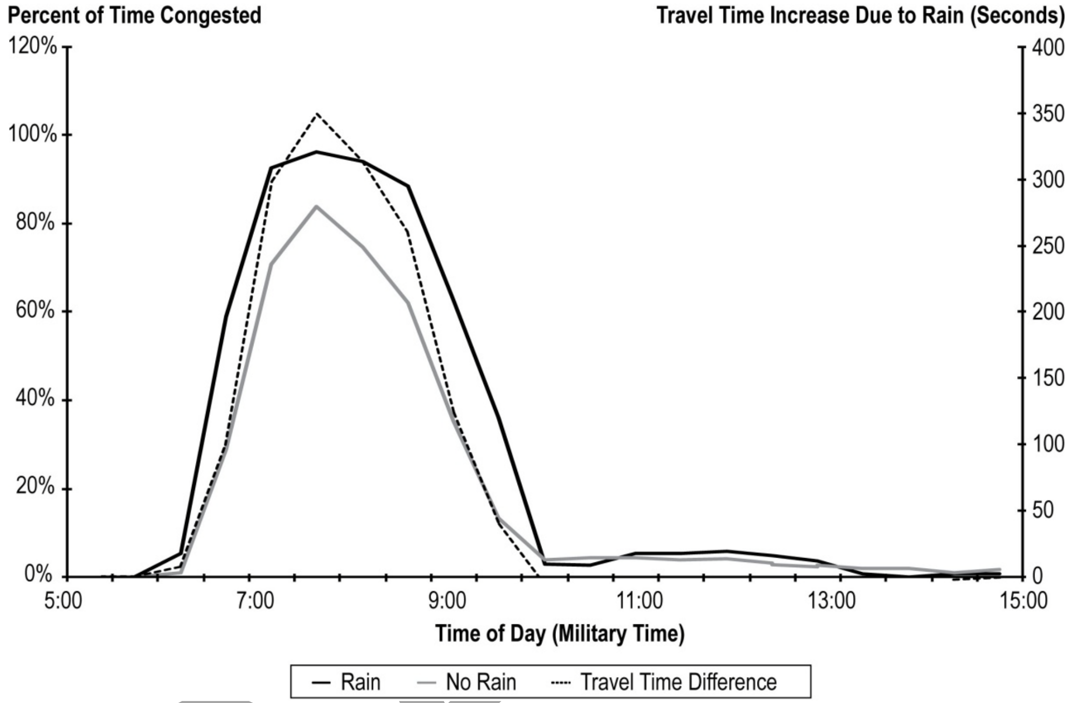


Figure 5.4 The Probability of Being in Congestion: Rain versus No Rain
I-90 Westbound from Issaquah to Bellevue



The greater probability of congestion early in the peak period and the longer queues that result from that early start to congestion also mean longer travel times on rainy days. Figure 5.5 illustrates how mean travel times increase along with the increased probability of being in congestion. This graphic shows the probability of congestion having formed by time of day when the roadway is dry (grey) or has been rained on in the last hour (black). It also shows the *change in mean travel time* when rain has fallen (dashed), where the travel-time increase is shown on the right hand axis. As can be seen in this figure, at no time does the mean travel-time decrease with statistical significance when rain is present. Interestingly, Figure 5.5 also shows that the declining volumes at the end of the commute period quickly moderate the travel-time effects of the congestion developed as a result of early queue formation in the rain. That is, even though the queues are longer and the travel times worse in the peak period, the mean travel time for a trip starting at the end of the commute period is only marginally worse than normal, and by the end of the peak period, travel times are nearly the same as normal, regardless of whether rain has fallen.

Figure 5.5 The Correspondence of an Increase in Mean Travel Times with the Increase in Probability of Congestion Due to Rain
I-90 Westbound from Issaquah

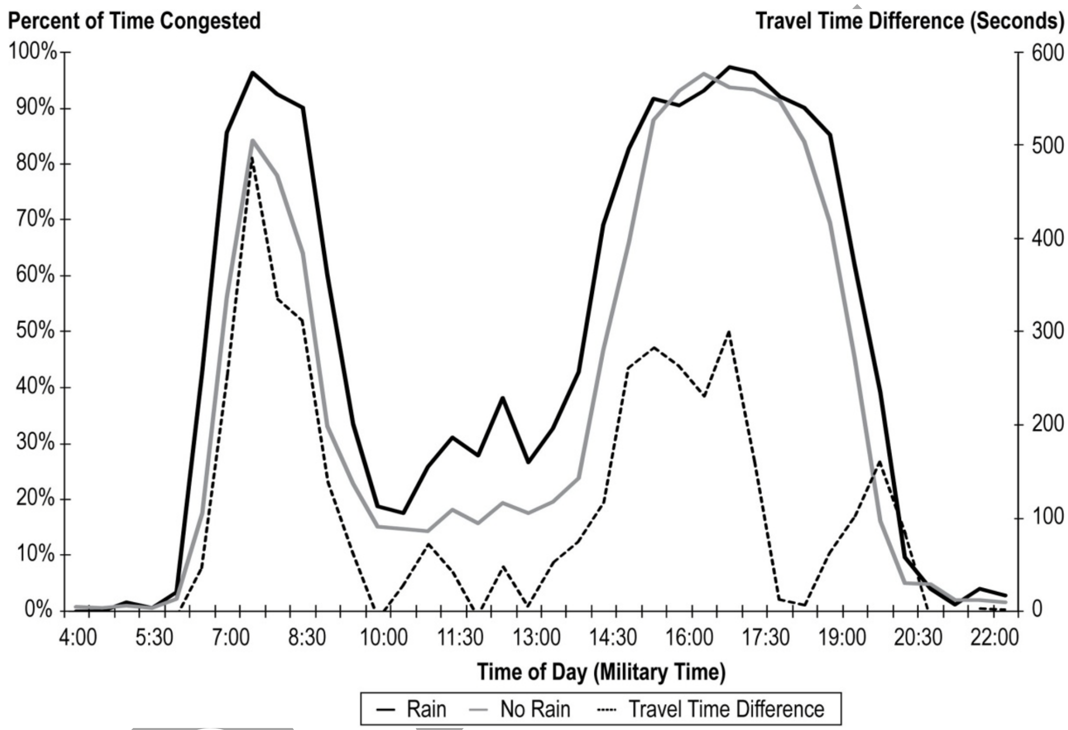


While the effects shown in Figure 5.5 were observed fairly universally for all roadway segments studied, further analysis of the 42 study segments revealed two significant differences in the effects of rain between less congested and more congested roadway segments. First, on the more congested segments, enough volume exists during the middle of the day that rain causes an increased likelihood of congestion forming during mid-day periods. On less congested roadway segments this is not the case. The project team believes that on road segments that operate near capacity during mid-day, the decreasing roadway efficiency caused by wet roadways is sufficient to create congestion, irrespective of increases in crash rates caused by the wet pavement. (Additional analysis is required to determine the effects of the increased accident rates versus the simple effect of wet pavements.) On less heavily traveled (and thus less congested) roadway segments, the modest loss of efficiency caused by wet pavement does not create conditions that result in congestion, except on rare occasions when major crashes occur.

The second significant difference between heavily congested and less heavily congested roadway segments is that on the most congested segments, the probability of congestion during the heart of the peak period approaches 100 percent. As a result, rain does not increase the probability of congestion forming during those periods. On less congested roadways, there are lower volume commute periods (e.g., the workdays near major holidays) when congestion may not form. Rainfall on those lower volume work days may decrease roadway performance to the degree sufficient for congestion to form.

Figure 5.5 illustrates the effects of rain on a moderately congested roadway segment (there are no "uncongested" freeway segments in the Seattle region). Figure 5.6 illustrates how rain affects a heavily congested segment. In this figure, it is easy to see that the probability that congestion will form does not change significantly during the core of the p.m. peak period. However, during the early portion of the P.M. peak, travel times do increase when rain falls. This is because queues form earlier than normal and are, therefore, longer than normal at later points in the day. Interestingly, in Figure 5.6 the travel time increases in the rain are briefly moderated just after the midpoint of the P.M. peak period. The increases in travel time caused by rain approach zero shortly before 6:00 p.m. (18 on the *x*-axis of the graph), only to rebound by 6:30 p.m. This outcome does not represent a lack of effect from the rain on commute times. Instead, it is an artifact of the roadway segmentation used for this specific analysis. On this particular roadway segment, the normal queue extends roughly to the end of the roadway analysis segment at the peak of the p.m. peak period. This maximum queue length occurs at roughly 6:00 p.m. Because the section already is fully congested, estimated travel times for the segment do not increase **on the study section** when it rains, and thus travel times do not increase. Instead, travel times increase on the upstream section of the roadway (in this case the SR 520 Redmond westbound study section) because the queue from the first section has extended back onto the second. Thus, **travelers** do experience slower trip times, but the reported travel time **on this section** is not worse. As the "extra long queue" moderates towards the end of the peak period, travel times on the Seattle test section again increase, simply because the normal queue is once again shorter than the length of the entire roadway section.

Figure 5.6 The Correspondence of an Increase in Mean Travel Times with the Increase in Probability of Congestion Due to Rain
SR 520 Westbound: Bellevue toward Seattle



Research (*4*), (*5*, pp. 24-30) (and most drivers' personal experience) has shown that high winds frequently cause motorists to drive more slowly and carefully, as wind can affect vehicle handling. Under high winds, many drivers slow slightly. As with rain, this more cautious approach to driving under heavy wind conditions can negatively affect the relationship of vehicle volume and speed, causing the roadway to operate less efficiently. Given high enough traffic volumes, this loss of efficiency results in congestion, whereas under normal circumstances it would not form. Under these conditions, wind will result in statistically significant increases in travel time.

An analysis of roadway performance and wind data in the Seattle region supported these basic findings. However, the analytical tests performed on the Seattle test corridors showed that travel times in all test corridors were not equally affected by wind. In fact, in many corridors, wind did not have any statistically significant effect on travel times. In other corridors, wind had a very high impact on roadway performance. Table 5.6 gives examples of how wind affects various corridors differently, even though the corridors are directly connected. Table 5.6 also gives examples of the results of the sensitivity tests performed with different wind speeds to separate "windy" from "not windy" conditions.

As can be seen in Table 5.6, the SR 520 Bridge is affected by even relatively moderate winds (10 mph sustained wind speeds). This is because the bridge is a two-mile-long floating span. The roadway is two lanes in each direction with no shoulders. In even moderate wind, a driver crossing the bridge can feel the bridge sway. The wind also can create some spray, as wind-driven waves break against the bridge. The result is that drivers slow down. Because the bridge operates near capacity 12 to 14 hours each weekday, these wind effects are sufficient to cause congestion.

The I-90 bridge, located nearby to the south, also is affected by wind, but to a lesser extent than the SR 520 bridge. This is most likely due to a combination of factors, including the facts that the I-90 bridge is more modern, has full shoulders, and sits higher off the water (and, therefore, experiences less wind driven spray). Interestingly, the evening commute across the I-90 bridge is affected by wind whereas the morning commute is not, even though traffic volumes are similar in both periods. Part of this is because the definition of the test section that included the I-90 bridge also included a large segment of nonbridge travel across Mercer Island. Back-ups on the bridge affecting eastbound traffic actually create some free-flow conditions on the island itself, decreasing the travel-time impact of the wind. However, wind-caused back-ups significantly affect the upstream section of eastbound I-90 (the Seattle section also shown in 5.6). This explains why the I-90 Seattle section is statistically affected by wind in the morning, even though it does not include the bridge itself. At more moderate wind speeds (e.g., 10 mph sustained winds), none of the I-90 segments show a statistically significant change in expected travel time.

Looking at the I-5 segments included in Table 5.6, it can be seen that wind affects some corridors in some peak periods, but not all corridors or all peak periods within all corridors. In general, high peak-period volumes relative to their capacity make roadway segments more likely to be affected by high winds. Other reasons that a roadway may be susceptible to winds are that the road segment is exposed to high levels of wind (the I-5 North Seattle segment crosses the Ship Canal bridge, an exposed portion of road where wind is often felt) or that the segment is immediately upstream of another segment that is wind affected. (The I-5 North King segment is upstream of the I-5 North Seattle segment. The I-5 Everett segment is considerably farther north and does not experience spillback from North King or North Seattle segments, except in very extreme cases.)

Table 5.6 Example Effects of Wind on Travel Times by Corridor
Seconds

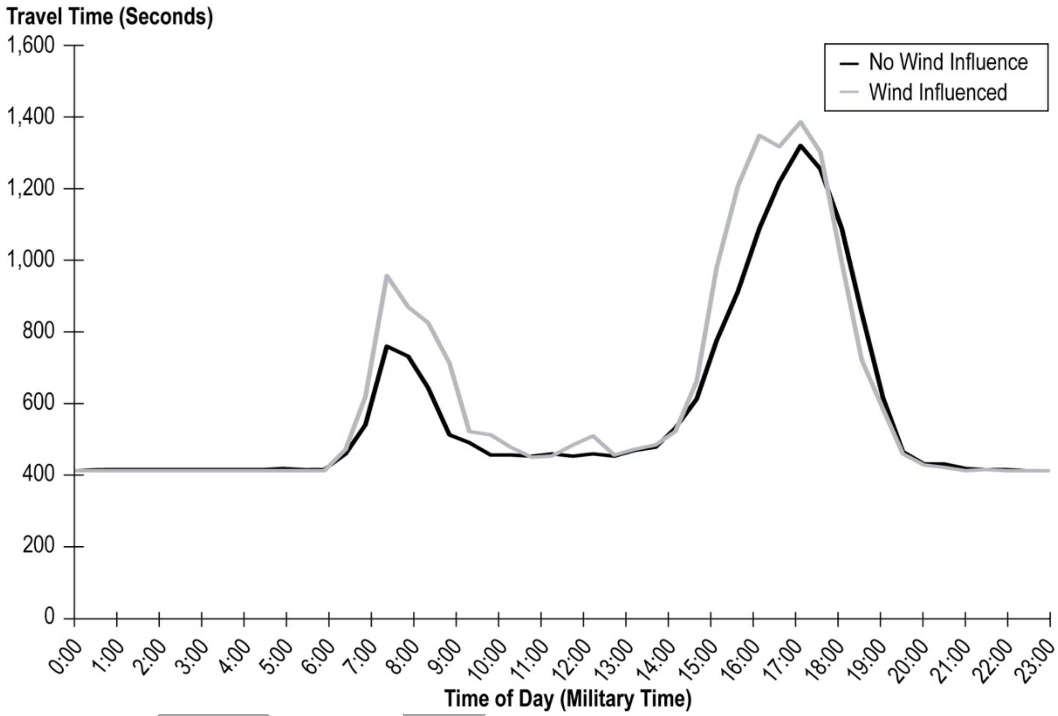
Route	Mean Travel Time A.M. Peak: With Wind[a]	Mean Travel Time A.M. Peak: Without Wind[b]	Difference	Statistically Significant?	Mean Travel Time P.M. Peak: With Wind[a]	Mean Travel Time P.M. Peak: Without Wind[b]	Difference	Statistically Significant?
I-5 Everett – Southbound	190	207	-17	No	191	209	-18	No
I-5 North King – Southbound	759	690	68	Yes	400	422	-22	No
I-5 North Seattle – Southbound	751	606	145	Yes	926	686	239	Yes
I-5 South Northbound	1,671	1,073	598	Yes	649	649	0	No
SR 520 Seattle Westbound	1,020	638	382	Yes	1,548	1,052	495	Yes
I-90 Bridge Eastbound	425	410	15	No	543	437	106	Yes
I-90 Seattle Eastbound	198	169	29	Yes	151	115	36	Yes
SR 520 Seattle Westbound 10 mph Wind Speed	781	626	154	Yes	1,093	1,049	44	Yes
I-90 Bridge Eastbound 10 mph Wind Speed	434	407	27	No	431	441	-10	No
I-90 Seattle Eastbound 10 mph Wind Speed	174	169	5	No	107	118	-12	No

[a] Sustained wind speed is greater than 16 mph.

[b] Sustained wind speed is less than or equal to 16 mph.

Figure 5.7 illustrates how wind affects the SR 520 bridge westbound, while Figure 5.8 illustrates the I-90 eastbound bridge section. In both figures, it can be seen that the primary effects of wind are in the peak periods when traffic volumes are highest. If the same graphic were presented with a higher wind speed, more impacts would be seen in the middle of the day, especially on SR 520.

Figure 5.7 Mean Travel Times by Time of Day in Wind and No-Wind Conditions
SR 520 Westbound: Bellevue toward Seattle

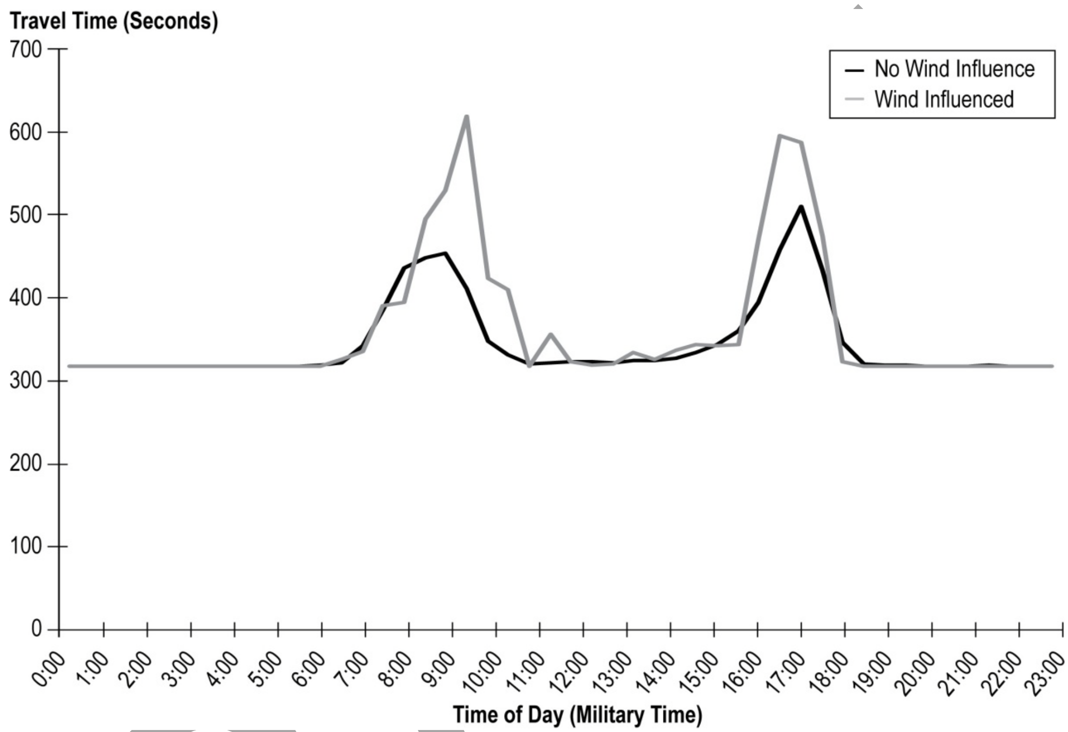


In Figure 5.8, wind appears to have a significant effect on expected travel times during the later portion of the a.m. peak period, but not on the earlier portion of the peak. This helps explain why the difference in mean travel times shown in Table 5.6 is not statistically significant.

In summary, the analysis of the impacts of bad weather on congestion formation on Seattle freeways identified the following major conclusions:

- Small disruptions, such as those caused by moderate amounts of rain or even spray from wet pavements, only cause congestion when they occur in combination with sufficient volume relative to the available capacity;
- Precipitation can affect roadway performance as long as the roadway remains wet;
- The probability that bad weather will significantly affect roadway performance on any given roadway section is a function of the expected demand/capacity condition of that road section and the significance of the weather event (e.g., light rain versus a heavy thundershower); and
- Bad weather also increases the probability of crashes occurring, which further increases the probability of significantly increased travel times.

Figure 5.8 Mean Travel Times by Time of Day in Wind and No-Wind Conditions
I-90 Bridge Section Eastbound: Seattle toward Bellevue



Given Seattle's relatively benign climate, it can be said that most weather impacts in the Seattle region are small, at least in terms of the changes in vehicle speed and throughput that they directly cause. During most parts of the day, on most roadway segments, the travel-time changes that these small differences in speed create are not statistically significant. *However, when those small changes occur in combination with large traffic volumes, especially during the beginning shoulder of a peak period, those small changes can result in congestion that will, in turn, generate much more significant increases in expected travel times.*

The use of rain variables that account for the continuing presence of spray from wet roadways suggests that spray has as much of an impact on roadway performance as moderate rainfall itself. Similarly, except in the case of heavy snowfall (when low visibility affects drivers' behavior), the major impacts of snow are the result of snow accumulation, not the snowfall itself. Anecdotal evidence of this same effect also was apparent for ice formation in Seattle. The project team attempted to compute times when black ice formation might be present by using humidity and temperature data from the SeaTac weather station. However, these factors did not result in successful identification of ice formation in the informal tests conducted during the winter of 2008. Therefore, we conclude that using regional weather station data is not an effective way to accurately determine the presence of snow and ice on roadways.

The effects of wind are similar to those of rain. High winds cause motorists to drive more cautiously. (The degree to which they adjust their behavior for a given wind condition is a function of the roadway section: How wide are the lanes? Are there shoulders? How exposed is the roadway section to wind?) This in turn reduces the functional capacity of the roadway during high wind conditions. These effects do not appear to be as uniform as the effects of rain, since geographic differences in terrain and geometric differences in roadway right-of-way appear to play bigger roles in determining the effects of wind on roadway performance than they do in the case of rain.

Where wind is significant and traffic volumes are light, travel times increase only marginally, in direct proportion to the slowing that individual vehicles exhibit under windy conditions. However, when volumes are high, the reduced functional roadway capacity resulting from motorists' voluntary slowing can create congestion that would not occur under average weather conditions. That congestion frequently becomes self-sustaining during peak periods; that is, the queue itself creates a further decrease in functional roadway capacity, which further increases the length of the queue and increases travel times on the roadway section.

The Effects of Incidents and Crashes

The effects of crashes and other kinds of traffic disruptions are of significant interest both because they are common causes of travel delay and because they are disruptions over which operating agencies have some level of control. That is, highway agencies cannot prevent rain, but they can design roadways to minimize the number and severity of crashes, and they can respond effectively and efficiently to crashes to limit their duration. Consequently, the project team looked at the effects of both crashes and noncrash incidents.

Incidents and crashes differ from weather in three significant ways. First, incidents and crashes are highly correlated with traffic volume, while weather is not. More crashes occur when volumes increase, but increasing volumes do not affect rainfall. Therefore, crashes and incidents are not evenly distributed over time, whereas bad weather (at least in Seattle) is much more evenly distributed throughout the day.

Second, incidents and crashes have small "footprints" in comparison to weather. That is, a crash/incident occurs at a specific location, which has a relatively small geographic scope (this does not include any queues that may form), whereas the same weather generally occurs over a larger geographic area. This small footprint can have considerable impact on "segment-based" analysis procedures. This impact is discussed in the Methodology subsection below.

Finally, crashes and incidents are, in many ways, even more variable than weather. Incidents can be anything from minor debris in the roadway (e.g., pieces of a blown truck tire), to a distraction on the side of the road (e.g., a stalled car), to a fatal crash.

Methodology

Considerable research has been conducted to explore the impacts of incidents on roadway performance, especially in terms of vehicle throughput, queue formation, and roadway recovery at the incident scene. Much of this work has involved the use of queuing theory to explore the size and speed of queue formation, given incoming and exiting traffic volumes along with descriptors of specific incidents (duration, number of lanes closed). The intended result of most of these efforts has been to determine the benefits that can be gained from improvements in incident response efforts.

One limitation in these studies has been the fact that once queues form during peak periods, the queue itself can become its own self-sustaining bottleneck. Thus, even after the incident has been cleared, the back of the queue may become the point where congestion forms – replacing the incident scene that started the congestion. A second limitation is that a bottleneck at one point of a roadway segment has implications on the performance of the rest of that roadway segment, as well as the segments upstream and downstream from that segment.

Consequently, this project used two different approaches to examine the larger, corridor-long effects of incidents and crashes. The first approach examined the travel times that occur under incident or crash conditions. This analysis took advantage of the “influence” variables discussed previously (see the section Computed Variables Used to Track the Influence of Disruptions on Travel Times and Delays. Also see the variable definitions in Appendix A.) Using the previously discussed methodology, the influence of every crash and incident was noted in the five-minute travel-time records for each roadway test segment. As a result, it was possible, for any definition of “disruption,” to segregate the travel-time records for a given test section into two groups: those influenced by a specific type of disruption and those not influenced by that type of disruption.

Statistical tests could then be performed on those two groups. Because of the time series nature of travel times, combined with the time-lagged nature of the effects of incidents, these statistical comparisons were somewhat complex. (That is, traffic conditions at 7:00 a.m. on a Monday are different than those at 8:00 a.m. for that same stretch of road, so travel times at these two different times should not be directly compared. Similarly, a crash that happens at 7:00 a.m. has a different effect on travel time at 7:05 than it has at 7:15.) Because disruptions happen at different times during the day, the aggregated effects of these disruptions are complex.

The primary statistical tests used to compare influenced and noninfluenced travel times was an independent sample t-test. The majority of tests involved only data for Tuesdays, Wednesdays, and Thursdays to limit the effects that variations in day-of-week traffic volumes would have on the statistical results. This test was originally applied independently for each five-minute period. That is, influenced travel-time data for the 7:00 to 7:05 period for all Tuesdays through Thursdays were compared with noninfluenced travel times for that one period.

Because each five-minute time period occurred on a different day, each sample was truly independent of all other samples (that is, the 7:00 a.m. travel time today has no influence on the 7:00 a.m. travel time tomorrow). Because travel times were taken from only one five-minute period, the time dependent effects of travel also were removed.

The difficulty with this approach is that it required performing 288 statistical tests to examine the daily differences in incident-influenced and noninfluenced travel times. To reduce the analytical load, the project team grouped the 5-minute average travel times by 30-minute increments, with the statistical tests performed for each 30-minute interval.

In this approach, the six 5-minute travel times were treated as independent travel time estimates within that 30-minute period. For example, assume that no incident happens on a study corridor on March 7 until the 7:15 a.m. period. That incident influences the rest of the morning commute. The average 5-minute travel times stored in the 7:00, 7:05, and 7:10 analysis time periods are reported as not incident influenced. All three 5-minute average travel times are included in the computation of the travel-time distribution for the "not incident influenced" 30-minute period covering 7:00 to 7:29, while the three 5-minute periods from 7:15 to 7:25 are included in the influenced travel-time distribution for that same 7:00 to 7:29 period.

There were two advantages to the 30-minute approach. One was the reduction in the number of statistical tests that had to be performed and summarized. The second was the increase in the sample size for each test. The downside of the 30-minute test was that the six travel times were no longer truly independent samples, as the 7:05 travel time would be highly correlated to the 7:00 travel time.

When the results of tests conducted with both levels of aggregation were analyzed, little difference was found between the statistical outcomes of the 5- and 30-minute comparisons, so most analysis results in this report are presented in the 30-minute format to make the results more readable. When the results of the 5- and 30-minute analyses were compared, the most significant differences were found in the shoulders of the peak period. These differences did not change any of the basic conclusions of this report.

Statistical comparisons between influenced and noninfluenced travel times were made in a number of ways. This was possible because of the multiple ways that "influence" was calculated in the project database. "Influence" was examined for crashes (only crashes reported in the state accident records), for incidents (any incident reported by WSDOT's service patrol), for any incident reported by WITS that involved lane closures, or for any one of these types of disruptions. Travel times associated with these disruptions could then be compared with either all other travel times or only travel times when no disruption was influencing travel.

This flexibility allowed a very thorough comparison of incident-influenced conditions. In most cases, the best comparison was with "no known disruption currently influencing conditions," but in some cases it was important to make a comparison with all other travel times (for example, comparing travel times when crashes had influenced travel versus noncrash-influenced travel).

In most cases, nonholiday Tuesday through Thursday travel times were used as the population from which travel times were compared. Some analyses also were performed for weekends and for all weekdays combined. While these analyses were useful for describing total delay in a year caused by a specific type of disruption, they were not as useful in describing the effects of disruptions on travel times in comparison to normal conditions. Therefore, most results presented in this report involve Tuesday through Thursday (nonholiday) comparisons.

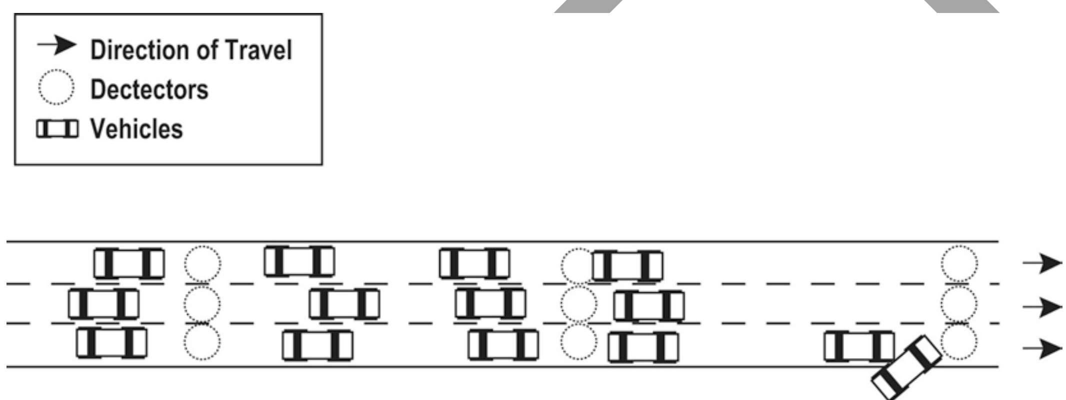
One difficulty with these comparisons is that they were not measures of what would have happened if the disruption had not taken place. They were simply comparisons of the expected conditions when a specific type of disruption occurred versus expected conditions when those types of events had not taken place. The research team hoped that by combining an entire year's worth of data, the number of events included in the database would limit the biases in travel-time impacts that could be associated with specific incidents occurring at specific times and locations. To make a direct comparison of actual conditions versus "what would have happened" would require a carefully calibrated microscale simulation model. Such an effort was well beyond the scope of this project.

Because they are not direct measures of "what would have happened," the resulting graphs and computed statistics must be used carefully. They describe the differences in expected conditions *if a specific type of event has occurred **and** its influences are still being felt*. That second clause is important. One problem with not using a simulation to make this comparison is answering the question, "When does the influence of an event end?" The travel-time comparisons assumed that the effects of any disruption end once conditions return to what they were at the time the disruption took place – not the condition that would normally be present at that time. This definition was selected because a review of the project data set found a large number of cases in which travel times were much faster than normal, then an event occurred and travel times slowed. However, they never degraded to the point of "normal" conditions, and then they returned to the faster than normal conditions that existed before the disruption. If "normal" travel times had been used as the measure of influence, these events would have had no influence. But they obviously caused delay. As a result, the definition of influence was based on travel times returning to preexisting conditions.

A second limitation with the corridor-based analysis process described above was caused by the site-specific nature of crash and incident impacts relative to the roadway segmentation used for the analysis. The disadvantage of using travel times is that travel time is a function of selected segment end points, and those defined segments may or may not include all of the effects (e.g., slow moving vehicles) caused by a given incident. Figures 5.9 through 5.11 illustrate this problem. Taken together, they show how the location of a crash/incident within a corridor can influence how effectively the measured travel times in a test section reflect the delays caused by that crash/incident.

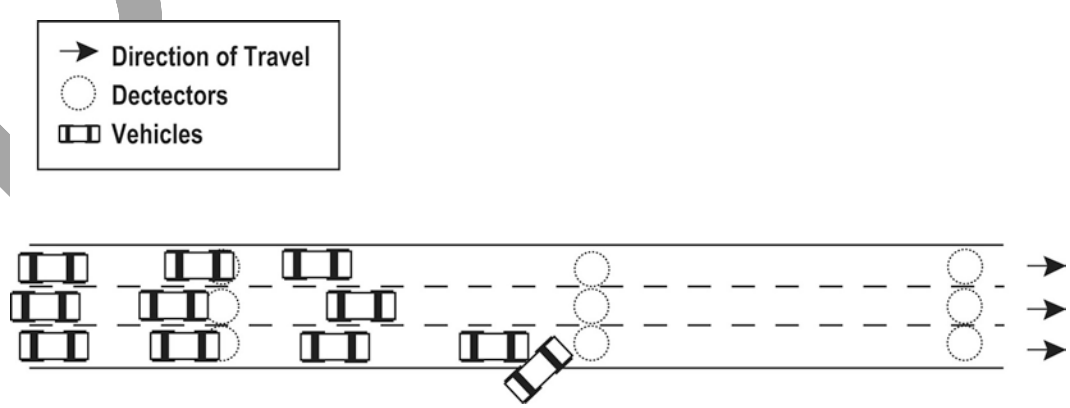
In Figure 5.9, the crash happens near the downstream end of the roadway segment. In this case, travel times measured in the corridor capture all of the delays occurring in the test section, unless the queue is longer than the test section. (This did happen on our test sections, but given the two-mile minimum length of those test sections, it was unusual.)

Figure 5.9 Illustration of a Crash at the Downstream End of a Test Corridor



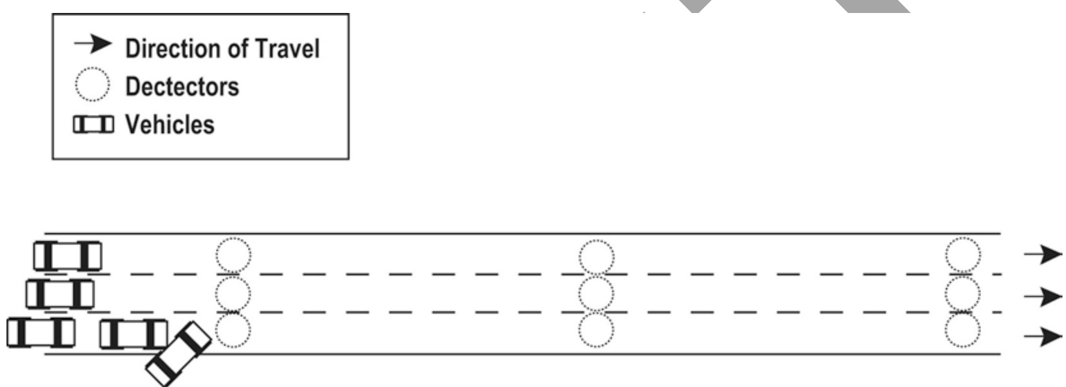
In Figure 5.10, the crash happens in the middle of the test section. In this case, if the queue is minor, all of that queue and the travel-time influences of that queue are contained in the test corridor. However, if the queue is long, it will extend back into the upstream roadway segment, creating delays on that segment that are not explained by an incident or crash within that segment. Thus, the study segment that contains the crash will see some, but not all, of the delays associated with the crash, while the upstream segment will see unexplained congestion.

Figure 5.10 Illustration of a Crash in the Middle of a Test Corridor



In Figure 5.11, the crash occurs near the upstream end of the study segment. In this case, the study segment will not experience the majority of the delays caused by the crash. Those delays will occur on the test section upstream of the study section. The study section is likely to show good travel times because in this study, travel times are based on multiple point speed measurements, and the queues at the upstream end will allow the majority of the study segment to operate in a free-flow condition.

Figure 5.11 Illustration of a Crash at the Upstream End of a Test Corridor



The moderately long roadway segments and the careful selection of the breakpoints between those roadway segments that were used in this study limited the frequency with which congestion crossed segment boundaries, but there were still many occasions when this happened. The travel-time analyses presented in the following section do not effectively account for these cross-segment boundary occurrences. When they occurred, the slower travel times these extended queues caused were associated with normal (or nonincident) conditions. As a result, the comparisons between “=incident-influenced”= and “nonincident-influenced” conditions described below should be considered conservative measures of the effects of incidents on travel times and travel-time reliability, as many off-segment effects of crashes and incidents were not accounted for.

While being useful in describing the effects that different types of disruptions have on travel time, the definition of influence described above and the statistical travel-time comparison that was based on that definition have significant explanatory limitations. In particular, it does not do a good job of answering questions such as, “What impact does a crash have on my commute?” because different times and locations of such as disruption will result in different outcomes, and because it cannot be known when the individual asking that question makes his trip. Consequently, a second type of analysis was performed that examined changes in congestion from a different perspective.

In this second set of analyses, the study team defined “when congestion ends” at the end of both the a.m. and p.m. peak periods. The idea came from two factors observed in the development of the influence variables. 1) Once congestion starts (often as a result of a disruption) during the peak period, that congestion tends to last until the end of the peak. 2) While the previously described analysis can predict how much longer a given trip will last once a disruption has occurred, it does not estimate how long that effect will last. Determining how much longer congestion lasts would provide insight into that missing piece of information.

To perform the required analysis, "End of Congestion" was defined as being the time when 20 consecutive minutes (four 5-minute periods) of travel time were less than travel time at the speed limit plus five percent. The 20-minute interval was selected to account for modest fluctuations in travel times (vehicle speeds) caused by unstable traffic flow occurring as congestion eases. The five percent value was selected as a result of sensitivity tests; while it represents a fairly small increase in travel time, it does appear to identify the effects of modest congestion that occur at a single location within a longer corridor.

Once the end of congestion was identified for each peak period for each day, three sets of travel-time statistics were then computed for all nonholiday Tuesdays, Wednesdays, and Thursdays describing the time that congestion ended for days when: 1) *any* crash occurred (the crash must have occurred after 4:00 a.m. for the morning peak-period test, or after 3:00 p.m. for the evening peak-period test.); 2) *any* noncrash incident occurred; or 3) no incident occurred. (Only one "end of congestion" as assigned for each peak period for each day. That was the first time period that met the selected criteria. There were instances when disruptions of one type occurred after "congestion ended" creating a second congestion period within the traditional hours associated with the peak period. These cases were treated as occurring after the peak period had ended.) These statistics were then compared by using both normal and nonparametric statistical tests to determine the extent to which crashes and other types of traffic disruptions can be expected to extend peak-period congestion.

One problem with the "end of congestion" analysis was that when the above definition of congestion was used, for 11 test sections the mean time of day when the a.m. peak-period congestion ended was well after noon. In fact, a.m. peak-period congestion on these corridors frequently did not end until after 6:00 p.m.! A review of the travel times routinely experienced on these routes showed that a variety of traffic flow conditions (e.g., excessive merging at bottlenecks near the end of the corridor, large volumes of heavy trucks) frequently kept these road segments operating slightly below the speed limit even during late morning and mid-day periods. These routes all operated at or above the speed limit during late night hours and during many mid-day hours. But they routinely operated at speeds lower than the speed limit during the middle of the day for reasons other than traffic disruptions.

This "normal condition" limited the benefit of the intended analysis. As a result, for the A.M. peak period on these 11 routes, "end of congestion" was redefined as being sustained speeds within either 10 or 20 percent of the speed limit, depending on the corridor. The intent of this new, corridor-specific definition was simply to allow better examination of how crashes and other disruptions affect when slow travel **associated with peak-period volumes** ends.

These lowered expectations were tested on other corridors and for other periods. The results were generally not good. Use of lowered average travel speeds as the definition of end of peak-period congestion frequently caused the "end of congestion" flag to be set during obviously congested conditions on these other routes. This was particularly true in the afternoon peak period, when all routes reached travel times within five percent of that achieved at the speed limit by a "reasonable" time of day. Consequently, the slower speed that was required to allow this approach to be used for the 11 roadway segments in the A.M. peak period was used only for those 11 sections and only for the A.M. peak period.

Results – Travel-Time Effects of Incidents and Crashes

In general, the effects of crashes and incidents in general on travel times were similar to each other and to the expected travel times that resulted from rainfall. That is, the shape of the expected (mean) travel-time patterns by time of day when incidents and crashes occurred were similar in shape to the expected travel times when rain fell. These similarities are illustrated in Figures 5.12 through 5.14.

Figure 5.12 Mean Travel Times under Rain, Crash, or Noncrash Traffic Incident Conditions
I-5 Northbound South Corridor

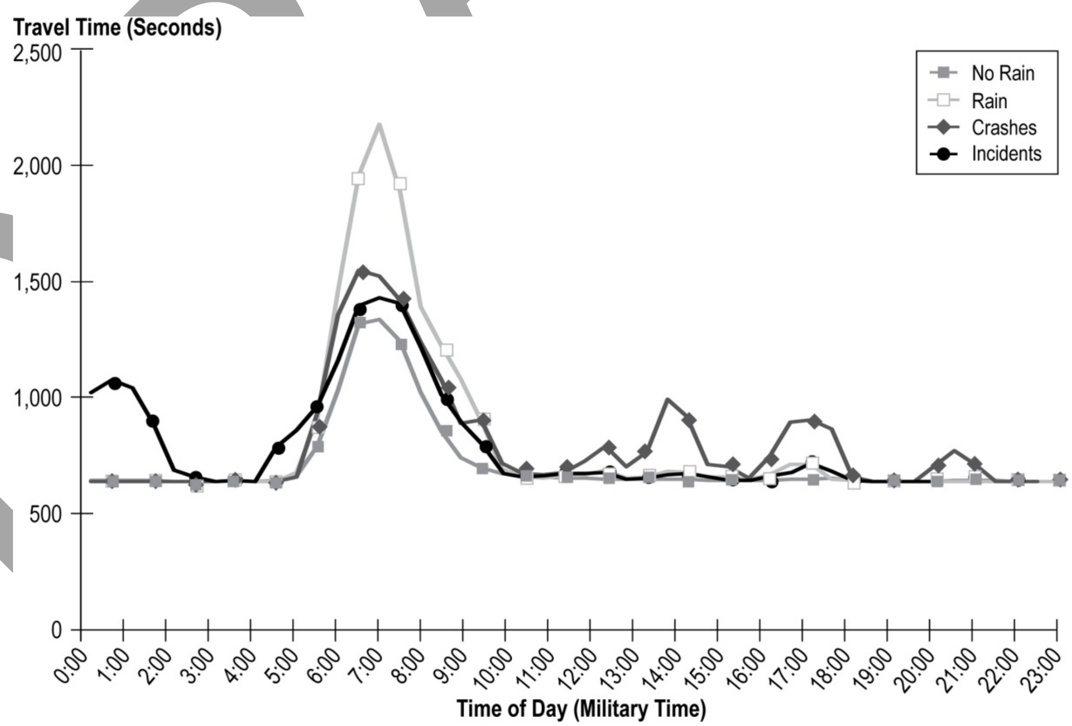


Figure 5.13 Mean Travel Times under Rain, Crash, or Noncrash Traffic Incident Conditions
I-5 Southbound Lynnwood Corridor

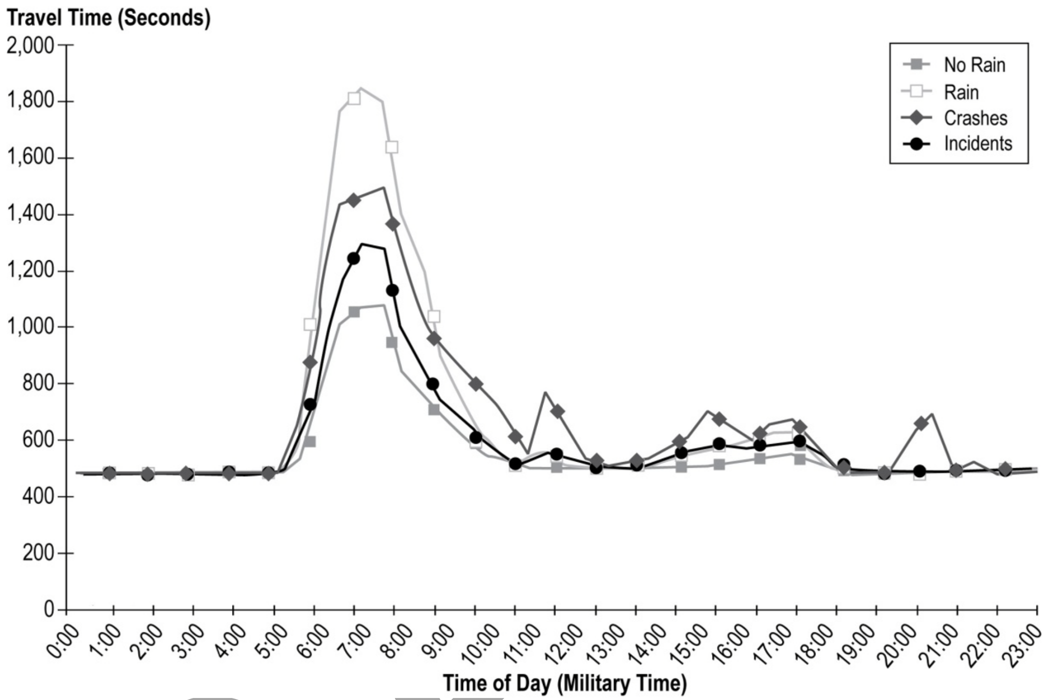
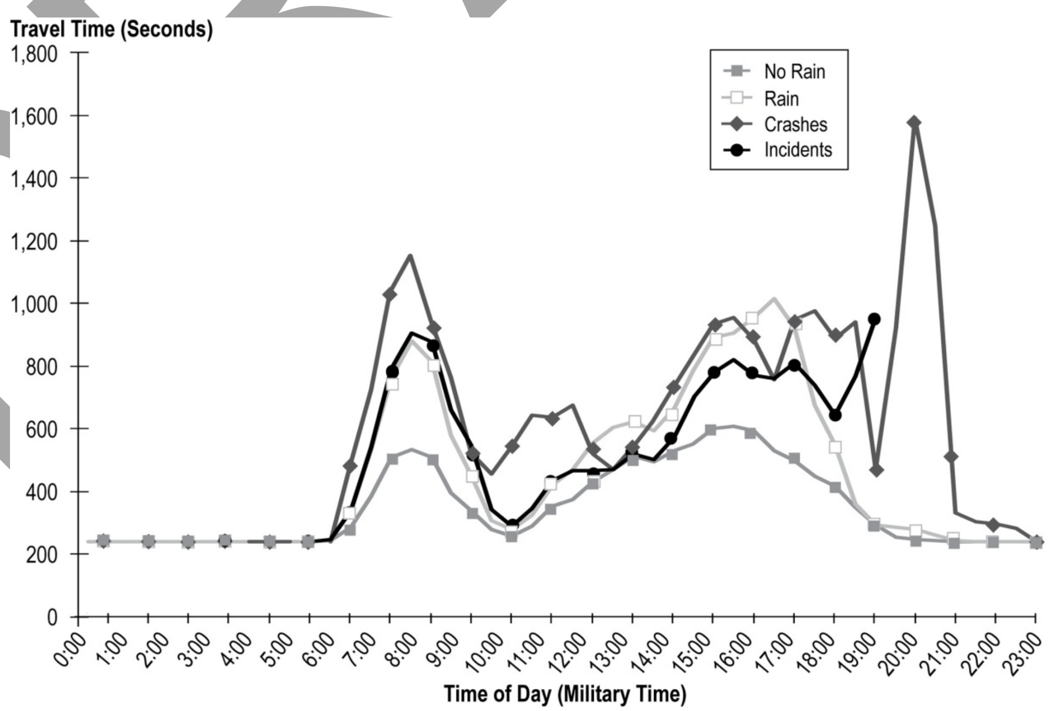


Figure 5.14 Mean Travel Times under Rain, Crash, or Noncrash Traffic Incident Conditions
I-5 Southbound North Seattle Corridor



All three figures (5.12 through 5.14) illustrate the mean travel time for nonholiday Tuesdays, Wednesdays, and Thursdays for all of 2006: 1) under nonrain conditions (regardless of incident conditions); 2) when rain has fallen within the last hour (regardless of incident conditions); 3) when a crash has occurred on the study section and is influencing traffic conditions; and 4) when any traffic incident has been reported as occurring on the study section by WSDOT's service patrols. Thus, the four expected travel-time conditions are not fully independent of each other. But each gives an excellent understanding of expected conditions in a way that might answer a traveler's question. (For example, the rain travel time line answers the question, "How long should I expect my commute trip to last on this corridor if it is raining?" The response to that question includes some days when crashes occur and others when they do not occur.) Note that the crash and incident travel time curves drop to zero when no reported crash or traffic incident-influenced travel during that specific period in 2006.

As can be seen in all three curves, when free-flow conditions are the routine condition, incidents and rain have little effect on mean travel times. In some cases, crashes create sufficient disruption that travel times increase in lower volume periods.

In the figures, the relative size of the travel-time changes measured during incident and crash conditions (for example, when compared to the "no rain" condition) is not consistent from corridor to corridor. These differences are caused by a variety of factors, including differences in: 1) the sizes of the incidents and crashes occurring on each study segment during 2006; 2) the locations of the incidents and crashes relative to the end points of each study segment; and 3) the volume/capacity ratio occurring on the study section at the time of the traffic disruption. Perhaps even more importantly, the travel-time statistics do not account for off-segment traffic disruptions. That is, case studies of a number of specific days in 2006 showed that congestion on one roadway segment can frequently grow to the point that it affects the upstream road segment. While roadway segment boundaries can be chosen to minimize the effects of known geometric bottlenecks, major traffic disruptions often create temporary bottlenecks that are not located at known bottleneck locations. The congestion on study segments caused by these off-segment events increases the "not influenced" travel times against which study outcomes are compared.

The combined result of these various factors is that the relative importance of any specific type of traffic disruption varies from study segment to study segment.

In the northbound I-5 South segment (Figure 5.12), rain has a more substantial effect on the A.M. peak-period travel times than do crashes. Late at night (midnight to 2:00 a.m.), incidents are seen to have a significant impact. (A review of these data indicated that the incidents in question occurred during a planned construction lane closure, resulting in a large roadway capacity reduction during that maintenance activity, with substantial congestion being the result.) In the middle of the afternoon and during the P.M. peak period (when the northbound I-5 South corridor is operating in the reverse of the peak direction and is, therefore, not usually congested), the primary causes of travel-time delays are crashes.

Figure 5.13, showing the Lynnwood corridor, (is likely the closest of the three figures to presenting the most "normal" image of the effects of both weather and traffic disruptions. In this figure, no late night congestion is apparent, although some late evening delays (~9:00 p.m.) are evident as a result of vehicle crashes. In the A.M. peak period, rain has the greatest effect in terms of increasing expected travel times. Both rain and vehicle crashes tend to cause travel delays slightly earlier in the A.M. peak period than do incidents, which track more closely to the "normal" peak-period travel times until almost the peak of the A.M. travel-time curve. Then the effects of incidents cause substantial additional travel time. In the P.M. peak period (again, on this corridor the P.M. peak is a reverse direction commute), only modest increases in travel times due to rain, incidents, or crashes occur, with crashes having the most significant impact.

Figure 5.14 illustrates a study corridor, North Seattle southbound, where travel times routinely degrade in both peak periods. This corridor differs from the other two examples in that crashes have a more significant impact on mean travel time in the a.m. peak than does rain. This is partly due to the fact that this corridor ends in two back-to-back C-class weaving sections that constitute both a major routine bottleneck and a high accident location. The result is that most of the causes of congestion in this section occur within this section. Congestion spill-back from downstream roadway segments on rainy days is not as significant a factor on this section as it is on the Lynnwood section. Consequently, crashes are more often a factor, especially in the morning.

Another important difference that can be seen in comparing Figure 5.14 with Figures 5.12 and 5.13 is the amount of off-peak congestion shown in Figure 5.14. The I-5 North Seattle roadway corridor carries considerable traffic volume relative to the roadway's capacity even in off-peak periods in the southbound direction. That traffic volume frequently results in moderate southbound congestion, even in the middle of the day. As a result, even relatively minor traffic incidents – or bad weather – can start with a moderate situation in the middle of the day and make it considerably worse, while Figures 5.12 and 5.13 show that traffic disruptions have relatively little impact on mid-day and evening roadway performance on the other example roadway segments.

Thus, the impacts of any disruption are a function of the underlying traffic volume condition during which that disruption occurs. From that basis, the next most important factor is the size of the disruption that is imposed on the traffic stream. Therefore, crashes frequently have more significant effects during times of lower volume. But during peak conditions, the simple creation of congestion, which can occur given a much smaller disruption, may be as significant as the size of the disruption itself. That is, once the roadway congests, a large disruption adds only a marginal increase to the delay, whereas a smaller disruption occurring before congestion forms can create an even larger change in expected travel times during the course of the peak period because of the growth of the queue associated with the initial congestion point.

Results – Effects of Crashes or Noncrash Incidents on Peak-Period Travel Time and Travel Reliability

The above section illustrates that traffic volumes during Seattle's peak periods are sufficient on many corridors to create congestion, and that congestion may result in a variety of travel times. When the effects of disruptions are added to those traffic volumes, travel times generally increase, as illustrated in Figures 5.12 through 5.14. When incident-influenced travel times were computed, as shown in Figures 5.12 through 5.14, only incidents that had a "still active" **(**Where "still active" means that travel times in the test section are slower than measured when the disruption was actually in place.) effect on roadway performance were considered. One difficulty with this approach is that it is hard to explain. It also does not generalize well.

For a different approach to looking at the effects of traffic disruptions on travel times, this study computed the expected mean, 80th percentile, and 95th percentile peak-period travel times for each study corridor, accounting for whether a disruption (crash or noncrash reported incident) had taken place. This approach basically answers the question, "If a crash (or other noncrash disruption) occurs today, how much worse will my commute be?"

To analytically answer this question, each nonholiday Tuesday through Thursday, five-minute travel time was placed into one of three categories: 1) not influenced; 2) influenced by a crash; or 3) influenced by a reported noncrash incident. Once a disruption had occurred during a peak period, all remaining five-minute travel times for the rest of that peak period were assumed to be influenced by that event. The A.M. peak was assumed to occur between 6:30 and 9:30 a.m. Any disruption that occurred after 4:00 a.m. was included in the analysis. The P.M. peak was assumed to occur between 3:00 and 7:00 p.m. Only traffic disruptions that occurred after 2:00 p.m. were included in the analysis. If a crash occurred at 5:00 p.m. the five-minute travel times prior to 5:00 p.m. were classified as noninfluenced, while those after 5:00 p.m. were crash influenced. If both a crash and a noncrash incident occurred, all time periods after the crash were considered crash influenced. Because the mean, 80th, and 95th percentiles travel times were computed from the entire pool of travel times within each classification of trips, this approach did create a minor bias toward lower travel times in the noninfluenced category, as a disproportionate number of travel times for that category were taken from the early (least congested) portion of the peak periods. This was somewhat balanced by the inability of this analysis to account for the effects of congestion spillback from one roadway segment to another.

The results of this analysis are shown in Table 5.7, which describes the impacts of crashes and noncrash incidents on the mean travel time computed for the A.M. peak period. For each study corridor, the mean travel-time increase (in seconds) caused by noncrash traffic incidents is presented. This is then shown as a percentage change in study section travel time in comparison to the mean travel time with no disruption. The percentage increase in travel time associated with a crash is then shown to illustrate the relative significance of crashes and noncrash traffic disruptions. The 42 study segments are sorted in order from most congested to least congested on the basis of their median and mean travel rates for all weekdays.

In Table 5.7, it can be seen that the mean travel time increases when traffic disruptions occur for all corridor study segments that have a mean travel rate of greater than 1.0. **(**A travel rate equal to 1.0 indicates that vehicles can operate at the speed limit: 60 mph or 1 minute per mile.) For all but four of those corridors, the occurrence of a crash has a greater impact on expected travel times than a reported noncrash incident. A more mixed effect of both crashes and noncrash incidents is evident for corridors that do not routinely exhibit at least some modest level of congestion. No direct correlation is observable between the delays that occur in response to traffic incidents and either the mean or median travel rates.

The P.M. peak period version of Table 5.7 is shown in Table 5.8. As with the A.M. peak results, all of the P.M. corridors with a median travel rate of greater than 1.0 show increases in mean travel time when any kind of traffic disruption occurs. Crashes result in a greater increase in the mean travel time than noncrash incidents on all but four of the study corridors. Because P.M. peak travel is different than that in the A.M. peak, these are different corridors than in the A.M. peak.

Other than the basic, if obvious, conclusion that traffic disruptions can be expected to increase travel times for moderate to heavily congested travel corridors, there are relatively few patterns in the data contained in Tables 5.7 and 5.8. There appears to be no consistent relationship between the percentage change in travel time and the base statistics that describe mean peak-period travel conditions (either mean travel rate or median travel rate). On some heavily congested corridors (e.g., I-405 Bellevue southbound P.M. peak, I-5 North Seattle southbound P.M. peak, I-5 South northbound A.M. peak), crashes and other incidents cause dramatic increases in expected travel times, even doubling the expected time to traverse the study section. On other heavily congested corridors (e.g., I-405 Eastgate southbound P.M. peak, I-405 Kennydale northbound A.M. peak), the travel time effects are considerably smaller – in the range of a 10 to 25 percent increase in expected travel times.

When looked at more comprehensively, noncrash incidents increase travel times an average of 17 percent in the morning and 21 percent in the evening on corridors that have mean peak-period travel rates of above 1.10. However, mean travel time changes range from 9 percent to 75 percent in the morning. In the evening, travel times change from 6 to 119 percent. If only crashes are considered, the A.M. peak changes range from 14 percent to 90 percent, with an average of 40 percent. The p.m. changes range from 9 to 176 percent, with an average of 41 percent.

Table 5.7 Effects of Incidents and Crashes on A.M. Peak-Period Travel Times

Study Corridor	A.M. Peak Travel Rate		Mean Travel Time Increase Due To All Traffic Incidents	Percent Increase over "Nonincident" Conditions	
	Mean	Median			If A Crash Occurs
I-405 Kennydale Northbound – A.M. Peak	3.66	3.4	179	11%	17%
I-405 North Southbound – A.M. Peak	2.82	2.4	347	35%	45%
I-5 North King Southbound – A.M. Peak	2.07	1.8	139	22%	43%
I-5 Seattle CBD Northbound – A.M. Peak	1.91	1.8	361	51%	57%
I-405 Kirkland Southbound – A.M. Peak	1.76	1.8	80	9%	14%
SR 520 Sea Eastbound – A.M. Peak	1.70	1.8	98	13%	32%
I-5 Lynwood Southbound – A.M. Peak	1.89	1.6	251	31%	60%
I-5 South Northbound – A.M. Peak	1.75	1.6	364	43%	58%
SR 167 Auburn Northbound – A.M. Peak	1.68	1.6	21	8%	15%
I-405 Eastgate Northbound – A.M. Peak	1.66	1.6	17	8%	24%
I-5 Seattle North Southbound – A.M. Peak	2.15	1.4	232	47%	84%
I-405 Kennydale Southbound – A.M. Peak	1.54	1.4	96	15%	34%
I-405 South Southbound – A.M. Peak	1.45	1.4	50	28%	14%
SR 167 Renton Northbound – A.M. Peak	1.62	1.2	390	75%	76%
SR 520 Sea Westbound – A.M. Peak	1.51	1.2	183	30%	19%
I-5 Tukwilla Northbound – A.M. Peak	1.50	1.2	254	57%	76%
I-90 Issaquah Westbound – A.M. Peak	1.46	1.2	169	29%	60%
I-90 Bellevue Westbound – A.M. Peak	1.30	1.2	73	24%	22%
I-405 Bellevue Northbound – A.M. Peak	1.27	1.2	39	12%	27%
I-405 South Northbound – A.M. Peak	1.24	1.2	30	19%	15%
I-90 Seattle Eastbound – A.M. Peak	1.96	1	50	27%	36%
I-90 Seattle Westbound – A.M. Peak	1.20	1	20	21%	27%
I-90 Bridge Eastbound – A.M. Peak	1.18	1	40	9%	38%
I-405 Bellevue Southbound – A.M. Peak	1.16	1	25	11%	62%
I-5 Everett Southbound – A.M. Peak	1.15	1	39	20%	90%
I-90 Bridge Westbound – A.M. Peak	1.15	1	40	11%	22%
I-5 Seattle CBD Southbound – A.M. Peak	1.10	1	48	9%	24%
SR 167 Auburn Southbound – A.M. Peak	1.06	1	-2	-1%	-6%
I-405 Eastgate Southbound – A.M. Peak	1.05	1	9	7%	76%
SR 167 Renton Southbound – A.M. Peak	1.04	1	*-1*	0%	*-6%*
I-5 Tukwilla Southbound – A.M. Peak	1.02	1	14	3%	*-2%*
SR 520 Red Westbound – A.M. Peak	1.02	1	29	8%	7%
I-405 North Northbound – A.M. Peak	1.02	1	8	2%	4%
I-5 Everett Northbound – A.M. Peak	1.01	1	5	3%	51%
I-5 Lynwood Northbound – A.M. Peak	1.01	1	16	3%	52%
I-5 Seattle North Northbound – A.M. Peak	1.01	1	3	1%	0%
I-90 Bellevue Eastbound – A.M. Peak	1.01	1	*-1*	*-1%*	0%
I-5 South Southbound – A.M. Peak	1.00	1	23	4%	3%
I-405 Kirkland Northbound – A.M. Peak	1.00	1	7	1%	1%
SR 520 Red Eastbound A.M. Peak	1.00	1	1	0%	0%
I-90 Issaquah Eastbound – A.M. Peak	1.00	1	*-1*	0%	0%
I-5 North King Northbound – A.M. Peak	1.00	1	1	0%	0%

A review of base data for a sample of these corridors suggested that two factors contribute to this variation. In some cases, the noninfluenced annual mean travel time is significantly affected by downstream congestion, where that downstream congestion is caused both by routine conditions and by traffic disruptions on those downstream roadway segments. The result of this downstream congestion backing up on the study section is that an abnormally high mean travel time for nondisruption-influenced travel times occurs on the study section. This in turn makes small both the absolute and percentage differences in travel times that are influenced by crashes.

The second factor is simply the number and variety of incidents/crashes occurring in the different test sections. Some traffic disruptions are more significant in terms of the number of lanes they block and the time at which they occur. A modest number of very bad traffic disruptions can cause a fairly high increase in the mean travel time because of the modest number of data points in each sample.

To further explore the effects of incidents and crashes on travel-time reliability, Tables 5.9 and 5.10 describe the measured changes in the 80th and 95th percentile travel times when crashes and noncrash incidents take place. Similar to Tables 5.7 and 5.8, these two tables also are sorted from most congested to least congested study corridor. Table 5.9 presents the changes to a.m. peak period travel times. Table 5.10 presents the p.m. peak results.

Table 5.8 Effects of Incidents and Crashes on P.M. Peak-Period Travel Times

Study Corridor	P.M. Peak Travel Rate Mean	P.M. Peak Travel Rate Median	Mean Travel Time Increase Due To All Traffic Incidents	Percent Increase over "Nonincident" Conditions	Percent Increase over "Nonincident" Conditions: If A Crash Occurs
I-405 Bellevue Southbound – P.M. Peak	3.73	3.6	400	88%	102%
I-405 Eastgate Southbound – P.M. Peak	2.73	2.6	29	10%	25%
SR 520 Sea Westbound – P.M. Peak	2.72	2.6	230	23%	18%
I-405 South Northbound – P.M. Peak	2.58	2.6	47	17%	14%
I-5 Seattle North Southbound – P.M. Peak	2.56	2	410	119%	138%
I-405 Kirkland Northbound – P.M. Peak	1.99	2	127	14%	26%
I-5 Seattle CBD Northbound – P.M. Peak	1.96	1.8	350	52%	60%
I-405 Kennydale Southbound – P.M. Peak	1.90	1.8	109	15%	23%
I-5 North King Northbound – P.M. Peak	1.79	1.8	92	17%	24%
I-5 Seattle CBD Southbound – P.M. Peak	1.72	1.8	153	22%	30%
SR 167 Auburn Southbound – P.M. Peak	1.96	1.6	90	29%	33%
SR 520 Red Eastbound – P.M. Peak	1.87	1.6	83	14%	34%
I-5 South Southbound – P.M. Peak	1.76	1.6	265	30%	46%
I-405 North Northbound – P.M. Peak	1.61	1.6	37	6%	29%
I-5 Everett Northbound – P.M. Peak	1.87	1.4	128	50%	55%
I-5 Seattle North Northbound – P.M. Peak	1.74	1.4	73	18%	29%
SR 167 Renton Southbound – P.M. Peak	1.63	1.4	180	31%	57%
I-405 South Southbound – P.M. Peak	1.52	1.4	79	43%	26%
I-90 Bridge Westbound – P.M. Peak	1.73	1.2	122	25%	12%
SR 520 Sea Eastbound – P.M. Peak	1.49	1.2	115	20%	34%
I-5 Lynwood Northbound – P.M. Peak	1.38	1.2	101	17%	45%
I-405 Bellevue Northbound – P.M. Peak	1.34	1.2	89	35%	68%
I-90 Seattle Westbound – P.M. Peak	1.13	1.2	7	8%	9%
SR 520 Red Westbound – P.M. Peak	1.49	1	168	38%	40%
I-90 Seattle Eastbound – P.M. Peak	1.43	1	84	72%	54%
I-90 Bridge Eastbound – P.M. Peak	1.40	1	111	27%	35%
I-5 North King Southbound – P.M. Peak	1.33	1	232	67%	176%
I-90 Bellevue Westbound – P.M. Peak	1.30	1	154	63%	96%
I-5 Tukwilla Southbound – P.M. Peak	1.19	1	102	22%	66%
SR 167 Renton Northbound – P.M. Peak	1.17	1	151	37%	40%
I-405 Kennydale Northbound – P.M. Peak	1.17	1	84	17%	56%
I-90 Bellevue Eastbound – P.M. Peak	1.11	1	48	19%	50%
I-5 Everett Southbound – P.M. Peak	1.10	1	16	8%	63%
I-5 Lynwood Southbound – P.M. Peak	1.10	1	59	11%	44%
I-405 North Southbound – P.M. Peak	1.09	1	64	16%	37%
I-405 Kirkland Southbound – P.M. Peak	1.09	1	101	19%	27%
I-5 Tukwilla Northbound – P.M. Peak	1.07	1	96	24%	81%
SR 167 Auburn Northbound – P.M. Peak	1.05	1	13	6%	16%
I-405 Eastgate Northbound – P.M. Peak	1.04	1	19	16%	18%
I-90 Issaquah Eastbound – P.M. Peak	1.01	1	0	0%	-1%
I-5 South Northbound – P.M. Peak	1.01	1	14	2%	6%
I-90 Issaquah Westbound – P.M. Peak	1.00	1	17	4%	5%

Table 5.9 Effects of Crashes and Noncrash Incidents on A.M. Peak Period 80th and 95th Percentile Travel Times

Study Corridor	Mean A.M. Peak Travel Rate	Travel Time Under Noncrash Incident Conditions Percent Increase		Travel Time Under Crash Conditions Percent Increase	
		in 80th Percentile	in 95th Percentile	in 80th Percentile	in 95th Percentile
I-405 Kennydale Northbound – A.M. Peak	3.66	6.3%	10.9%	9.4%	8.2%
I-405 North Southbound – A.M. Peak	2.82	*-6.4%*	9.6%	2.1%	13.5%
I-5 North King Southbound – A.M. Peak	2.07	0.0%	*-5.3%*	16.8%	25.8%
I-5 Seattle CBD Northbound – A.M. Peak	1.91	15.4%	17.1%	40.5%	35.4%
I-405 Kirkland Southbound – A.M. Peak	1.76	*-2.2%*	*-4.6%*	1.1%	2.3%
SR 520 Sea Eastbound – A.M. Peak	1.70	5.6%	12.0%	20.5%	52.5%
I-5 Lynwood Southbound – A.M. Peak	1.89	*-16.0%*	*-15.4%*	9.5%	15.0%
I-5 South Northbound – A.M. Peak	1.75	*-18.6%*	*-16.8%*	*-6.1%*	*-0.1%*
SR 167 Auburn Northbound – A.M. Peak	1.68	2.3%	7.5%	18.3%	37.9%
I-405 Eastgate Northbound – A.M. Peak	1.66	5.5%	6.7%	6.8%	30.9%
I-5 Seattle North Southbound – A.M. Peak	2.15	2.5%	*-0.1%*	31.3%	24.7%
I-405 Kennydale Southbound – A.M. Peak	1.54	*-1.7%*	10.1%	21.7%	27.8%
I-405 South Southbound – A.M. Peak	1.45	2.7%	20.3%	*-0.5%*	17.0%
SR 167 Renton Northbound – A.M. Peak	1.62	*-4.2%*	*-14.7%*	84.8%	61.8%
SR 520 Sea Westbound – A.M. Peak	1.51	*-0.2%*	*-4.1%*	17.9%	12.7%
I-5 Tukwilla Northbound – A.M. Peak	1.50	*-5.4%*	*-13.4%*	16.8%	12.3%
I-90 Issaquah Westbound – A.M. Peak	1.46	21.0%	0.5%	28.3%	36.2%
I-90 Bellevue Westbound – A.M. Peak	1.30	-0.5%	30.2%	12.6%	10.8%
I-405 Bellevue Northbound – A.M. Peak	1.27	18.5%	23.9%	33.4%	35.2%
I-405 South Northbound – A.M. Peak	1.24	0.6%	*-0.5%*	2.7%	9.7%
I-90 Seattle Eastbound – A.M. Peak	1.96	*-2.1%*	*-9.7%*	23.3%	45.8%
I-90 Seattle Westbound – A.M. Peak	1.20	9.2%	*-5.9%*	35.0%	11.8%
I-90 Bridge Eastbound – A.M. Peak	1.18	34.1%	12.7%	51.2%	41.5%
I-405 Bellevue Southbound – A.M. Peak	1.16	0.3%	*-5.1%*	93.2%	114.6%
I-5 Everett Southbound – A.M. Peak	1.15	*-2.6%*	*-29.2%*	4.1%	17.6%
I-90 Bridge Westbound – A.M. Peak	1.15	*0.0%*	*-1.0%*	56.2%	162.0%
I-5 Seattle CBD Southbound – A.M. Peak	1.10	1.8%	*-1.3%*	13.0%	28.6%
SR 167 Auburn Southbound – A.M. Peak	1.06	2.7%	8.8%	No crashes	A.M. Peak
I-405 Eastgate Southbound – A.M. Peak	1.05	0.3%	*-0.1%*	6.5%	76.5%
SR 167 Renton Southbound – A.M. Peak	1.04	2.5%	1.3%	0.8%	0.1%
I-5 Tukwilla Southbound – A.M. Peak	1.02	*0.0%*	*-0.4%*	0.4%	0.4%
SR 520 Red Westbound – A.M. Peak	1.02	0.6%	12.7%	29.3%	76.6%
I-405 North Northbound – A.M. Peak	1.02	*-0.2%*	1.1%	1.2%	6.2%
I-5 Everett Northbound – A.M. Peak	1.01	*-0.1%*	*-0.1%*	1.2%	38.4%
I-5 Lynwood Northbound – A.M. Peak	1.01	0.1%	0.1%	0.6%	195.6%
I-5 Seattle North Northbound – A.M. Peak	1.01	2.3%	2.9%	5.9%	5.3%
I-90 Bellevue Eastbound – A.M. Peak	1.01	0.0%	0.9%	0.0%	0.7%
I-5 South Southbound – A.M. Peak	1.00	0.0%	0.0%	0.0%	19.6%
I-405 Kirkland Northbound – A.M. Peak	1.00	0.2%	2.4%	0.2%	0.2%
SR 520 Red Eastbound – A.M. Peak	1.00	*-10.5%*	*-14.9%*	*-9.3%*	*-16.5%*
I-90 Issaquah Eastbound – A.M. Peak	1.00	0.0%	0.0%	0.0%	0.0%
I-5 North King Northbound – A.M. Peak	1.00	0.0%	0.0%	0.0%	0.0%

Table 5.10 Effects of Crashes and Noncrash Incidents on P.M. Peak Period 80th and 95th Percentile Travel Times

Study Corridor	Mean P.M. Peak Travel Rate	Travel Time Under Noncrash Incident Conditions Percent Increase: in 80th Percentile	Travel Time Under Noncrash Incident Conditions Percent Increase: in 95th Percentile	Travel Time Under Crash Conditions Percent Increase: in 80th Percentile	Travel Time Under Crash Conditions Percent Increase: in 95th Percentile
I-405 Bellevue Southbound – P.M. Peak	3.73	9.8%	*-3.4%*	10.4%	0.3%
I-405 Eastgate Southbound – P.M. Peak	2.73	3.0%	*-5.8%*	6.4%	27.3%
SR 520 Sea Westbound – P.M. Peak	2.72	21.4%	4.1%	25.7%	1.7%
I-405 South Northbound – P.M. Peak	2.58	12.4%	7.8%	7.0%	8.4%
I-5 Seattle North Southbound – P.M. Peak	2.56	5.2%	1.3%	21.8%	14.9%
I-405 Kirkland Northbound – P.M. Peak	1.99	4.6%	3.6%	18.7%	27.6%
I-5 Seattle CBD Northbound – P.M. Peak	1.96	29.5%	26.0%	52.4%	30.8%
I-405 Kennydale Southbound – P.M. Peak	1.90	*-11.6%*	9.0%	*-6.4%*	*-0.1%*
I-5 North King Northbound – P.M. Peak	1.79	12.6%	10.9%	11.3%	17.1%
I-5 Seattle CBD Southbound – P.M. Peak	1.72	2.4%	*-3.1%*	5.2%	12.7%
SR 167 Auburn Southbound – P.M. Peak	1.96	0.6%	22.5%	29.4%	11.2%
SR 520 Red Eastbound – P.M. Peak	1.87	*-10.5%*	*-14.9%*	*-9.3%*	*-16.5%*
I-5 South Southbound – P.M. Peak	1.76	10.3%	9.8%	16.8%	34.9%
I-405 North Northbound – P.M. Peak	1.61	8.4%	30.5%	27.4%	59.5%
I-5 Everett Northbound – P.M. Peak	1.87	*-6.8%*	*-0.2%*	*-3.4%*	2.5%
I-5 Seattle North Northbound – P.M. Peak	1.74	9.4%	11.4%	18.3%	0.1%
SR 167 Renton Southbound – P.M. Peak	1.63	15.9%	16.3%	48.2%	67.7%
I-405 South Southbound – P.M. Peak	1.52	5.1%	6.9%	7.8%	22.6%
I-90 Bridge Westbound – P.M. Peak	1.73	48.8%	29.6%	47.5%	13.4%
SR 520 Sea Eastbound – P.M. Peak	1.49	24.4%	21.3%	32.1%	42.9%
I-5 Lynwood Northbound – P.M. Peak	1.38	12.8%	2.4%	43.1%	60.9%
I-405 Bellevue Northbound – P.M. Peak	1.34	7.3%	*-8.0%*	54.5%	68.1%
I-90 Seattle Westbound – P.M. Peak	1.13	0.6%	7.7%	1.7%	9.5%
SR 520 Red Westbound – P.M. Peak	1.49	169.2%	23.4%	171.8%	50.9%
I-90 Seattle Eastbound – P.M. Peak	1.43	25.9%	*-31.4%*	33.4%	13.2%
I-90 Bridge Eastbound – P.M. Peak	1.40	51.3%	15.4%	83.5%	21.5%
I-5 North King Southbound – P.M. Peak	1.33	9.9%	86.8%	151.5%	114.6%
I-90 Bellevue Westbound – P.M. Peak	1.30	494.3%	244.6%	213.0%	107.2%
I-5 Tukwilla Southbound – P.M. Peak	1.19	8.4%	7.9%	48.6%	18.0%
SR 167 Renton Northbound – P.M. Peak	1.17	6.3%	23.1%	26.3%	44.4%
I-405 Kennydale Northbound – P.M. Peak	1.17	7.1%	*-3.9%*	40.4%	98.1%
I-90 Bellevue Eastbound – P.M. Peak	1.11	3.2%	*-0.2%*	19.0%	419.0%
I-5 Everett Southbound – P.M. Peak	1.10	5.9%	8.6%	57.5%	149.3%
I-5 Lynwood Southbound – P.M. Peak	1.10	*-0.4%*	*-7.2%*	20.6%	41.3%
I-405 North Southbound – P.M. Peak	1.09	0.3%	45.0%	58.1%	41.6%
I-405 Kirkland Southbound – P.M. Peak	1.09	6.6%	19.3%	20.9%	29.1%
I-5 Tukwilla Northbound – P.M. Peak	1.07	2.1%	*-6.7%*	113.7%	146.3%
SR 167 Auburn Northbound – P.M. Peak	1.05	5.4%	139.6%	61.0%	58.6%
I-405 Eastgate Northbound – P.M. Peak	1.04	*-2.0%*	*-6.8%*	26.7%	142.6%
I-90 Issaquah Eastbound – P.M. Peak	1.01	1.2%	1.0%	0.1%	*-6.0%*
I-5 South Northbound – P.M. Peak	1.01	*-0.2%*	*-0.1%*	4.7%	77.8%
I-90 Issaquah Westbound – P.M. Peak	1.00	0.1%	3.5%	*-0.4%*	*-0.5%*

Similarities between the tables are that, in most cases, crashes have a greater impact than noncrash traffic incidents in both the A.M. and P.M. peak periods. In addition, the least congested corridors in both peaks generally show the least change in the measured 80th and 95th percentile travel times when crashes and other traffic incidents occur.

The most significant difference is that all corridors with median peak period travel rates for all weekdays above 1.0 or mean weekday travel rates above 1.10 show an increase in mean travel times on days when either a crash or noncrash incident occurred, but *many corridors do not show increased 80th or 95th percentile travel times under those same incident conditions, especially for noncrash incidents*. The effects of noncrash incidents are particularly mixed. Eleven of 27 corridors in the A.M. peak period and four of 34 corridors in the P.M. peak period do not have increased 80th percentile travel times due to noncrash incidents. Only two corridors in the morning and three corridors in the afternoon among these moderately to heavily congested corridors have peak periods in which the 80th percentile travel times do not increase under crash conditions. Similarly, 15 of these corridors in the morning and 10 of them in the afternoon do not show an increased 95th percentile travel time. Only one corridor in the a.m. peak and two in the P.M. peak have 95th percentile travel times that do not increase when crashes occurred. In all cases, several additional corridors show only marginal changes in these statistics.

If the results for the corridors with average weekday mean travel rates above 1.10 are simply averaged:

- Noncrash incidents increase the 80th percentile only 2 percent in the A.M. peak and 29 percent in the P.M. peak;
- Noncrash incidents increase the 95th percentile only 1 percent in the A.M. peak and 16 percent in the P.M. peak;
- Crashes increase the 80th percentile 24 percent in the A.M. peak and 39 percent in the P.M. peak; and
- Crashes increase the 95th percentile travel times 33 percent in the A.M. peak and 47 percent in the P.M. peak.

Taken together, these results indicate that noncrash incidents are mostly responsible for modest changes in travel times. Those changes are more pronounced during periods of higher traffic volume and are thus generally more significant in the P.M. peak than during the A.M. peak. Noncrash incidents generally have very modest impacts on the worst travel days.

On the other hand, crashes have more substantial impacts on both the A.M. and P.M. peak periods. The fact that an accident has occurred can be expected to add 20 to 40 percent to the travel times in much of the travel-time distribution curve, whether that is the mean, 80th percentile, or 95th percentile travel time, with some crashes being responsible for much larger increases.

Results – Changes in When Peak Period Congestion Ends as a Result of Incidents

In Figures 5.12 through 5.14, only those travel times influenced by an incident or crash were included in the computation of the mean travel time associated with incidents and crashes. The problem with this (or any) approach to defining the influence of disruptions on travel times is understanding when those influences *end*. That is, the definition of "incident influence" used in the above section means that only incidents that have a still active (Where "still active" means that travel times in the test section are slower than those measured when the disruption was occurring.) effect on roadway performance are considered when "incident-influenced travel time" is computed. If an incident is quickly cleared and the disruption is minimized, how does that event affect the travel time experienced?

To give a better understanding of the effects of incidents and crashes, an entirely different examination of the impacts of those disruptions is discussed below. This subsection examines when congestion, as part of the normal peak period increases in travel demand, can be expected to end. A quick examination of Figures 5.12 through 5.14 shows that mean travel times slow earlier in the day and last longer into the day whenever traffic disruptions occur. From the motorists' perspective, this means not only that their trip during the heart of the commute is longer, but that even if they have delayed their trip until after the "normal" peak period, they may still be stuck in congestion.

To examine this phenomenon, the project team computed when the A.M. and P.M. peak periods normally end for each study corridor. We then examined whether the ending time of the peak period changed as a result of the occurrence of crashes or noncrash incidents. The resulting summary statistics for these analyses are shown in Tables 5.11 and 5.12. (All of the statistics generated from this analysis are shown in Appendix D.) The tables are sorted so that the study sections with the slowest, most congested corridors (as defined by their peak period *median* travel rate, in minutes per mile) are at the top of the table, and the fastest, least congested corridors are at the bottom. Within a given travel rate, routes are sorted by their *mean* travel rate. Both tables show the mean time of day when congestion ends on days that do not experience reported incidents or crashes, and the mean difference (in minutes) in the time of day for the end of congestion for each corridor when at least one crash or incident was reported within the study section in the indicated direction of travel. (If both a crash and a non-crash incident occur, the day is classified as being affected by a crash. For the A.M. peak, the crash or incident must have taken place after 4:00 a.m. and before the "end of congestion" is reached. For the P.M. peak, the crash or incident must have taken place after 3:00 p.m. and before the "end of congestion" is reached.) Statistical comparisons were performed by using the nonparametric Anderson-Darling K-Sample test, with *p*-values of less than 0.01 being used to determine those "end of congestion" times that were statistically significant. Statistically insignificant differences are set to zero in Tables 5.9 and 5.10.

Table 5.11 Effects of Incidents and Crashes on the Time That Congestion Abates After the Evening Peak Period

Study Corridor	P.M. Peak Travel Rate Mean	P.M. Peak Travel Rate Median	"Normal" Time When Congestion Abates	Additional Congestion Time After a Noncrash	Additional Congestion Time After a Crash
I-405 Bellevue Southbound – p.m. Peak	3.73	3.6	19:44	0:00	0:20
I-405 Eastgate Southbound – p.m. Peak	2.73	2.6	19:12	0:00	0:15
SR 520 Sea Westbound – p.m. Peak	2.72	2.6	20:00	0:00	0:12
I-405 South Northbound – p.m. Peak	2.58	2.6	20:41	0:00	0:00
I-5 Seattle North Southbound – p.m. Peak	2.56	2	18:49	0:00	0:31
I-405 Kirkland Northbound – p.m. Peak	1.99	2	19:03	0:00	0:11
I-5 Seattle CBD Northbound – p.m. Peak	1.96	1.8	18:53	0:00	0:00
I-405 Kennydale Southbound – P.M. Peak	1.90	1.8	19:27	0:00	0:00
I-5 North King Northbound – P.M. Peak	1.79	1.8	18:55	0:00	0:12
I-5 Seattle CBD Southbound – P.M. Peak	1.72	1.8	18:20	0:00	0:00
SR 167 Auburn Southbound – P.M. Peak	1.96	1.6	18:47	0:00	0:08
SR 520 Red Eastbound – P.M. Peak	1.87	1.6	19:09	0:00	0:00
I-5 South Southbound – P.M. Peak	1.76	1.6	18:08	0:00	0:00
I-405 North Northbound – P.M. Peak	1.61	1.6	19:18	0:00	0:14
I-5 Everett Northbound – P.M. Peak	1.87	1.4	17:08	0:28	0:58
I-5 Seattle North Northbound – P.M. Peak	1.74	1.4	18:34	0:00	0:00
SR 167 Renton Southbound – P.M. Peak	1.63	1.4	18:47	0:00	0:00
I-405 South Southbound – P.M. Peak	1.52	1.4	19:36	0:00	0:00
I-90 Bridge Westbound – P.M. Peak	1.73	1.2	18:25	0:34	0:48
SR 520 Sea Eastbound – P.M. Peak	1.49	1.2	18:52	0:00	0:22
I-5 Lynwood Northbound – P.M. Peak	1.38	1.2	19:00	0:00	0:00
I-405 Bellevue Northbound – P.M. Peak	1.34	1.2	18:09	0:00	0:27
I-90 Seattle Westbound – P.M. Peak	1.13	1.2	17:29	0:00	0:00
SR 520 Red Westbound – P.M. Peak	1.49	1	16:51	1:24	1:53
I-90 Seattle Eastbound – P.M. Peak	1.43	1	17:07	0:00	1:05
I-90 Bridge Eastbound – P.M. Peak	1.40	1	18:18	0:22	0:35
I-5 North King Southbound – P.M. Peak	1.33	1	16:47	0:29	1:57
I-90 Bellevue Westbound – P.M. Peak	1.30	1	16:13	1:21	2:10
I-5 Tukwilla Southbound – P.M. Peak	1.19	1	17:18	0:21	0:51
SR 167 Renton Northbound – P.M. Peak	1.17	1	17:22	0:27	0:57
I-405 Kennydale Northbound – P.M. Peak	1.17	1	18:05	0:00	0:23
I-90 Bellevue Eastbound – P.M. Peak	1.11	1	16:35	0:00	1:02
I-5 Everett Southbound – P.M. Peak	1.10	1	16:35	0:24	0:57
I-5 Lynwood Southbound – P.M. Peak	1.10	1	17:21	0:00	1:09
I-405 North Southbound – P.M. Peak	1.09	1	17:40	0:00	0:46
I-405 Kirkland Southbound – P.M. Peak	1.09	1	16:55	1:00	1:21
I-5 Tukwilla Northbound – P.M. Peak	1.07	1	16:23	0:23	1:56
SR 167 Auburn Northbound – P.M. Peak	1.05	1	17:31	0:00	0:00
I-405 Eastgate Northbound – P.M. Peak	1.04	1	16:24	0:00	0:47
I-90 Issaquah Eastbound – P.M. Peak	1.01	1	16:10	0:00	0:00
I-5 South Northbound – P.M. Peak	1.01	1	16:05	0:00	0:45
I-90 Issaquah Westbound – P.M. Peak	1.00	1	16:05	0:00	0:00

Table 5.12 Effects of Incidents and Crashes on the Time That Congestion Abates After the Morning Peak Period

Study Corridor	A.M. Peak Travel Rate: Mean	A.M. Peak Travel Rate: Median	"Normal" Time When Congestion Abates	Additional Congestion Time: After a Noncrash	Additional Congestion Time: After a Crash	Adjusted End of Congestion: Travel Time Value[a]
I-405 Kennydale Northbound – A.M. Peak	3.66	3.4	11:47	0:00	1:33	10%
I-405 North Southbound – A.M. Peak	2.82	2.4	9:56	1:27	2:09	
I-5 North King Southbound – A.M. Peak	2.07	1.8	11:06	0:48	1:29	10%
I-5 Seattle CBD Northbound – A.M. Peak	1.91	1.8	12:15	0:00	0:00	No disruption-free days
I-405 Kirkland Southbound – A.M. Peak	1.76	1.8	10:16	0:56	1:14	
SR 520 Sea Eastbound – A.M. Peak	1.70	1.8	11:54	6:02	6:53	
I-5 Lynwood Southbound – A.M. Peak	1.89	1.6	10:06	1:57	1:39	
I-5 South Northbound – A.M. Peak	1.75	1.6	9:16	0:00	0:22	
SR 167 Auburn Northbound – A.M. Peak	1.68	1.6	11:40	0:00	0:00	20%
I-405 Eastgate Northbound – A.M. Peak	1.66	1.6	11:38	0:00	1:04	10%
I-5 Seattle North Southbound – A.M. Peak	2.15	1.4	9:38	0:00	4:58	
I-405 Kennydale Southbound – A.M. Peak	1.54	1.4	9:08	1:19	1:23	20%
I-405 South Southbound – A.M. Peak	1.45	1.4	12:46	3:12	2:17	20%
SR 167 Renton Northbound – A.M. Peak	1.62	1.2	9:13	1:47	1:22	20%
SR 520 Sea Westbound – A.M. Peak	1.51	1.2	9:51	0:00	2:54	10%
I-5 Tukwilla Northbound – A.M. Peak	1.50	1.2	10:06	0:00	0:32	
I-90 Issaquah Westbound – A.M. Peak	1.46	1.2	9:10	0:00	0:33	
I-90 Bellevue Westbound – A.M. Peak	1.30	1.2	9:26	0:13	0:00	
I-405 Bellevue Northbound – A.M. Peak	1.27	1.2	11:01	3:34	5:00	10%
I-405 South Northbound – A.M. Peak	1.24	1.2	8:21	4:49	7:47	20%
I-90 Seattle Eastbound – A.M. Peak	1.96	1	8:45	0:00	1:05	
I-90 Seattle Westbound – A.M. Peak	1.20	1	7:35	0:42	1:52	
I-90 Bridge Eastbound – A.M. Peak	1.18	1	9:23	0:45	1:04	
I-405 Bellevue Southbound – A.M. Peak	1.16	1	8:27	7:56	11:07	10%
I-5 Everett Southbound – A.M. Peak	1.15	1	7:08	0:00	1:06	
I-90 Bridge Westbound – A.M. Peak	1.15	1	8:04	0:26	1:30	
I-5 Seattle CBD Southbound – A.M. Peak	1.10	1	9:28	0:00	4:57	
SR 167 Auburn Southbound – A.M. Peak	1.06	1	8:58	7:29	9:59	
I-405 Eastgate Southbound – A.M. Peak	1.05	1	7:22	0:00	0:32	
SR 167 Renton Southbound – A.M. Peak	1.04	1	9:42	7:33	7:30	
I-5 Tukwilla Southbound – A.M. Peak	1.02	1	7:08	0:00	7:51	
SR 520 Red Westbound – A.M. Peak	1.02	1	7:09	0:56	2:10	
I-405 North Northbound – A.M. Peak	1.02	1	7:56	0:12	1:47	
I-5 Everett Northbound – A.M. Peak	1.01	1	7:05	0:00	0:14	
I-5 Lynwood Northbound – A.M. Peak	1.01	1	7:13	0:00	0:00	
I-5 Seattle North Northbound – A.M. Peak	1.01	1	7:07	0:00	0:00	
I-90 Bellevue Eastbound – A.M. Peak	1.01	1	7:05	0:00	0:00	
I-5 South Southbound – A.M. Peak	1.00	1	7:07	0:08	0:00	
I-405 Kirkland Northbound – A.M. Peak	1.00	1	7:05	0:05	0:00	
SR 520 Red Eastbound – A.M. Peak	1.00	1	7:05	0:00	0:00	
I-90 Issaquah Eastbound – A.M. Peak	1.00	1	7:05	0:00	0:00	
I-5 North King Northbound – A.M. Peak	1.00	1	7:05	0:00	0:00	

[a] For the "end of congestion" to occur *before* noon after the A.M. peak period on days *without incidents or crashes* on some study corridors, it was necessary to change the definition of "congestion" from 20 consecutive minutes of average travel times being faster than 1.05 times the travel time at the speed limit to either 1.10 times the travel times at the speed limit (indicated by the value of 10 percent) or 1.20 times for travel time at the speed limit (indicated by 20 percent).

In Table 5.11, congestion in the I-405 southbound corridor through Bellevue normally ends at 7:44 p.m. if no disruptions have occurred. If a noncrash incident occurs after 3:00 p.m., it can be expected to last 13 minutes longer (7:57 p.m.). Congestion in that same study corridor lasts 20 minutes longer than "normal" if a crash has occurred. The very next row in the table shows that the next section of I-405 downstream of Bellevue (I-405 Eastgate southbound) does not experience a statistically significant change in the time that p.m. peak period congestion abates if an incident occurs. However, crashes on the Eastgate section do have a statistically significant effect, adding 15 minutes to the duration of slow evening traffic conditions on this roadway section.

While the nature (size, duration, and specific location) of incidents affects exactly how much disruption each causes, and these differences in incident size/ duration are not directly accounted for in these tables, some generalizations can be made from these tables. Among these are the following:

- Incidents that occur in the evening peak period have little measurable effect on the time that peak period congestion abates for: 1) very heavily congested roadway sections; or 2) very lightly congested sections;
- Crashes extend the evening commute period's congestion more significantly than noncrash incidents, and they are more likely to affect roadway performance than other kinds of incidents; and
- The duration of congestion on a surprising number of corridors is not significantly affected by a crash occurring on that section.

Of the 18 corridors with a median P.M. peak period travel rate of 1.4 or greater, the end of congestion was extended by noncrash incidents in a statistically significant manner for only one. For less than half (9 of 19) of the study, corridors with a median travel rate equal to the speed limit was the "end of congestion time" extended when incidents occurred.

The effects of incidents and crashes in the morning peak period described in Table 5.12 have several significant differences from those shown for the evening peak period in Table 5.11. The most significant difference is that the heavily congested a.m. corridors are much more sensitive to incidents than their p.m. peak period counterparts. None of the 14 corridors with P.M. peak median travel rates above 1.4 have congestion durations that show sensitivity to noncrash incidents, whereas 5 of the 10 A.M. peak corridors operating at this level of congestion are sensitive to noncrash incidents. One of the other study corridors (I-5 Seattle CBD northbound) had so many disruptions that no comparison can be made. (The I-5 Seattle CBD northbound study segment had only one day among all nonholiday Tuesdays, Wednesdays, and Thursdays in 2006 that did not contain either a crash or a WITS reported incident. One day is not sufficient to make a statistically significant comparison.)

A second difference between the morning and evening periods is the size of the change when incidents and crashes do affect the end of congestion. In the evening, when incidents and crashes have an effect, the mean change in the duration of the peak period tends to be between 15 minutes and an hour, at most. (Thirty-five out of 45 statistically significant difference are less than one hour.) In the morning peak period, on the other hand, corridors affected by crashes and other incidents routinely see congestion extend for more than an hour, and in many cases, multiple hours.

However, at the less congested end of the congestion distribution, the morning peak period is similar to the evening peak period. More than half of the study corridors with a median travel rate equal to the speed limit (1.0) have congestion ending times that are not statistically affected by incidents. The majority of these corridors also have a mean travel rate of less than 1.02. These same corridors also are reasonably insensitive to congestion caused by crashes. These results indicate that if traffic volume relative to capacity is low enough to not produce even light routine congestion, then only very large incidents and crashes will create congestion.

These observed differences further strengthen the primary finding of this study: the overriding factor affecting travel-time reliability is the background traffic volume.

While there are many differences in the A.M. and P.M. peak periods, one of the key differences is that in the morning, the leading (early) shoulder has very low traffic volumes. Therefore, as noted earlier, incidents tend to have little impact early in the A.M. peak period. In the evening, traffic volume drops off very rapidly at the end of the peak period. Therefore, congestion frequently abates rapidly at the end of the peak period, simply because traffic volumes are low enough for queues to clear. At the end of the morning peak, traffic volumes remain modest because a variety of noncommute trips are made in those periods. Thus, incident congestion formed during the A.M. peak tends to last much longer than incident congestion formed in the P.M. peak.

Conversely, significant incidents that occur well before the start of the p.m. peak period have the potential to cause the entire P.M. peak period to be congested if they are not cleared quickly, while incidents occurring an hour before the start of the a.m. peak are far less likely to affect the morning commute, if they are cleared with even modest speed.

Summary – The Causes of Congestion

Congestion occurs where there is too much volume and too little roadway capacity. This can occur because:

- Traffic demand is too great for the designed roadway capacity; or
- Some disruption reduces functional roadway capacity (supply) to levels below demand.

Demand varies, both as a result of repeating travel patterns (e.g., time of day, day of week, seasonal patterns) and as a result of unusual activity that causes more travelers than typical to use a roadway at a given time. These unusual activities can be planned events, such as a major sporting event, or unplanned events, such as vehicles diverting to one roadway to avoid congestion on another.

Functional roadway capacity (supply) can vary as a result of numerous factors, including weather, traffic management strategies (work zones, the application of different traffic control plans), and a variety of traffic incidents that disrupt the normal operations of a roadway.

This combination of supply and demand effects are generally categorized into seven categories, known as "the seven sources of congestion":

1. Traffic incidents;
2. Weather;
3. Work zones;
4. Fluctuations in demand;
5. Special events;
6. Traffic control devices; and
7. Bottlenecks/inadequate base capacity.

These factors interact in the formation of congestion, and the relative importance of any one of these factors varies from location to location.

In many rural areas, demand is routinely low relative to roadway capacity. Consequently, delay only happens when major disruptions occur, usually as a result of bad weather (e.g., snow), a major traffic incident, or reductions in roadway capacity due to road construction and maintenance activities.

In other rural areas, especially those that experience recreational traffic flows, large and somewhat predictable surges of traffic demand create traffic congestion during times of peak demand. Similarly, in suburban and urban areas, traffic flows associated with work and other common activities often reach levels that typically push traffic demand beyond available roadway capacity, creating routine congestion. In both of these cases, a large percentage increase in congestion can occur on top of the existing base congestion as a result of a disruption in roadway operations, especially when that disruption occurs during times of high traffic volumes.

Lastly, in larger urban areas, traffic can routinely exceed roadway capacity for many hours each work day. In these areas, numerous roads operate near capacity for many additional hours of the day. Disruptions on these roads can add large amounts of delay, but that added delay may be only a modest percentage increase in total annual delay. (In simple terms, routine congestion already may have slowed traffic, so that a fender-bender in the existing queue slows vehicles only a little more because they already are moving slowly.)

Forty-two directional roadway sections were studied in this specific analysis. All of those sections experienced at least some routine congestion in either the A.M. or P.M. peak periods. Many sections experienced routine congestion during only one of the peak periods; however, a number of the study sections experienced significant congestion in both peaks, as well as periodic congestion in the middle of the day.

Table 5.13 summarizes the amount of delay influenced by each type of disruption tracked in this study. (Delay was computed for each five-minute time interval of 2006 for each roadway segment. Delay, in units of vehicle-seconds, was calculated for each roadway segment as follows: (Actual Travel Time – Travel Time at the Speed Limit) * Roadway Segment Volume.) "Percentage of delay" was computed by totaling all vehicle hours of delay in the region associated with each of the types of disruptions, and then dividing by the sum of all measured delays. Where more than one disruption occurred simultaneously, that delay is "credited" to both causes in Table 5.13. Thus the sum of the percentages exceeds 100 percent.

Table 5.13 Percentage of Delay by Type of Disruption Influencing Congestion[a]

Causes of Congestion Ongoing Disruptions that Influence Congestion Duration and Severity	Percentage of Delay
Incidents	38.5%
Crashes	19.5%
Bad Weather (Rain)	17.7%
Construction[b]	1.2%
No Cause Indicated (Mostly Volume)	42.2%

[a] Delays that occurred when more than one type of disruption influenced the size and scope of that delay were counted in each of the categories of disruption and, therefore, the percentages total to more than 100 percent.

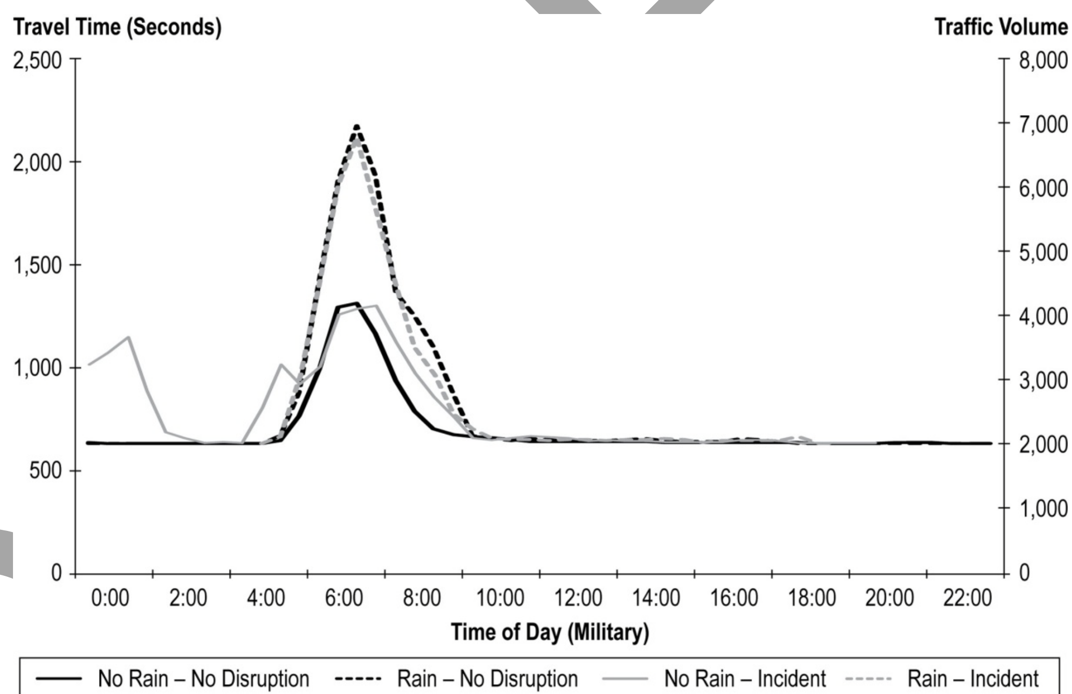
[b] "Construction delays" do not include any delays caused because general roadway capacity was reduced as a result of temporarily narrowed or reconfigured lanes. It was computed only when construction work actively took place along the roadway.

Taken at face value, this simple summary table supports the commonly heard statement that "incidents and crashes cause between 40 and 60 percent of all delay." In reality, a considerable portion of the delay associated with incidents and crashes in Table 5.13 also is "caused" by large traffic volumes. Therefore, the amount of delay "caused" by incidents is actually less than that indicated in Table 5.13. There were numerous examples in the analysis data set of significant crashes and other incidents that caused little or no congestion because of when they occurred. These showed that without sufficient volume, an incident causes no measurable change in delay.

5.3.4 The Travel-Time Impacts Caused by Disruptions

In the Seattle area, many incidents take place during peak periods, causing already existing congestion to grow worse. Figure 5.15 illustrates the interwoven effects of incidents, bad weather, and traffic volumes on travel times on I-5 northbound heading toward downtown Seattle. This graphic shows that congestion forms only as traffic volumes peak. It also shows that the resulting congestion reduces observed throughput while increasing travel times. In addition, it illustrates how all types of disruptions to normal roadway performance (rain, crashes, noncrash incidents) cause congestion to start earlier and last longer during the peak period, while increasing travel times during the normally congested times.

Figure 5.15 Travel Times on I-5 Given Disruptions and Traffic Volume Northbound South Section

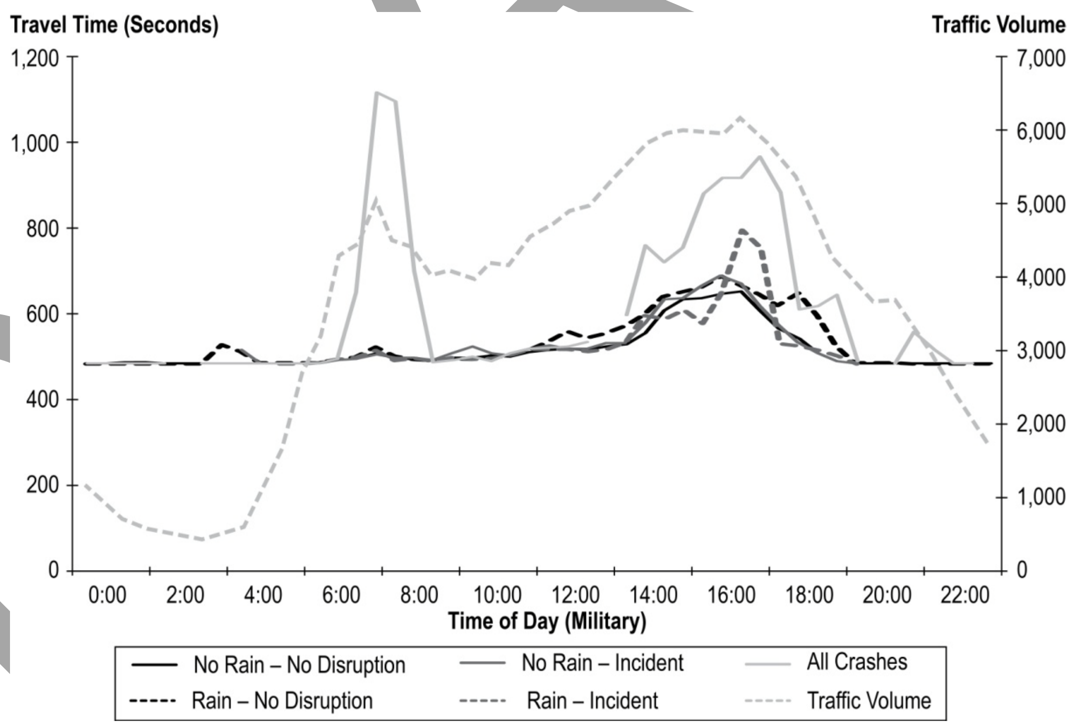


Incidents and other disruptions also can cause congestion to form during times of the day that are normally free from congestion. However, congestion only forms when the disruption lowers functional capacity below traffic demand. Thus, as seen in Figure 5.15 on this section of I-5, minor disruptions such as rain or noncrash incidents do not cause congestion in the mid-day or the evening peak period (the off-peak direction) on this section of roadway. For this four-lane freeway section, enough unused capacity exists during those periods that modest disruptions to roadway capacity do not cause congestion, although some crashes do cause sufficient disruption to create congestion during these off-peak periods. Late at night, because construction activity was taking place along this roadway segment, even smaller incidents – combined with those construction lane closures – caused congestion to form.

Thus volume, relative to roadway capacity, is a key component of congestion formation, and in urban areas it is likely to be the primary source of congestion. Disruptions then significantly increase the delay that the basic volume condition creates.

The fact that traffic volume is the basis of congestion also has an impact on how various traffic disruptions affect travel patterns. Not only does traffic volume affect whether an incident causes congestion, but it affects how long that congestion lasts once the primary incident has been removed. The Seattle data showed that in the morning peaks, disruptions have a more noticeable effect on the timing of the end of the peak period, while in the evening the opposite is true. In the afternoon, as can be seen in Figure 5.16, disruptions begin to cause greater travel-time changes well before the start of the traditional peak period. However, most congestion ends very close to when congestion under "no rain-no disruption" conditions would occur anyway. (The effects of late night crashes can be seen in the graph, however.)

Figure 5.16 Travel Times on I-5 Given Disruptions and Traffic Volume Northbound Lynnwood Section



The volume lines in Figures 5.15 and 5.16 explain why this occurs. Very early in the A.M. peak period, insufficient volume exists to cause congestion to form. Once volumes grow and congestion occurs, disruptions (incidents/rain) make that congestion worse. Because mid-day volumes are still fairly high, residual queues can take a long time to clear.

In the P.M., those same fairly high mid-day volumes (especially for corridors experiencing peak direction movements) mean that even small disruptions are likely to cause congestion before the normal start of the P.M. peak period. However, even though queues grow larger than usual during those peak periods, the sharp decline in traffic volumes at the end of the P.M. peak means that those queues tend to dissipate quickly at the end of the peak period – as long as the disruption has been cleared.

While results vary dramatically between study sections, if the results of all 42 study sections are simply averaged, in the morning, a crash occurring during the A.M. peak period adds an average of 2 hours and 17 minutes to the duration of the morning's peak-period congestion. In the P.M. peak, the fact that a crash occurred on a study section adds only adds 33 minutes to the time when congestion normally can be expected to clear. Similarly, a noncrash incident adds 1 hour and 14 minutes to the morning peak, whereas in the p.m. only 10 minutes are added to the time that congestion can be expected to last.

As seen in Figure 5.15, travel times also generally increase within the peak period when disruptions occur to normal freeway flow. If the peak period is held constant (6:30 to 9:30 a.m. for the morning peak, and 3:00 to 7:00 p.m. for the evening peak), average travel times during those periods increase when a crash or noncrash incident occurs on a roadway segment. a.m. travel times increase in corridors that experience even modest A.M.-peak-period congestion by 17 percent when noncrash incidents occur. Noncrash incidents increase P.M. travel times an average of 21 percent on corridors that experience any routine increase in P.M. peak travel. In both the A.M. and P.M. peaks, crashes add roughly 40 percent to the expected travel times.

These effects do vary significantly from corridor to corridor, depending on the nature of the traffic volumes and routine congestion patterns. They also change dramatically within any given corridor on the basis of the size, duration, and timing of the disruption. Interestingly, 80^{th} and 95^{th} percentile travel times are less affected by noncrash incidents, whereas crashes generally have significant impacts on both of these performance measures. This is not surprising because noncrash incidents tend to be smaller disruptions and, consequently, have less of an impact on those very bad days when congestion is at its worse, whereas crashes are often one of the contributing factors to very bad commute days.

5.3.5 Summary

Analysis of 42 roadway segments in the Seattle area showed that a majority of travel delay in the region is the direct result of traffic volume demand exceeding available roadway capacity. Whenever they occur, incidents, crashes, and bad weather add significantly to the delays that can be otherwise expected. The largest of these disruptions play a significant role in the worst travel times that travelers experience on these roadways. However, the relative importance of any one type of disruption tends to vary considerably from corridor to corridor.

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6.0 Before/After Studies of Reliability Improvements

6.1 INTRODUCTION

The research team pursued an empirical approach to studying the determinants of reliability, and specifically, how reliability changes with improvements. This was done because there already is a great deal of ***continuous*** travel-time data being collected by public agencies, i.e., traffic management centers (TMC), and we had grown comfortable with using these data on past projects. (Technically, TMC data are almost exclusively speed, volume, and lane occupancy measurements from roadway-based detectors, but if the detectors are closely spaced (one-half-mile or less), travel times can be reasonably estimated from them. Even if the resulting travel-time estimates are off the "true" value, the variability (which we use to define reliability) would still be internally consistent. Further, relative changes (as percents) are likely to be in line with perfectly and continuously measured distance-based travel times, a standard which has not yet been achieved in practice.) Continuous travel-time data is an absolute requirement for empirical studies of reliability, as reliability is defined by how travel times vary over a considerable time span. Exploratory research revealed that six months of data is the minimum amount of data necessary for urban freeways where winter weather is not a problem; more data will be needed where winter weather causes problems on a significant number of days. We have striven for a complete year's worth of data in developing reliability patterns, and have achieved this in all but a few cases.

Because of the need to obtain traffic data of the highest quality and that considered moderately to severely congested locations, the research team did not initially seek out locations that were candidates for before/after studies. Rather, we first sought data from locations that we knew from previous experience would satisfy the project requirements. Our approach was then to identify before/after improvements in these areas. Fortunately, we identified 17 before/after instances at our study locations. However, these covered only a few types of reliability improvements, which we knew from the beginning would be difficult to cover completely. (Hence, the reliance on statistical model development as specified in our original work plan.) The types of improvements studied were:

- Ramp metering (four locations);
- Incident management large truck rapid clearance policies (two locations);
- Freeway service patrol implementation (two locations);

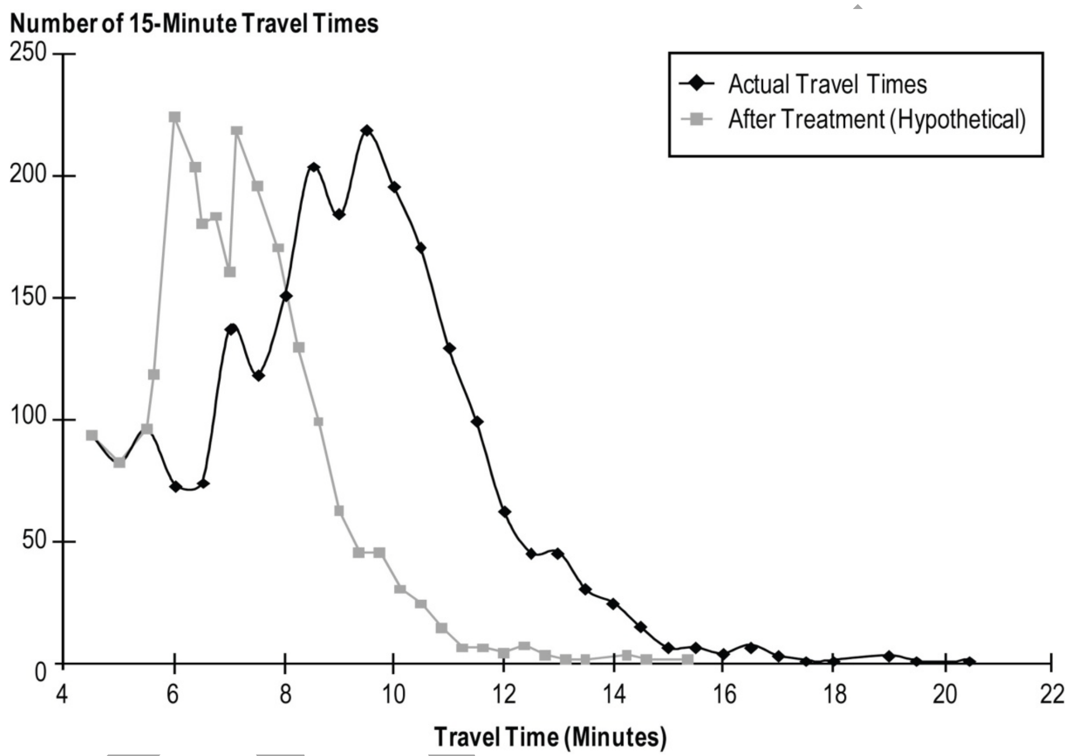
- High occupancy/toll (HOT) lane conversion (one location); and
- Capacity additions/bottleneck improvements (eight locations).

Previous work by members of the research team provided preliminary insight into what could be expected from the before/after tests (*1*). In a hypothetical experiment, travel-time data for a complete year on a heavily congested section of I-75 in Atlanta were used. From the travel-time distribution, all of the abnormally high travel times (those greater than seven minutes for the 4.05-mile corridor) were artificially reduced by an across-the-board 25 percent. This was done to "simulate" that a wide variety of improvements on travel times, including capital improvements and operations strategies that target the events that cause higher than normal travel times. (This is no way constitutes a real before/after condition, just a hypothetical one.) As shown in Figure 6.1 and Table 6.1, the effect is to reduce delay ***and*** improve reliability.

Because the analysis reduced the travel times of **all** higher-than-normal travel times (not just the days when disruptions occurred), the experiment is especially relevant for gauging the effects of capital improvements, which will improve travel times on all days, not just the ones with disruptions. The results show that such strategies will improve both the average travel time **and** reliability.

Another previous study by members of the team developed predictive models for recurring and incident delay using a stochastic modeling approach (*2*). In this approach, a simple test link was used in conjunction with a queuing model to estimate the total delay caused by congestion on the link. Both demand volumes and incident characteristics were allowed to vary stochastically; basically this was a Monte Carlo simulation that for any given run determined whether an incident occurred and if it did, what its lane blocking and duration characteristics were. A series of equations were fit to the results of the Monte Carlo simulation. The results showed that both recurring and incident delay are positively correlated with the AADT-to-capacity (AADT/C) ratio (Table 6.2). Note that the units used to define delay in Table 6.2 are different because recurring delay is a function of the number of vehicles trying to get through a bottleneck. Incident delay is a function of both number of vehicles and section length; longer sections will have more incidents.

Figure 6.1 Actual and Improved (Hypothetical) Peak-Period Travel Times on I-75 Southbound
Central Atlanta, 2002



Source: Reference (*1*).

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Table 6.1 Effect of Treating Unreliable Travel Times on I-75 in Central Atlanta
Hypothetical

		Southbound, 4:00 to 7:00 p.m.
Travel Time Measure	Observed Travel Times	Abnormally High Travel Times Reduced by 25 Percent
Average Travel Time (Minutes)	9.0	7.1
95th Percentile (Minutes)	13.1	9.8
Buffer Time Index	46%	39%

Source: Reference (*1*).

Table 6.2 Model-Developed Relationship Between AADT/C and Delay

AADT/C	Recurring Delay Due to Queues (Hours per Vehicle)	Incident Delay (Hours per Vehicle-Mile)
8	0.0000	0.0011
9	0.0086	0.0019
10	0.0271	0.0029
11	0.0551	0.0042
12	0.0924	0.0056
13	0.1389	0.0072
14	0.1942	0.0088

Source: Reference (*2*).

6.2 RESULTS

A full description of the before/after analyses is given in Appendix B. A review of the results in Appendix B showed that the Buffer Index is an unstable indicator of changes in reliability, sometimes showing an increase, sometimes a decrease, even when average congestion has decreased. This is consistent with the results presented in Section 4.0. As a result, we have chosen to use the Planning Time Index (PTI), the 95th percentile travel time divided by the free-flow travel time, to be the primary reliability metric. A summary of the findings appears in Table 6.3. In nearly all cases, the improvements studied proved to be beneficial for both average congestion and reliability. The two cases in Minneapolis-St. Paul that showed increases may be the result of data problems or major shifts in travel patterns in the "after" condition. The evaluation of adaptive ramp metering on I-210 is ongoing as the system continues to be refined, but the first results showed that algorithms were not operating as expected. Given the results from all of the sections showing positive effects on both average congestion and reliability, we are inclined not to recommend use of the two Minneapolis studies and the I-210 study in user applications.

Table 6.3 Summary of Urban Freeway Before/After Studies

No.	Urban Area	Highways Covered	Improvement	Reliability Impacts (Peak Period)
1	Los Angeles	I-210	Ramp Metering: Design, field implementation, and evaluation of new advanced on-ramp control algorithms on westbound direction of I-210.	• Slight increases in average travel time and Planning Time Index (PTI) were observed. However, subsequent to this evaluation, the algorithms have been adjusted.
2	Bay Area	I-580	Ramp Metering.	• 22% reduction in average travel time. • 20% reduction in PTI.
3	Seattle	SR 520	Ramp Metering.	• 11% reduction in average travel time. • 12% reduction in PTI.
4	Atlanta	I-285, Northern Arc	Ramp Metering.	• 9% reduction in average travel time. • 7% reduction in PTI. • 3% increase in sustainable service rate.
5	Atlanta	All freeways inside beltway perimeter	Incident Management: Incentive program for reducing large truck crash incident duration (90 minutes).	• 13% reduction in large truck crash incident duration. • 9% reduction in lane-hours lost per large truck crash.
6	Los Angeles	I-710	Incident Management: Evaluation of pilot project to deploy towing service for big-rig tractor trailers.	• 10% reduction in average travel time. • 20% reduction in PTI.
7	San Diego	I-8	Incident Management: Expansion of the existing Freeway Service Patrol Beat-7 on I-8.	• 3% reduction in average travel time. • 4% reduction in PTI.
8	San Diego	SR 52	Incident Management: Expansion of the existing Freeway Service Patrol.	• 20% reduction in average travel time. • 10% reduction in PTI.
9	Minneapolis-St. Paul	I-94	Capacity Expansion: Add third lane in each direction.	• 43% reduction in average travel time. • 46% reduction in PTI.
10	Minneapolis-St. Paul	I-494	Capacity Expansion: Add third lane in each direction.	• 31% reduction in average travel time. • 16% reduction in PTI.

No.	Urban Area	Highways Covered	Improvement	Reliability Impacts (Peak Period)
11	Minneapolis-St. Paul	I-394	Capacity Expansion: Add auxiliary lanes westbound.	• 35% reduction in average travel time. • 38% reduction in PTI.
12	Minneapolis-St. Paul	Highway 169	Capacity Expansion: Convert signalized intersections to diamond interchanges.	• 16% increase in average travel time. • 11% reduction in PTI.
13	Minneapolis-St. Paul	Highway 100	Capacity Expansion: Add third lane northbound. Add auxiliary lane southbound. Convert Highway 7 interchange from a clover leaf to a folded diamond.	• 20% reduction in average travel time. • 30% increase in PTI.
14	Seattle	I-405 Southbound	Capacity Expansion: Addition of one general purpose lane.	• 11% reduction in average travel time. • 11 reduction in PTI.
15	Seattle	I-405 Northbound	Capacity Expansion: Addition of one general purpose lane.	• 42% reduction in average travel time. • 35% reduction in PTI.
16	Seattle	I-405/SR 167 Interchange	Capacity Expansion: Grade separation ramp connecting the southbound I-405 off-ramp with the southbound SR 167 on-ramp.	• 20% reduction in average travel time. • 23% reduction in PTI.
17	Minneapolis-St. Paul	I-394	HOT lane conversion.	• 8% reduction in average travel time. • 30% reduction in PTI.

Note: Complete results are given in Appendix B.

[a] Long study segment: 16 miles; study section influenced by downstream bottleneck.

References

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2. Cambridge Systematics, Inc., Harry Cohen, and SAIC, *Sketch Methods for Estimating Incident-Related Impacts*, prepared for FHWA (December 1998).

7.0 Cross-Sectional Statistical Analysis of Reliability

7.1 Potential Model Forms

7.1.1 Background

The primary goal of the statistical analysis was to produce a highly practical set of relationships that could be used to predict reliability, especially within the contexts of existing technical applications such as travel demand forecasting models, simulation models, and the *Highway Capacity Manual*. The Phase 1 Report proposed two model forms to be investigated: 1) a detailed deterministic model that uses all the data being collected to the maximum degree ("Data-Rich Model"); and 2) a simpler model based on the fact that many of the applications (HCM and travel demand forecasting models) work in an environment with limited data ("Data-Poor Model"). The former will reveal a deep understanding of reliability and its causal factors while the latter makes the relationships operational for many applications.

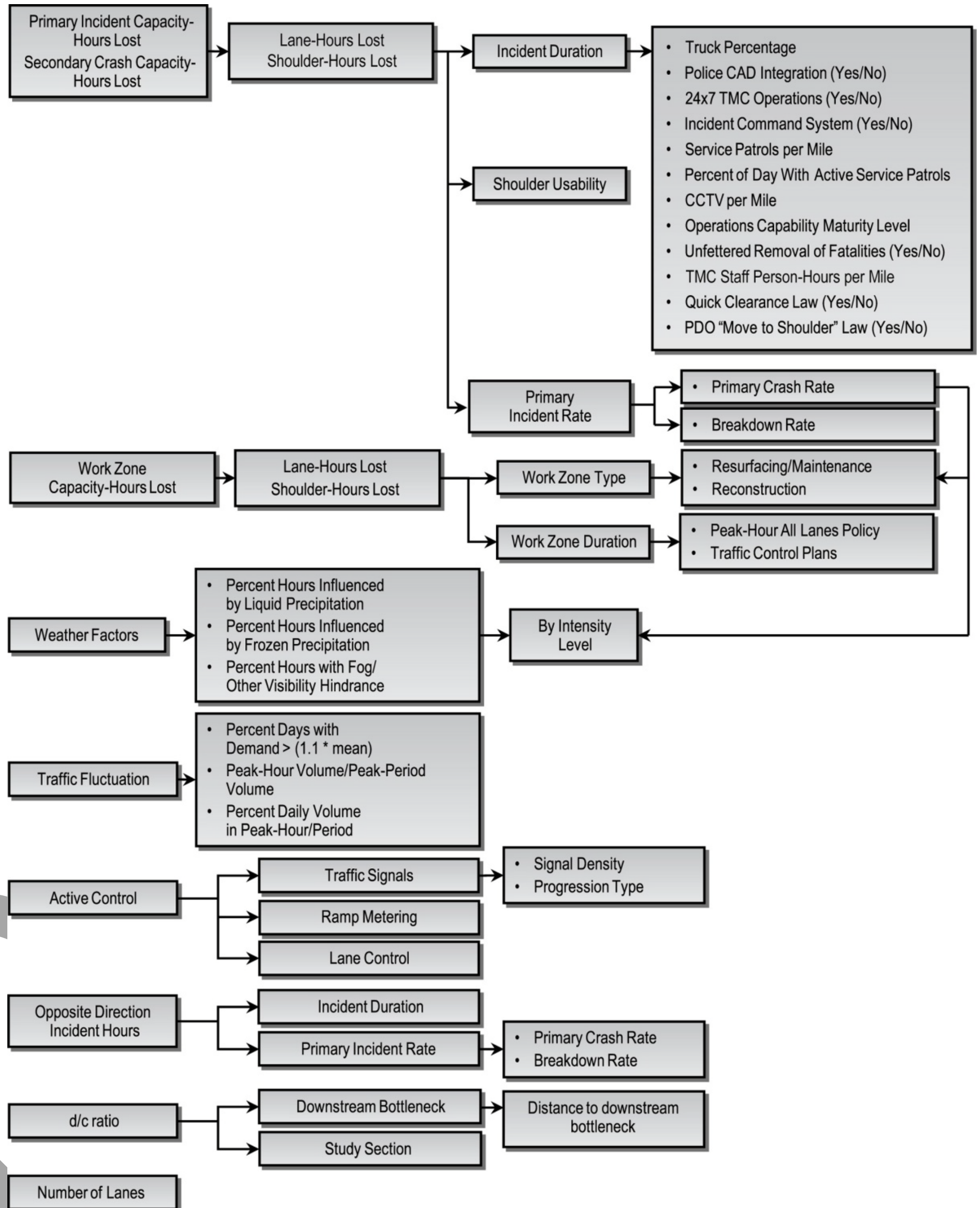
It should be pointed out that the model forms are aimed at predicting reliability, which is based on summarizing travel times that occur over the course of a year. So, every observation in the analysis dataset represents summarized conditions for study section for a year. The statistical models are not designed to predict what a specific travel time will be given a set of conditions (e.g., volume, weather, and incident characteristics). Such prediction can be done with a variety of other analytic methods, such as microsimulation. Prediction or the probability of a specific travel time occurring is related to reliability, but it is not the purpose of this research, i.e., to predict reliability metrics. However, the microscale analysis done for the congestion-by-source analysis (Section 7.0) does get down to this level.

7.1.2 Data-Rich Model

This model structure is mechanistic in nature; based on the research teams past experience, we have postulated the factors ("the mechanisms") that cause unreliable travel times. It also is a "tiered" model where the independent variables at lower levels (left side of the model chain) become dependent variables at higher levels.

The structure of the deterministic (tiered) model is outlined in Figure 7.1.

Figure 7.1 Variables and Tiered Structure for the Mechanistic ("Data-Rich") Model



Notes: 1) "→" means "…is a function of…"
2) Primary Incident and Secondary Crash hours lost are modeled similarly.

The structure can be explained as a series of causal mechanisms that influence each other. Each tier is constructed so that the most immediate and direct influences (independent variables) are used to explain the effect of the dependent variable. For example, considering the effects of incidents, it is postulated that incident-related reliability is most directly affected by the "capacity-hours" lost (a combination of lane and shoulder hours lost due to blockages) due to incidents. The capacity-hours lost attributable to incidents are directly affected (i.e., caused) by incident duration, the usability of shoulders, and the incident rate, and so on.

The key feature of this model structure is that improvements can be traced to a relatively small number of factors (discussed in the next section). This reduces the need to observe reliability changes in before/after experiments. As discussed earlier, to conduct before/after tests of all improvements would be cost-prohibitive. An explanation of the factors in Figure 7.1 follows:

- Reliability = f{d/c, distance to downstream bottleneck, number of lanes, primary incident capacity-hours lost, secondary crash capacity-hours lost, opposite direction incident hours (rubbernecking of incidents in the opposite direction by motorists in the study direction), work zone capacity-hours lost, weather factors, traffic fluctuation, active control type}. (Note "capacity-hours lost" is a way to combine lane-hours lost and shoulder-hours lost for incidents as well as an approximation for the additional lost because of work-zone visual effects. This is not the measured capacity loss, but the straight translation of lanes and shoulders lost to HCM-based (theoretical) capacity. Measured capacity loss due to incidents will be greater.)
  - Reliability is measured by one of the metrics in Section 2.0; d/c (Demand-to-capacity ratio): demand is measured as the average for the time slice under study; capacity is physical (HCM) capacity. d/c should be estimated as the average for the study section or, alternately, the critical (highest) d/c ratio for the links on the study section.
  - Incident Capacity-Hours Lost **(**Lane-hours lost may be used instead of capacity-hours lost because it can be measured directly; capacity is a "transformed" measures as it requires using analytic methods to calculate.) = f{incident duration, primary incident rate, shoulder usability}:
    - » Duration = f{equipment, IM policies, truck percentage}. (Truck percent is used as a surrogate to capture the different types of incidents that can occur (lateral locations, blockages)).
    - » Primary Incident Rate = f{primary crash rate breakdowns}. **(**It was not our intent to conduct a detailed safety analysis yielding a predictive relationship for accident (crash) rate. Crash reduction factors, as recently compiled by FHWA (*Desktop Reference for Crash Reduction Factors,* Report No. FHWA-SA-07-015, September 2007) can be used a way to trace the impacts of safety-related geometric improvements through to changes in reliability.)

  - » Shoulder usability is the presence of a wide enough shoulder to store vehicles involved in a minor crash or breakdown.
- – Opposite direction incident hours = f{incident duration, incident rate} (for the opposite direction of travel):
  - » Duration = f{equipment, IM policies, truck percentage}; and
  - » Primary Incident Rate = f{primary crash rate, breakdowns}.
- – Work Zone Capacity-Hours Lost = f{work zone type, work zone duration}:
  - » Work Zone Duration = f{work zone management policies}.
- – Weather Factors = f{precipitation type, precipitation intensity, temperature, fog}.

7.1.3 Data-Poor Model

Originally, a model form using a combination of easily obtained data items was envisioned (Table 7.1). The reason for this simpler form was to be compatible with many user applications where detailed data are not available.

However, during the course of the research, the team decided on a different strategy for the data-poor model. As discussed in the next section, it became apparent that that all of the reliability metrics could be predicted as a function of mean travel time. This greatly simplifies the construction of the data-poor model and makes it compatible with most existing analytic methods.

Table 7.1 Original Independent Variables for the Data-Poor Model

Weather Variables
Same as for data-rich model form
Incident Variables
Annual collisions per million vehicle-miles traveled
Proportion of collisions that are fatal or injury
Incident duration
Design/Control Variables
Design capacity
Speed limit
Average signal delay (if applicable)
Traffic management activities (ramp metering, freeway service patrol, etc.)
Demand Variables
Hourly, Weekly, Seasonal Demand Profile over course of year

7.2 Relationship Between Mean Travel Time and Reliability Metrics

7.2.1 Link-Level: Urban Freeways

Exploratory Research

All travel demand models and traffic operations models can predict mean speeds of traffic and, therefore, mean travel-time rates. With the mean travel-time rate (minutes per mile) and the predicted 95 percent travel-time rate, one then can compute the Buffer Index. An analysis was undertaken with a small dataset to develop equations for predicting the 95 percent travel-time rate as a function of the mean travel-time rate (minutes per mile).

The equations were developed for the weekday peak periods for two freeway corridors:

1. San Mateo 101 Freeway between I-280 in San Francisco and SR 114 in Palo Alto, California, a distance of 27 miles.
2. Alameda I-238/I-580 Freeways between I-238 in San Leandro and I-205 in Tracy, California, a distance of 33 miles.

Nineteen days of toll tag vehicle travel-time data were collected for San Mateo 101 during the hours of 6:00 to 10:00 a.m. and 2:30 to 7:30 p.m. each weekday (excluding holidays) between January 5, 2009 and January 31, 2009 for four directional segments ranging from 10.8 to 15.9 miles in length. Sample sizes ranged between 8,500 and 19,200 toll-tag equipped vehicles for each direction for each peak period. A total of eight data points on reliability were obtained. A data point consists of mean, standard deviation, and 95 percentile travel-time measurements for each direction of travel on each segment for each peak period. The data for San Mateo 101 is given in Table 7.2. Figure 7.2 shows the regression curves fitted to the data.

Sixteen days of toll tag vehicle travel-time data were collected for the Alameda 238 and 580 freeways during the hours of 5:00 to 9:00 a.m. and 2:30 to 7:30 p.m. each weekday (excluding holidays) between May 2, 2008 and May 23, 2008 for six directional segments ranging from 2 to 21 miles in length. A total of 12 data points on reliability were obtained. A data point consists of mean, standard deviation, and 95 percentile travel-time measurements for each direction of travel on each segment for each peak period.

The data for Alameda 238/580 is given in Table 7.3. Figure 7.3 shows the regression curves fitted to the data. Figure 7.4 shows the combined Alameda and San Mateo freeway reliability relationships.

The results for this exploratory research were very encouraging. They implied that prediction of the reliability metrics could pivot off the mean travel time.

This led us to examine both link-level and section-level predictive models using more complete datasets.

Table 7.2 San Mateo 101 Reliability Data

Segment	Stretch	Miles	Peak	Mean	Standard Deviation	95 Percent	Buffer Index	Sample
SR 101 Northbound	Palo Alto (SR 114) to SR 92	10.75	6:00 to 10:00 a.m.	38.4	31.2	132.2	244%	8,598
SR 101 Northbound	Palo Alto (SR 114) to SR 92	10.75	2:30 to 7:30 p.m.	27.8	15.2	73.5	164%	19,145
SR 101 Southbound	SR 92 to Palo Alto (SR 114)	10.75	6:00 to 10:00 a.m.	36.3	29.4	124.6	243%	17,321
SR 101 Southbound	SR 92 to Palo Alto (SR 114)	10.75	2:30 to 7:30 p.m.	26.0	18.9	82.8	219%	9,864
SR 101 Northbound	SR 92 to I-280	15.85	6:00 to 10:00 a.m.	46.5	29.8	136.0	193%	9,395
SR 101 Northbound	SR 92 to I-280	15.85	2:30 to 7:30 p.m.	33.5	24.6	107.2	220%	10,696
SR 101 Southbound	I-280 to SR 92	15.85	6:00 to 10:00 a.m.	48.9	34.5	152.5	212%	17,679
SR 101 Southbound	I-280 to SR 92	15.85	2:30 to 7:30 p.m.	44.6	22.8	113.1	154%	13,108

Note: All entries are in minutes or percentages.

Table 7.3 Reliability Data for Alameda I-238/I-580

Segment	Stretch	Miles	Peak	Mean	Standard Deviation	95 Percent	Buffer Index
I-238 Westbound	I-580 to I-880	2	5:00 to 9:00 a.m.	4.3	0.8	6.6	55%
I-238 Westbound	I-580 to I-880	2	2:30 to 7:30 p.m.	4.4	2.4	11.7	164%
I-238 Eastbound	I-880 to I-580	2	5:00 to 9:00 a.m.	2.2	0.1	2.7	19%
I-238 Eastbound	I-880 to I-580	2	2:30 to 7:30 p.m.	3.2	10.0	33.0	947%
I-580 Eastbound	I-238 to I-680	10	5:00 to 9:00 a.m.	9.7	0.4	10.9	12%
I-580 Eastbound	I-238 to I-680	10	2:30 to 7:30 p.m.	11.2	2.9	19.8	77%
I-580 Westbound	I-680 to I-238	10	5:00 to 9:00 a.m.	10.1	1.3	14.1	40%
I-580 Westbound	I-680 to I-238	10	2:30 to 7:30 p.m.	9.3	0.5	10.7	15%
I-580 Eastbound	I-680 to I-205	21	5:00 to 9:00 a.m.	20.5	0.5	21.9	7%
I-580 Eastbound	I-680 to I-205	21	2:30 to 7:30 p.m.	27.3	4.4	40.5	48%
I-580 Westbound	I-205 to I-680	21	5:00 to 9:00 a.m.	29.4	6.2	48.0	63%
I-580 Westbound	I-205 to I-680	21	2:30 to 7:30 p.m.	21.4	0.6	23.3	9%

Figure 7.2 Reliability Relationships for San Mateo 101
Weekday A.M./P.M. Peak Periods, January 5 to January 31, 2010

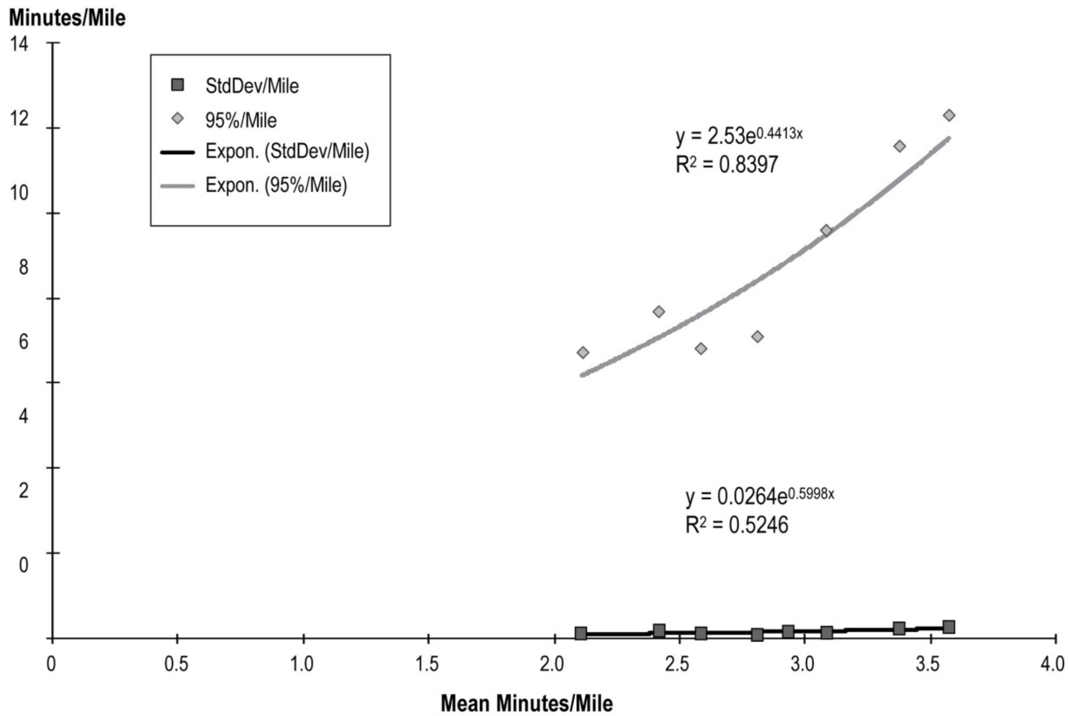


Figure 7.3 Reliability Relationships for Alameda 238/580
Weekday A.M./P.M. Peak Periods, May 2 to May 23, 2008

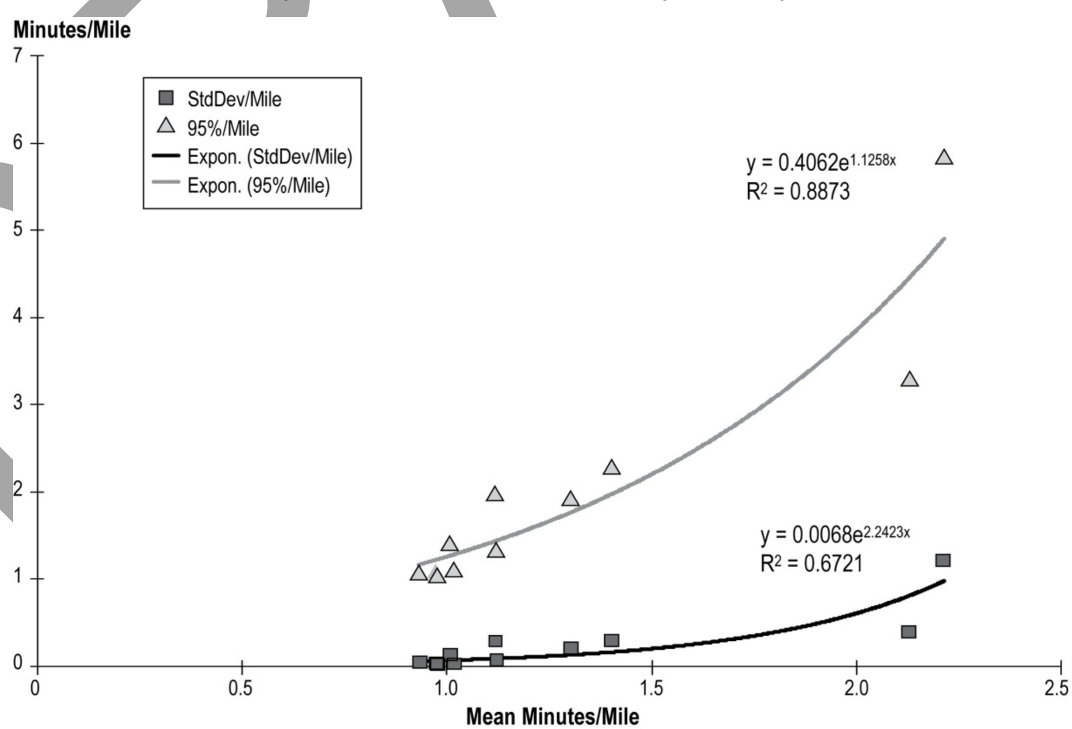
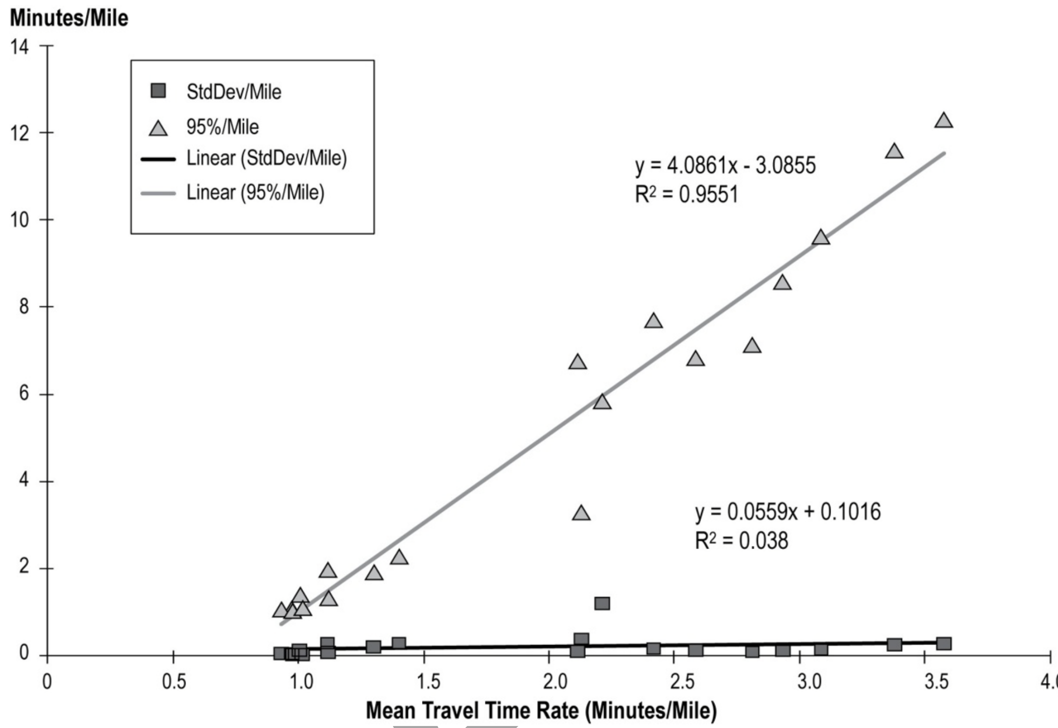


Figure 7.4 Combined 101/238/580 Travel-Time Reliability Data Relationships
Exploratory



Final Link-Level Reliability Predictive Models (as a Function of the Mean Travel Time)

Data from 164 detector locations on the Atlanta study sections were analyzed. (A detector is considered to represent conditions on a "link," where a link on a freeway is between interchanges.) The Travel Time Index (TTI) was computed separately for the peak period and mid-day time periods and combined into a single dataset; this was done in order to get data over a wide range of congestion conditions. Figures 7.5 and 7.6 show the relationships between the mean and the 95th percentile TTI and 80th percentile TTI, respectively. Linear, exponential, and logarithmic regression models were fit to these data; the exponent form was found to provide the best fit. The models were fit without an intercept term so that when the mean TTI is 1.0, the percentile values also will be 1.0. (The lack of an intercept term means that the calculated R^2 values are not meaningful. Instead, Root Mean Square Error (RMSE) is used as the goodness-of-fit measure. The RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data – how close the observed data points are to the model's predicted values. Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response, and is the most important criterion for fit if the main purpose of the model is prediction, which is our aim here.) The predictive equations are:

95^{th} *Percentile TTI = MeanTTI*$^{1.6954}$ (RSME=0.163; alpha level of coefficient < 0.0001) [6]

80^{th} *Percentile TTI = MeanTTI*$^{1.3162}$ (RMSE=0.074; alpha level of coefficient < 0.0001) [7]

StandardDeviation = (MeanTTI – 1) $^{0.5231}$ (RMSE = 0.6; alpha level of coefficient < 0.0001) [8]

It is extremely important to note that in the data used to develop these equations, *MeanTTI* is the grand (overall) mean – since it was developed from continuous detector data it includes all of the possible influences on congestion (e.g., incidents and inclement weather). Most applications and models that predict mean travel time, speeds, etc., almost always only consider recurring congestion. Therefore, an adjustment must be made to the recurring-only travel time so that it corresponds to the grand mean shown in equations 6 through 8.

Data from the Atlanta and Seattle study sections were used to develop the recurring-only adjustment factor. For the peak period time slice, a simple assignment was made for each section: if either an incident or weather occurred on a particular day, the resulting TTI was considered to be nonrecurring. Otherwise it was assigned as recurring. The analysis showed that the nonrecurring TTI was 26.4 percent higher than the recurring TTI in Atlanta and 28.7 percent higher in Seattle. (The section-by-section data for Seattle is presented in Table 7.4.) The ratio of the overall mean to the recurring mean was also computed for the peak period; in Atlanta the overall mean TTI was 12.1 percent higher than the recurring-only TTI and in Seattle it was 13.0 percent higher. Seattle data were also used to develop recurring:nonrecurring ratios for the mid-day and weekend time periods (Table 7.5). However, as noted in Section 5.0, the amount of nonrecurring delay depends very much on the base level or recurring delay, so applying percentages can be misleading. Therefore, the peak period, mid-day, and weekend/holiday results were pooled and a regression equation was developed:

$$OverallMeanTTI = 1.0274 * RecurringMeanTTI^{1.2204} \quad [9]$$

(R^2 = 0.910; alpha level of coefficients = 0.001 and 0.0001, respectively, n = 167)

Where: *OverallMeanTTI* is the *MeanTTI in the predictive equations*

RecurringMeanTTI is the mean TTI that considers recurring sources only.

Figure 7.5 Ninety-Fifth Percentile versus Mean
Atlanta Study Links

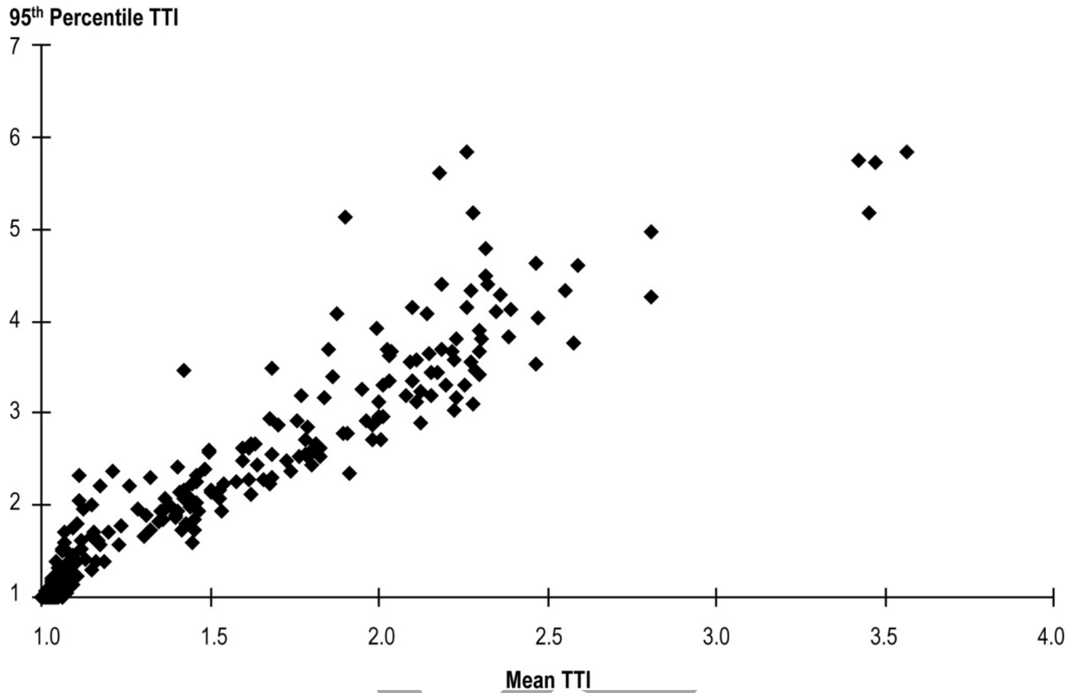


Figure 7.6 Eightieth Percentile versus the Mean
Atlanta Study Links

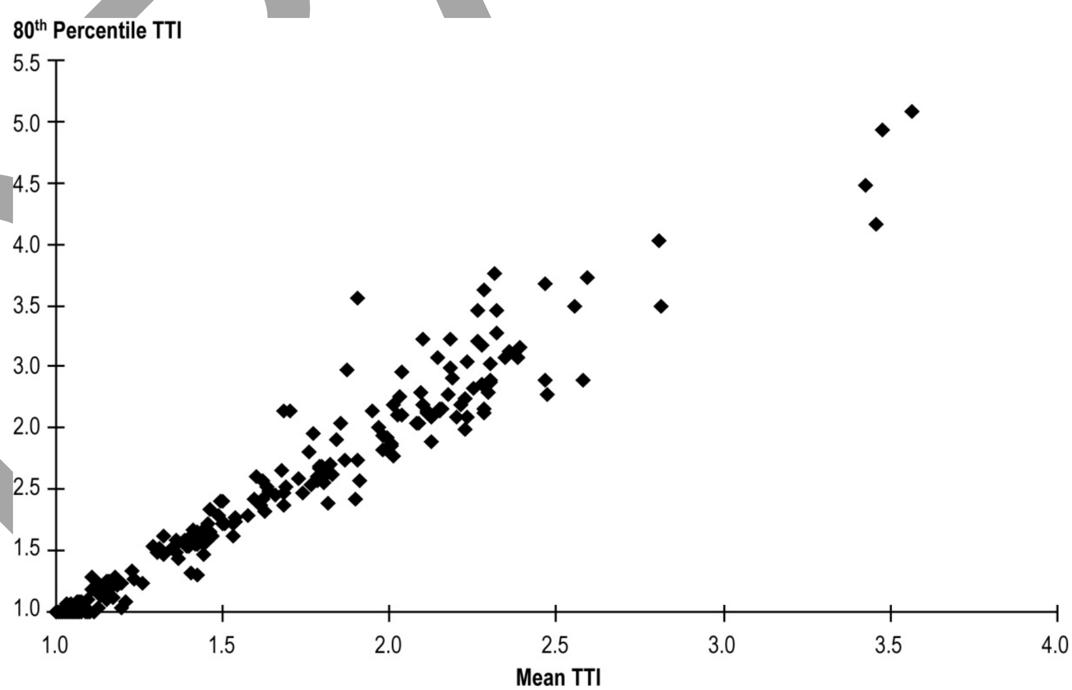


Table 7.4 Recurring, Nonrecurring, and Total TTIs
Seattle Study Sections, Peak Period

Section	Direction	Congestion Type	Mean TTI	Std Dev TTI
I-405 Bellevue Northbound	A.M.	Nonrecurring	1.418	0.422
		Recurring	1.215	0.252
		Total	1.281	0.252
I-405 Bellevue Northbound	P.M.	Nonrecurring	1.672	0.800
		Recurring	1.206	0.274
		Total	1.346	0.274
I-405 Kennydale Northbound	A.M.	Nonrecurring	4.405	1.699
		Recurring	3.198	1.480
		Total	3.657	1.480
I-405 Kennydale Northbound	P.M.	Nonrecurring	1.347	0.517
		Recurring	1.130	0.212
		Total	1.186	0.212
I-405 Kennydale Southbound	A.M.	Nonrecurring	1.915	0.686
		Recurring	1.427	0.395
		Total	1.539	0.395
I-405 Kennydale Southbound	P.M.	Nonrecurring	2.200	0.975
		Recurring	1.730	0.579
		Total	1.898	0.579
I-405 Kirkland Northbound	A.M.	Nonrecurring	1.017	0.055
		Recurring	1.009	0.016
		Total	1.011	0.016
I-405 Kirkland Northbound	P.M.	Nonrecurring	2.120	0.788
		Recurring	1.712	0.677
		Total	1.995	0.677
I-405 Kirkland Southbound	A.M.	Nonrecurring	1.917	0.535
		Recurring	1.574	0.450
		Total	1.766	0.450
I-405 Kirkland Southbound	P.M.	Nonrecurring	1.161	0.303
		Recurring	1.032	0.097
		Total	1.104	0.097
I-405 North Northbound	A.M.	Nonrecurring	1.065	0.095
		Recurring	1.039	0.082
		Total	1.045	0.082
I-405 North Northbound	P.M.	Nonrecurring	1.687	0.454
		Recurring	1.550	0.414
		Total	1.609	0.414
I-405 North Southbound	A.M.	Nonrecurring	3.534	1.879
		Recurring	2.254	1.320
		Total	2.820	1.320
I-405 North Southbound	P.M.	Nonrecurring	1.239	0.558

Section	Direction	Congestion Type	Mean TTI	Std Dev TTI
		Recurring	1.084	0.220
		Total	1.123	0.220
I-405 South Northbound	A.M.	Nonrecurring	1.320	0.526
		Recurring	1.222	0.210
		Total	1.241	0.210
I-405 South Northbound	P.M.	Nonrecurring	2.810	1.008
		Recurring	2.420	0.719
		Total	2.578	0.719
I-405 South Southbound	A.M.	Nonrecurring	1.566	0.736
		Recurring	1.425	0.433
		Total	1.446	0.433
I-405 South Southbound	P.M.	Nonrecurring	1.807	0.981
		Recurring	1.447	0.497
		Total	1.522	0.497
I-5 Everett Northbound	A.M.	Nonrecurring	1.053	0.344
		Recurring	1.015	0.090
		Total	1.026	0.090
I-5 Everett Northbound	P.M.	Nonrecurring	2.253	1.337
		Recurring	1.483	0.895
		Total	1.872	0.895
I-5 Everett Southbound	A.M.	Nonrecurring	1.306	0.734
		Recurring	1.072	0.280
		Total	1.152	0.280
I-5 Everett Southbound	P.M.	Nonrecurring	1.167	0.416
		Recurring	1.069	0.192
		Total	1.105	0.192
I-5 Lynnwood Northbound	A.M.	Nonrecurring	1.811	1.412
		Recurring	1.303	0.680
		Total	1.443	0.680
I-5 Lynnwood Northbound	P.M.	Nonrecurring	1.483	0.717
		Recurring	1.171	0.345
		Total	1.312	0.345
I-5 Lynnwood Southbound	A.M.	Nonrecurring	2.238	1.151
		Recurring	1.572	0.641
		Total	1.898	0.641
I-5 Lynnwood Southbound	P.M.	Nonrecurring	1.246	0.719
		Recurring	1.069	0.118
		Total	1.117	0.118
I-5 North King Northbound	A.M.	Nonrecurring	1.002	0.012
		Recurring	1.001	0.010
		Total	1.001	0.010
I-5 North King Northbound	P.M.	Nonrecurring	1.935	0.543

Section	Direction	Congestion Type	Mean TTI	Std Dev TTI
		Recurring	1.572	0.541
		Total	1.791	0.541
I-5 North King Southbound	A.M.	Nonrecurring	2.547	1.068
		Recurring	1.856	0.669
		Total	2.068	0.669
I-5 North King Southbound	P.M.	Nonrecurring	1.749	1.327
		Recurring	1.089	0.401
		Total	1.345	0.401
I-5 Seattle CBD Northbound	A.M.	Nonrecurring	2.036	0.775
		Recurring	1.328	0.358
		Total	1.913	0.358
I-5 Seattle CBD Northbound	P.M.	Nonrecurring	2.110	0.845
		Recurring	1.365	0.409
		Total	1.961	0.409
I-5 Seattle CBD Southbound	A.M.	Nonrecurring	1.181	0.307
		Recurring	1.070	0.094
		Total	1.127	0.094
I-5 Seattle CBD Southbound	P.M.	Nonrecurring	1.852	0.487
		Recurring	1.420	0.349
		Total	1.721	0.349
I-5 Seattle North Northbound	A.M.	Nonrecurring	1.020	0.041
		Recurring	1.016	0.037
		Total	1.017	0.037
I-5 Seattle North Northbound	P.M.	Nonrecurring	1.913	0.843
		Recurring	1.525	0.905
		Total	1.741	0.905
I-5 Seattle North Southbound	A.M.	Nonrecurring	2.721	1.611
		Recurring	1.484	0.812
		Total	2.157	0.812
I-5 Seattle North Southbound	P.M.	Nonrecurring	3.044	1.654
		Recurring	1.385	0.749
		Total	2.560	0.749
I-5 South Northbound	A.M.	Nonrecurring	2.008	0.771
		Recurring	1.554	0.577
		Total	1.764	0.577
I-5 South Northbound	P.M.	Nonrecurring	1.020	0.111
		Recurring	1.005	0.049
		Total	1.014	0.049
I-5 South Southbound	A.M.	Nonrecurring	1.005	0.043
		Recurring	1.003	0.047
		Total	1.004	0.047

Section	Direction	Congestion Type	Mean TTI	Std Dev TTI
I-5 South Southbound	P.M.	Nonrecurring	2.038	0.780
		Recurring	1.426	0.522
		Total	1.761	0.522
I-5 Tukwila Northbound	A.M.	Nonrecurring	1.826	0.765
		Recurring	1.213	0.235
		Total	1.502	0.235
I-5 Tukwila Northbound	P.M.	Nonrecurring	1.243	0.425
		Recurring	1.017	0.031
		Total	1.082	0.031
I-5 Tukwila Southbound	A.M.	Nonrecurring	1.077	0.338
		Recurring	1.034	0.195
		Total	1.042	0.195
I-5 Tukwila Southbound	P.M.	Nonrecurring	1.353	0.487
		Recurring	1.116	0.273
		Total	1.205	0.273
I-90 Bellevue Eastbound	A.M.	Nonrecurring	1.003	0.024
		Recurring	1.008	0.051
		Total	1.007	0.051
I-90 Bellevue Eastbound	P.M.	Nonrecurring	1.221	0.598
		Recurring	1.097	0.211
		Total	1.117	0.211
I-90 Bellevue Westbound	A.M.	Nonrecurring	1.570	0.601
		Recurring	1.216	0.241
		Total	1.307	0.241
I-90 Bellevue Westbound	P.M.	Nonrecurring	1.509	1.058
		Recurring	1.026	0.214
		Total	1.305	0.214
I-90 Bridge Eastbound	A.M.	Nonrecurring	1.208	0.366
		Recurring	1.138	0.255
		Total	1.190	0.255
I-90 Bridge Eastbound	P.M.	Nonrecurring	1.592	0.624
		Recurring	1.143	0.280
		Total	1.414	0.280
I-90 Bridge Westbound	A.M.	Nonrecurring	1.373	0.435
		Recurring	1.116	0.238
		Total	1.159	0.238
I-90 Bridge Westbound	P.M.	Nonrecurring	2.233	1.022
		Recurring	1.551	0.748
		Total	1.739	0.748
I-90 Issaquah Eastbound	A.M.	Nonrecurring	1.000	0.008
		Recurring	1.001	0.017
		Total	1.001	0.017

Section	Direction	Congestion Type	Mean TTI	Std Dev TTI
I-90 Issaquah Eastbound	P.M.	Nonrecurring	1.049	0.121
		Recurring	1.016	0.052
		Total	1.023	0.052
I-90 Issaquah Westbound	A.M.	Nonrecurring	2.005	0.863
		Recurring	1.380	0.485
		Total	1.476	0.485
I-90 Issaquah Westbound	P.M.	Nonrecurring	1.010	0.025
		Recurring	1.016	0.038
		Total	1.015	0.038
I-90 Seattle Eastbound	A.M.	Nonrecurring	2.582	1.495
		Recurring	1.824	1.124
		Total	1.957	1.124
I-90 Seattle Eastbound	P.M.	Nonrecurring	2.185	1.610
		Recurring	1.294	0.760
		Total	1.432	0.760
I-90 Seattle Westbound	A.M.	Nonrecurring	1.423	0.527
		Recurring	1.095	0.288
		Total	1.210	0.288
I-90 Seattle Westbound	P.M.	Nonrecurring	1.192	0.199
		Recurring	1.118	0.132
		Total	1.140	0.132
SR 167 Auburn Northbound	A.M.	Nonrecurring	1.893	0.622
		Recurring	1.627	0.573
		Total	1.685	0.573
SR 167 Auburn Northbound	P.M.	Nonrecurring	1.094	0.181
		Recurring	1.058	0.058
		Total	1.067	0.058
SR 167 Auburn Southbound	A.M.	Nonrecurring	1.148	0.731
		Recurring	1.060	0.299
		Total	1.072	0.299
SR 167 Auburn Southbound	P.M.	Nonrecurring	2.487	1.280
		Recurring	1.739	0.878
		Total	1.961	0.878
SR 167 Renton Northbound	A.M.	Nonrecurring	1.802	1.124
		Recurring	1.325	0.356
		Total	1.624	0.356
SR 167 Renton Northbound	P.M.	Nonrecurring	1.244	0.465
		Recurring	1.032	0.106
		Total	1.172	0.106
SR 167 Renton Southbound	A.M.	Nonrecurring	1.060	0.063
		Recurring	1.055	0.064
		Total	1.056	0.064

Section	Direction	Congestion Type	Mean TTI	Std Dev TTI
SR 167 Renton Southbound	P.M.	Nonrecurring	2.163	1.054
		Recurring	1.423	0.541
		Total	1.637	0.541
SR 520 Red Eastbound	A.M.	Nonrecurring	1.017	0.053
		Recurring	1.010	0.014
		Total	1.011	0.014
SR 520 Red Eastbound	P.M.	Nonrecurring	2.148	0.951
		Recurring	1.595	0.483
		Total	1.869	0.483
SR 520 Red Westbound	A.M.	Nonrecurring	1.088	0.271
		Recurring	1.022	0.119
		Total	1.037	0.119
SR 520 Red Westbound	P.M.	Nonrecurring	1.764	1.307
		Recurring	1.163	0.628
		Total	1.498	0.628
SR 520 Sea Eastbound	A.M.	Nonrecurring	1.967	0.687
		Recurring	1.555	0.526
		Total	1.695	0.526
SR 520 Sea Eastbound	P.M.	Nonrecurring	1.632	0.595
		Recurring	1.370	0.378
		Total	1.483	0.378
SR 520 Sea Westbound	A.M.	Nonrecurring	1.843	0.780
		Recurring	1.353	0.487
		Total	1.509	0.487
SR 520 Sea Westbound	P.M.	Nonrecurring	3.004	1.003
		Recurring	2.370	0.994
		Total	2.722	0.994
I-405 Bellevue Southbound	A.M.	Nonrecurring	1.311	0.545
		Recurring	1.130	0.587
		Total	1.169	0.587
I-405 Bellevue Southbound	P.M.	Nonrecurring	4.163	1.562
		Recurring	2.006	0.975
		Total	3.731	0.975
I-405 Eastgate Northbound	A.M.	Nonrecurring	1.798	0.445
		Recurring	1.616	0.456
		Total	1.667	0.456
I-405 Eastgate Northbound	P.M.	Nonrecurring	1.104	0.283
		Recurring	1.042	0.124
		Total	1.058	0.124
I-405 Eastgate Southbound	A.M.	Nonrecurring	1.228	0.901
		Recurring	1.035	0.189
		Total	1.064	0.189

Section	Direction	Congestion Type	Mean TTI	Std Dev TTI
I-405 Eastgate Southbound	P.M.	Nonrecurring	3.048	1.265
		Recurring	2.581	0.786
		Total	2.728	0.786
ALL SECTIONS		Nonrecurring	1.733	
		Recurring	1.347	
		TOTAL	1.522	

Table 7.5 Recurring, Nonrecurring, and Total TTIs
Seattle Study Sections, Mid-Day and Weekend/Holidays

Time Period	Congestion Type	TTI
Mid-Day	Recurring	1.121
	Nonrecurring	1.227
	Total	**1.153**
Weekend/Holiday	Recurring	1.034
	Nonrecurring	1.142
	Total	**1.058**

Note: Mid-day as defined in the Seattle analysis is from 9:00 a.m. to 3:00 p.m. Weekend/Holiday excludes midnight to 4:00 a.m.

Table 7.4 also demonstrates that, even though travel-time variability (as measured by the standard deviation), is lower for disruption-free conditions, there still is a substantial amount of variability associated with recurring-only congestion.

7.2.2 Section-Level: Urban Freeways

Data from urban freeway study sections in Atlanta, Minneapolis, Jacksonville, Los Angeles, Houston, and San Diego were used to develop relationships between a wider set of reliability metrics and the mean TTI. The peak period and mid-day measurements were again combined to obtain a dataset that had both congested and uncongested observations. The relationships for selected travel-time metrics appear in Figures 7.7 through 7.14. The predictive equations appear below. Note that the parameters necessary to compute the Buffer Index and Skew Statistic are estimated.

Figure 7.7 Section-Level Relationship for Mean TTI and 10th Percentile

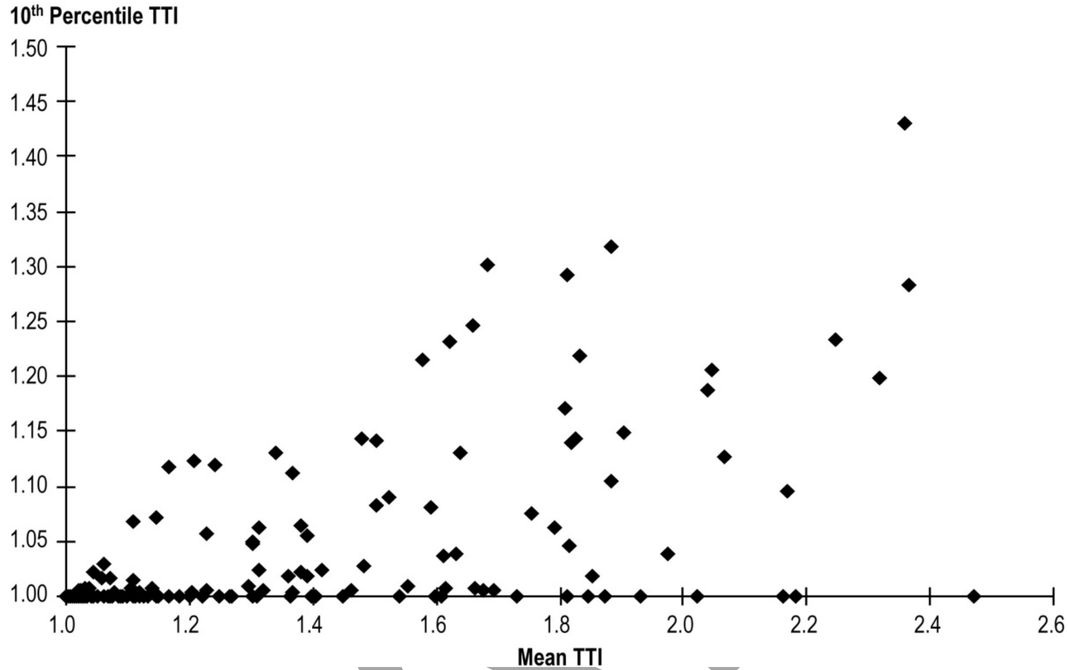


Figure 7.8 Section-Level Relationship for Mean TTI and Median TTI

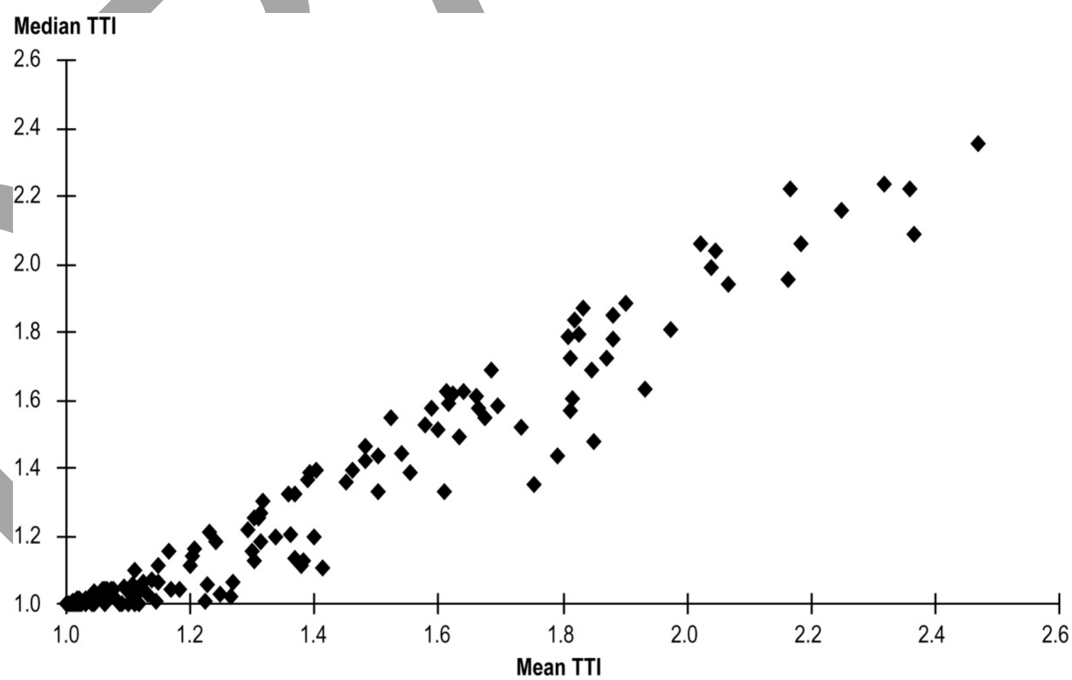


Figure 7.9 Section-Level Relationship for Mean TTI and 80th Percentile

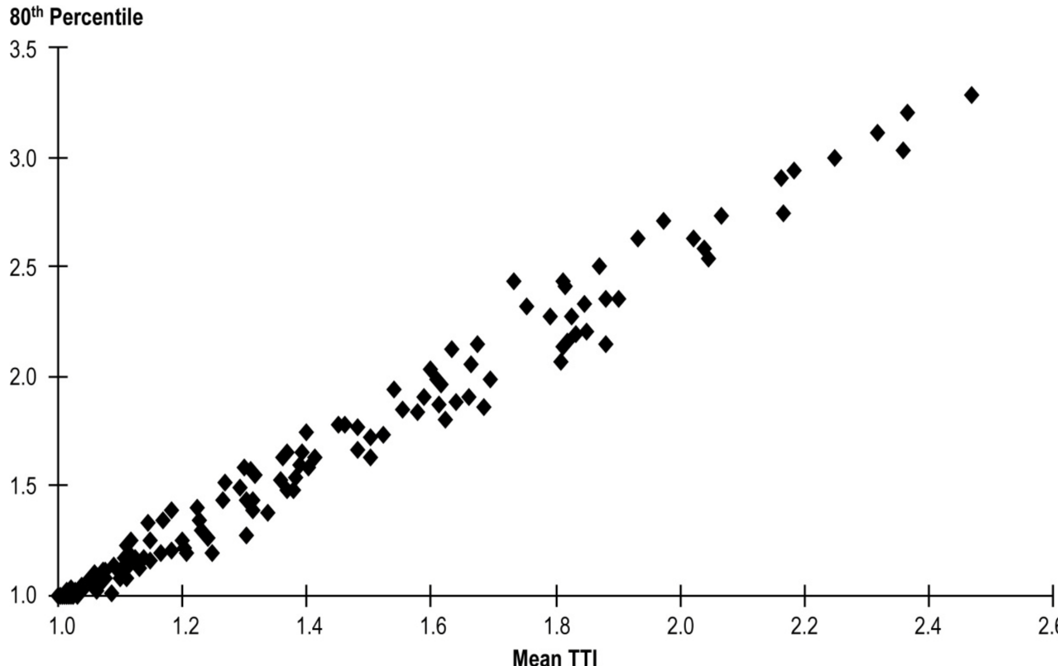


Figure 7.10 Section-Level Relationship for Mean TTI and 95th Percentile

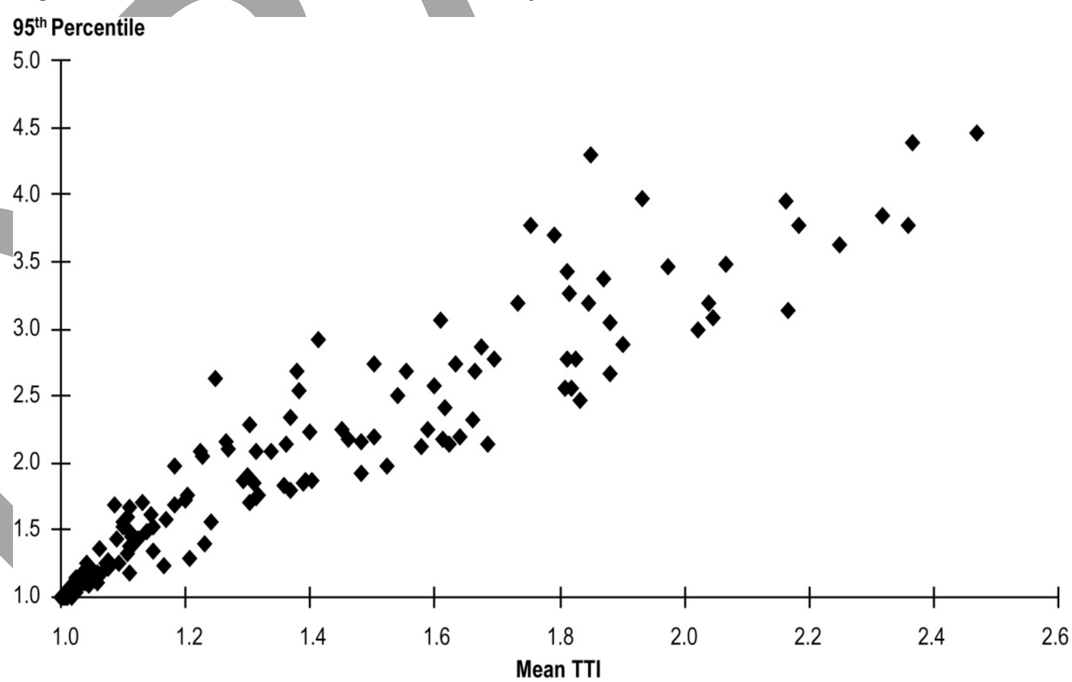


Figure 7.11 Section-Level Relationship for Mean TTI and On-Time at Median Plus 10 Percent

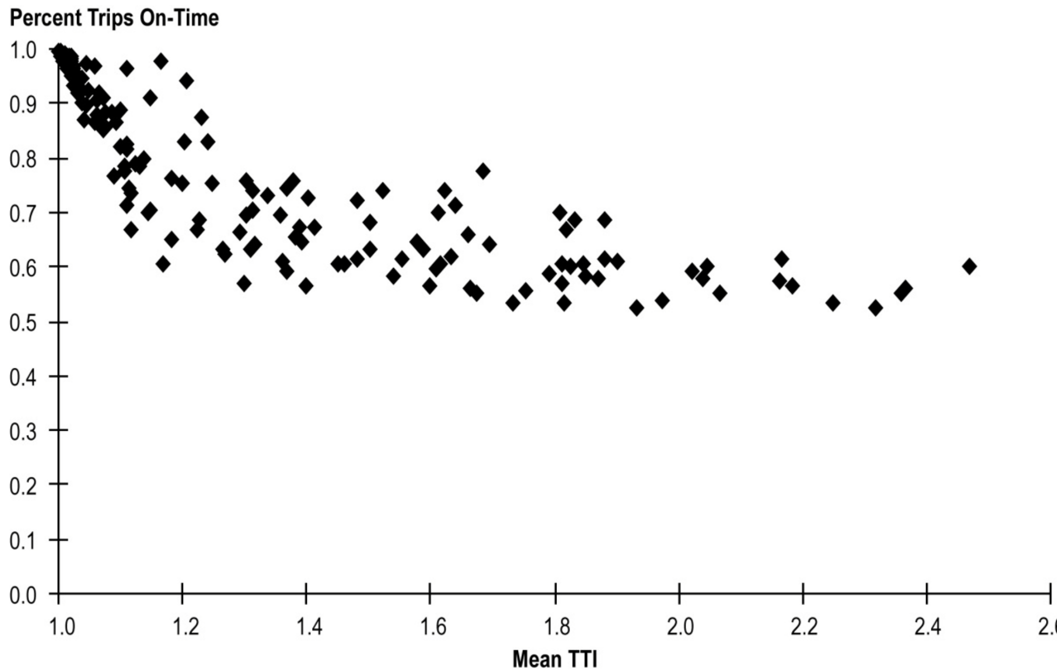


Figure 7.12 Section-Level Relationship for Mean TTI and On-Time at 45 Miles per Hour Threshold

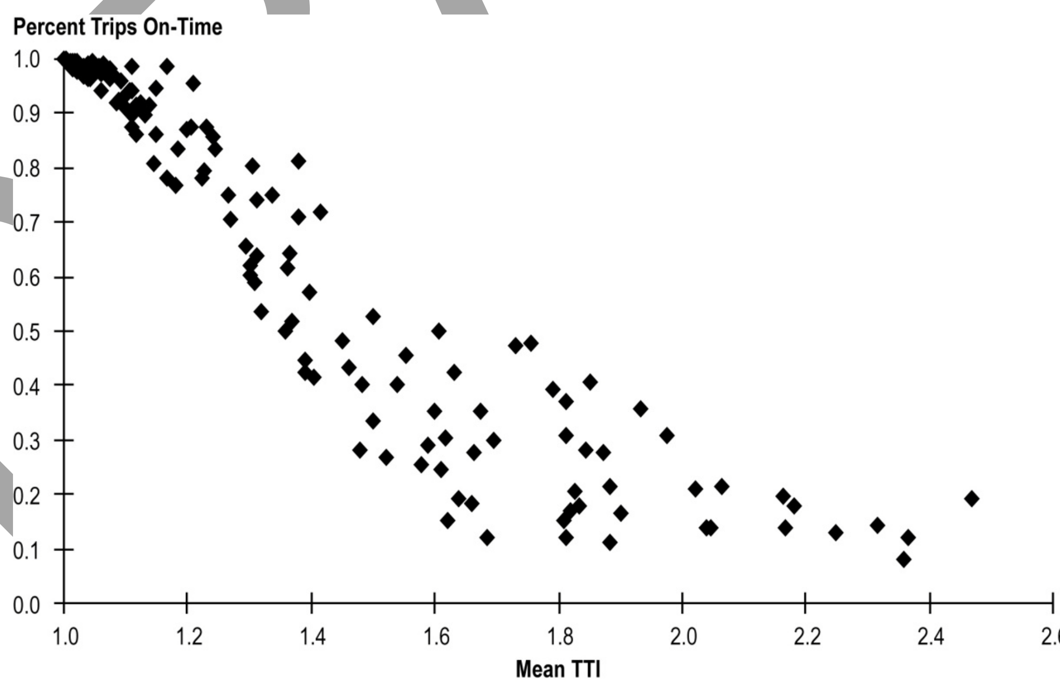


Figure 7.13 Section-Level Relationship for Mean TTI and On-Time at 30 mph Threshold

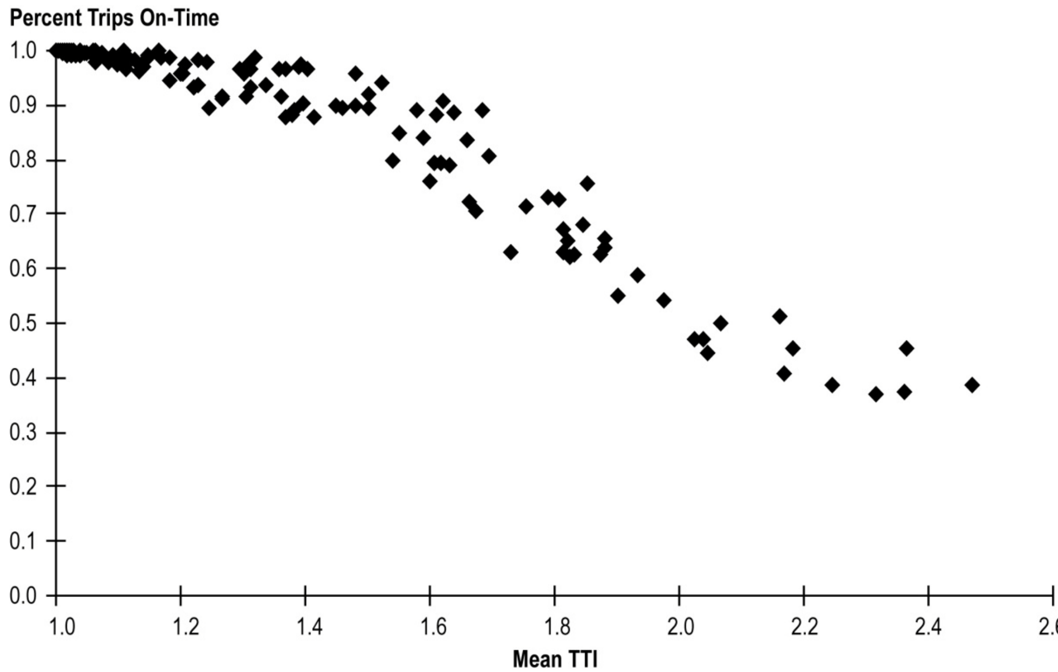
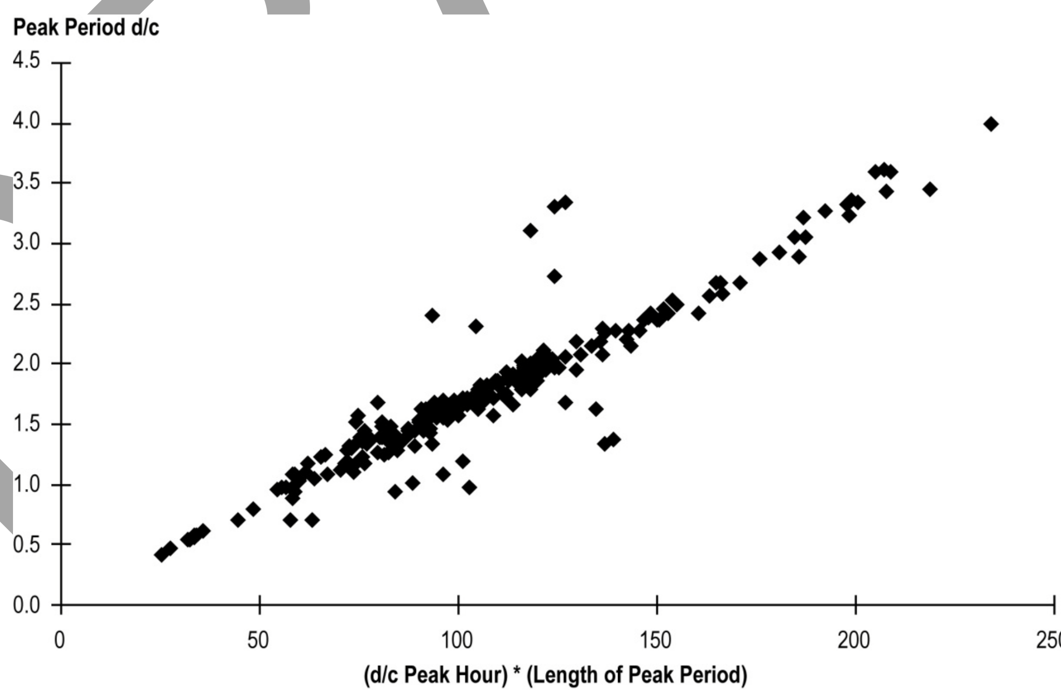


Figure 7.14 Predicting Peak Period d/c Ratio



$95^{th}\ Percentile\ TTI = MeanTTI^{1.8834}$ (RMSE=0.157; alpha level of coefficient < 0.0001) [10]

$90^{th}\ Percentile\ TTI = MeanTTI^{1.6424}$ (RMSE=0.094; alpha level of coefficient < 0.0001) [11]

$80^{th}\ Percentile\ TTI = MeanTTI^{1.365}$ (RMSE=0.045; alpha level of coefficient < 0.0001) [12]

$MedianTTI = MeanTTI^{0.8601}$ (RMSE=0.063; alpha level of coefficient < 0.0001) [13]

$10^{th}\ Percentile\ TTI = MeanTTI^{0.1524}$ (RMSE=0.054; alpha level of coefficient < 0.0001) [14]

$PctTripsOnTime10 = 1 - (0.4396 * (MeanTTI - 1)^{0.4361})$ [15]

Where: PctTripsOnTime10 is the percent of trips that occur below the threshold of 1.1 * MedianTTI

RMSE = 0.084

$PctTripsOnTime25 = 1 - (0.2861 * (MeanTTI - 1)^{0.5251})$ [16]

Where: PctTripsOnTime25 is the percent of trips that occur below the threshold of 1.25 * MedianTTI

RMSE = 0.075

$PctTripsOnTime50mph = 1 - (0.8985 * (MeanTTI - 1)^{0.6387})$ [17]

Where: PctTripsOnTime50mph is the percent of trips that occur at space mean speeds above the threshold of 50 mph

RMSE = 0.18

$PctTripsOnTime45mph = 1 - (0.8203 * (MeanTTI - 1)^{0.7692})$ [18]

Where: PctTripsOnTime45mph is the percent of trips that occur at space mean speeds above the threshold of 45 mph

RMSE = 0.14

$PctTripsOnTime30mph = 1 - (0.4139 * (MeanTTI - 1)^{1.5527})$ [19]

Where: PctTripsOnTime30mph is the percent of trips that occur at space mean speeds above the threshold of 30 mph

RMSE = 0.044

$$StandardDeviation = 0.6182 * (MeanTTI - 1)^{0.5404}$$ (R^2 = 0.781; alpha levels of coefficients < 0.0001) [20]

As with the link level, if the recurring-only mean TTI is available, it must be factored with Equation 9.

7.2.3 Signalized Arterials

The predictive equations for reliability metrics as a function of the mean for signalized arterials were obtained from the six Orlando study sections. Unlike urban freeways, there was no apparent relationship between the mean TTI and the on-time reliability metrics.

$99^{th}\ Percentile\ TTI = MeanTTI^{2.2120}$ (RMSE = 0.127; alpha level of coefficient < 0.0001) [21]

$97.5^{th}\ Percentile\ TTI = MeanTTI^{2.0845}$ (RMSE = 0.102; alpha level of coefficient < 0.0001)[22]

$95^{th}\ Percentile\ TTI = MeanTTI^{1.9125}$ (RMSE = 0.071; alpha level of coefficient < 0.0001) [23]

$80^{th}\ Percentile\ TTI = MeanTTI^{1.4067}$ (RMSE = 0.021; alpha level of coefficient < 0.0001) [24]

$MedianTTI = MeanTTI^{0.9149}$ (RMSE = 0.019; alpha level of coefficient < 0.0001) [25]

$10^{th}\ Percentile\ TTI = MeanTTI^{0.2689}$ (RMSE = 0.04; alpha level of coefficient < 0.0001) [26]

7.2.4 Rural Freeways

The predictive equations for reliability metrics as a function of the mean TTI for rural freeways were obtained from the I-45 (Texas) and I-95 (South Carolina) data. A total of four sections were used, two routes by each direction. The travel times used are for the entire segment (and, therefore, are long) and were derived using the vehicle trajectory method. These sections are not influenced by major urban areas or bottlenecks; examination of long-distance trips that pass through or otherwise touch urban areas is likely to reveal different patterns. An additional metric, the 97.5 percentile, was added because of the extreme skew in the travel-time distributions for long-distance rural trips. Note that the 10^{th} percentile TTI was found to be 1.0, which is to be expected under routinely uncongested conditions. It also is worth noting that for these rural sections, the mean TTI ranged from 1.025 to 1.045, extremely low values compared to the urban sections studied.

$$99^{th}\ Percentile\ TTI = MeanTTI^{4.2584}$$ (RMSE = 0.042, alpha level of coefficient = 0.0052) [27]

$$97.5^{th}\ Percentile\ TTI = MeanTTI^{2.6723}$$ (RMSE = 0.003; alpha level of coefficient < 0.0001) [28]

$$95^{th}\ Percentile\ TTI = MeanTTI^{2.1365}$$ (RMSE = 0.004%; alpha level of coefficient < 0.0001) [29]

$$80^{th}\ Percentile\ TTI = MeanTTI^{1.4923}$$ (RMSE = 0.001; alpha level of coefficient < 0.0001) [30]

$$MedianTTI = ManTTI^{0.8763}$$ (RMSE = 0.001; alpha level of coefficient < 0.0001) [31]

$$10^{th}\ Percentile\ TTI = 1.0$$ [32]

7.3 Statistical Modeling of Reliability

The modeling approach for the data-rich model form discussed in Section 7.1.2 was followed as closely as possible. The concept was to build a chain of relationships that are more deterministic in nature rather than just searching for a single predictive equation from the large set of independent variables available. Several observations should be made about the dataset that have implications for applications of the models:

- The study sections routinely experience relatively high levels of congestion.
- Operations activities, particularly incident management, are well developed in the areas studied. While it would have been interesting to study locations without such advanced activities, such locations in all likelihood would not have the data available for the research.
- The study sections have wide cross-sections, three or more lanes per direction, and number of lanes will generally influence the impact of lane closures. (The average number of lanes on the study sections was 3.6.) However, including number of lanes in the statistical models proved them to be insignificant statistically. This may be a function of the reduced sample sizes in each number of lanes category.
- Minneapolis/St. Paul was the only location with any substantial winter weather conditions. For this reason, frozen precipitation was not used as a potential predictor of reliability. Even in Minneapolis/St. Paul, the number of days with snowfall or icing is relatively limited throughout the course of a year, making it difficult for frozen precipitation to show up as statistically significant. Further, on days where snow or ice is forecast, it is likely that demand will be dramatically lowered: travelers seek other modes or decide not to travel. For these reasons, the reliability measures explored in this research are not useful descriptors of winter weather impacts.
- The above discussion points out an issue with trying to do statistical modeling of reliability. Rare events that cause extreme disruptions are difficult to relate to the percentiles of an annual travel-time distribution; the more common occurrences (e.g., bottleneck congestion, incidents, rainfall)

that tend to produce the statistically significant results. Further, diversion of demand during extreme disruptions will lessen the observed travel-time impacts below what they would have been in the face of full demand.

The dependent variables used in the statistical analysis were derived from the distributions of the Travel Time Index (TTI) for each analysis section. TTI was chosen because, as a unitless index, it is normalized for different section lengths. An alternative would have been to use the travel rate (minutes per mile). Since the TTI is computed as the actual travel rate divided by the ideal travel rate (i.e., the travel rate at the free-flow speed), the two measures are related. Several dependent variables based on the key moments of the TTI distributions were used: the mean TTI as well as the 10th, 50th (median), 80th, 95th, and 99th percentile TTIs were used. From these statistics, both the Buffer Index and Skew Statistic can be computed (see Table 4.4 for the formulas). Note that no adjustment for recurring-only conditions is necessary because the mean TTI predicted here includes both recurring and nonrecurring sources.

The first stage of this model form is to link reliability measures to lane-hours lost due to incidents and work zones, d/c ratio, and weather conditions. During initial investigations, it was noticed that including only incident lane-hours lost as opposed to the sum of incidents and work zones produced more reliable models. This spurred a review of the original data used in the analysis. We talked with personnel at the Atlanta traffic management center (TMC) as well as with personnel from Traffic.com. They admitted that work zone data is currently difficult to obtain and to code with accuracy. In Atlanta's case, sometimes the work zone units report their activities to the TMC; other times, the TMC enters work zone data they had not been notified of by simply viewing it through their closed circuit cameras. Further complicating matters is that the lane-blocking characteristics of a work zone usually changes over time, but the work zone units report only a single number representing the general condition. TMC personnel try to compensate by visually observing the work zone periodically, but this means that the work zone information is not updated frequently, resulting in coded durations that are longer than the actual ones. Finally, in the highly congested sections used in the analysis, lane closures during peak times are avoided whenever possible. In the case of Traffic.com, the number of reported work zones is extremely low.

For these reasons, we have chosen to include only incident lane-hours lost in the statistical models as the major event/disruption-related variable. In the case of Atlanta, if an active work zone with lane closures occurred during the time period of interest (e.g., the peak period), that day was excluded when compiling the final analysis dataset. In applying the models, we would expect lane-hours lost due to short-term work zones to have roughly the same impact as incidents. Long-term work zones will usually have an effect on demand – shifts to other routes, modes, and times of travel.

A variety of equation forms were tried, including natural logarithmic, Cobb-Douglas (multiplicative with exponents), and polynomials. The natural logarithmic form was selected because it has the feature of predicting a TTI of 1.0 when the independent variables are zero. The root mean square error (RMSE) was used as the primary goodness-of-fit measure. (Because the models were fit with no intercept term, to ensure continuity at the zero point, R^2 values could not be calculated – as with the simple models, RMSE is used as the goodness-of-fit measure.) For the significance of the coefficients, we used a generous alpha level of 0.1 to allow variables to stay in the equations.

7.3.1 First Stage Models

A large combination of independent variables were tested, with a focus on capturing the factors hypothesized to have an influence on reliability (Figure 7.1), where reliability is measured over the course of a year. The results for the first stage equations, the most important because they establish that reliability can be predicted from congestion-causing conditions, appear below. Separate equations were fit for the peak hour, peak period, mid-day, and weekday time periods. Summary statistics for the base data appear in Table 7.6.

Table 7.6 Summary Statistics for the Statistical Analysis

		Means			
	Section-Years		Annual Incident		
Time Slice	(No. Obs.)	DC_{crit}	Lane-Hours Lost	Average TTI	TTI 95th Percentile
Peak Hour	70	0.86	5.69	1.62	2.50
Peak Period	85	1.98	18.11	1.53	2.41
Mid-Day	91	2.13	13.15	1.06	1.21
Weekday	89	11.98	67.91	1.16	1.84

Peak Period

$$MeanTTI = e^{(0.09677 \cdot dc_{crit} + 0.00862 \cdot ILHL + 0.00904 \cdot Rain05Hrs)} \quad [33]$$

RMSE = 0.188; alpha level of coefficients: <0.0001, <0.0001, 0.0189

(In order of appearance in the equations.)

$$99^{th}\ Percentile\ TTI = e^{(0.33477 \cdot dc_{crit} + 0.012350 \cdot ILHL + 0.025315 \cdot Rain05Hrs)} \quad [34]$$

RMSE = 0.398; alpha level of coefficients: <0.0001, 0.0002, 0.0022

$$95^{th}\ Percentile\ TTI = e^{(0.23233 \cdot dc_{crit} + 0.01222 \cdot ILHL + 0.01777 \cdot Rain05Hrs)} \quad [35]$$

RMSE = 0.323; alpha level of coefficients: <0.0001, <0.0001, 0.0078

$$80^{th}\ Percentile\ TTI = e^{(0.13992 \cdot dc_{crit} + 0.01118 \cdot ILHL + 0.01271 \cdot Rain05Hrs)} \quad [36]$$

RMSE = 0.258; alpha level of coefficients: <0.0001, <0.0001, 0.0163

$$50^{th}\ Percentile\ TTI = e^{(0.09335*dc_{crit} + 0.00932*ILHL)} \quad [37]$$

RMSE = 0.205; alpha level of coefficients: <0.0001, <0.0001

$$10^{th}\ Percentile\ TTI = e^{(0.01180*dc_{crit} + 0.00145*ILHL)} \quad [38]$$

RMSE = 0.067; alpha level of coefficients: 0.0169, 0.0060

Peak Hour

$$MeanTTI = e^{(0.27886*dc_{crit} + 0.01089*ILHL + 0.02935*Rain05Hrs)} \quad [39]$$

RMSE = 0.264; alpha level of coefficients: 0.0008, 0.0094, 0.0838

$$99^{th}\ Percentile\ TTI = e^{(1.13062*dc_{crit} + 0.01242*ILHL)} \quad [40]$$

RMSE = 0.413; alpha level of coefficients: <0.0001, 0.0477

$$95^{th}\ Percentile\ TTI = e^{(0.63071*dc_{crit} + 0.01219*ILHL + 0.04744*Rain05Hrs)} \quad [41]$$

RMSE = 0.383; alpha level of coefficients: <0.0001, 0.0436, 0.0553

$$80^{th}\ Percentile\ TTI = e^{(0.52013*dc_{crit} + 0.01544*ILHL)} \quad [42]$$

RMSE = 0.341; alpha level of coefficients: <0.0001, 0.0031

$$50^{th}\ Percentile\ TTI = e^{(0.29097*dc_{crit} + 0.01380*ILHL)} \quad [43]$$

RMSE = 0.283; alpha level of coefficients: <0.0001, 0.0015

$$10^{th}\ Percentile\ TTI = e^{(0.07643*dc_{crit} + 0.00405*ILHL)} \quad [44]$$

RMSE = 0.152; alpha level of coefficients: 0.0081, 0.0748

Mid-day (11:00 a.m. to 2:00 p.m., weekdays.)

$$MeanTTI = e^{(0.02599*dc_{crit})} \quad [45]$$

RMSE = 0.075; alpha level of coefficient: <0.0001

$$99^{th}\ Percentile\ TTI = e^{(0.19167*dc_{crit})} \quad [46]$$

RMSE = 0.334; alpha level of coefficient: <0.0001

$$95^{th}\ Percentile\ TTI = e^{(0.07812*dc_{crit})} \quad [47]$$

RMSE = 0.218; alpha level of coefficient: <0.0001

$$80^{th}\ Percentile\ TTI = e^{(0.02612*dc_{crit})} \quad [48]$$

RMSE = 0.092; alpha level of coefficient: <0.0001

$$50^{th}\ Percentile\ TTI = e^{(0.01134*dc_{crit})} \quad [49]$$

RMSE = 0.218; alpha level of coefficient: <0.0001

$$10^{th}\ Percentile\ TTI = e^{(0.00389*dc_{crit})} \quad [50]$$

RMSE = 0.051; alpha level of coefficient: <0.0016

Weekday

$$MeanTTI = e^{(0.00949*dc_{average} + 0.00067*ILHL)} \quad [51]$$

RMSE = 0.293; alpha level of coefficients: <0.0001, 0.0051

$$99^{th}\ Percentile\ TTI = e^{(0.07028*dc_{average} + 0.00222*ILHL)} \quad [52]$$

RMSE = 0.389; alpha level of coefficients: <0.0001, 0.0261

$$95^{th}\ Percentile\ TTI = e^{(0.03632*dc_{average} + 0.00282*ILHL)} \quad [53]$$

RMSE = 0.318; alpha level of coefficients: <0.0001, 0.0007

$$80^{th}\ Percentile\ TTI = e^{(0.00842*dc_{average} + 0.00117*ILHL)} \quad [54]$$

RMSE = 0.147; alpha level of coefficients: 0.0004, 0.0023

$$50^{th}\ Percentile\ TTI = e^{(0.0021*dc_{average})} \quad [55]$$

RMSE = 0.047; alpha level of coefficients: <0.0001

$$10^{th}\ Percentile\ TTI = e^{(0.00047*dc_{average})} \quad [56]$$

RMSE = 0.02; alpha level of coefficients: 0.0121

Where: dc_{crit} = "critical" demand-to-capacity ratio on the study section (i.e., the highest d/c ratio for all the links on the section)

$dc_{average}$ = average demand-to-capacity ratio on the study section (i.e., the mean of the d/c ratio for all the links on the section)

ILHL = annual lane-hours lost due to incidents that occur within the time slice of interest (e.g., the peak period)

Rain05Hrs = Hours in the year where rainfall is >= 0.05 inches that occur within the time slice of interest

Several interaction terms involving volume or d/c ratio with event characteristics were also tried but failed to be significant in the regressions. We expected to find these terms to be important determinants of reliability, especially given the results of the exploratory research showing the strong effect that volume has. However, it must be remembered that the models are not attempting to predict congestion on any given day, when these interactions are very likely to be significant. Rather, over the course of a year (over which reliability is determined), the interaction affects appear to be negligible.

Likewise, in the case of extreme/rare weather events (e.g., fog, snow) there does not seem to be enough of these occurrences in our data to influence the annual summary metrics in a statistical sense. In the case of winter weather, unless the precipitation is unexpected, demand is likely to be lower as travelers forego trips or seek transit service. On an individual day, however, there is no denying that such events exert a strong influence on congestion. Hence, the reliance on a relatively common weather event, hourly rainfall greater than or equal to 0.05 inches, to explain weather effects on annual reliability.

The lane-hours lost factor was limited to just those related to incidents, for reasons discussed above. The study sections were all located on high volume, multilane roadways with significant congestion. Work zones during peak times are very likely not to involve lane closures; it is common practice to keep all lanes open during the peaks and to close them during offpeak times. Also, the coding of work zones, especially changes in lane closures over their duration, was found to be inconsistent in the datasets. Work zones are also rare events in general; some sections will have little or no work activity during a year, while incidents happen continuously. Finally, long-term work zones involving continuous lane closures will shift demand away from the facility. For these reasons, making a statistical connection with work zone related lane closures is difficult. However, we still believe that lane closures due to short-term work zones are roughly equal in their traffic effect as incidents. For this reason, we recommend that if short-term work zones close lanes during the peaks, that an estimate of the annual lane-hours lost due to them be made and added to the ILHL factor used in the equations.

Table 7.7 Analysis of Variance Statistics for Peak Models

Model	Dependent Variable	Independent Variable	Type I SS	Type III SS
Peak Period	Mean TTI	d/c	13.16	0.97
		ILHL	1.40	1.18
		HrsRain05	0.20	0.20
	Median TTI	d/c	9.54	1.66
		ILHL	1.47	1.47
	80th Percentile TTI	d/c	25.51	2.02
		ILHL	2.39	1.99
		HrsRain05	0.40	0.40
	95th Percentile TTI	d/c	53.54	5.58
		ILHL	2.97	2.38
		HrsRain05	0.78	0.78
	99th Percentile TTI	d/c	96.56	11.59
		ILHL	3.27	2.42
		HrsRain05	1.58	1.58
Peak Hour	Mean TTI	d/c	14.22	0.86
		ILHL	0.65	0.50
		HrsRain05	0.21	0.21
	Median TTI	d/c	11.66	2.46

	ILHL	0.87	0.87
80th Percentile TTI	d/c	29.17	7.87
	ILHL	1.09	1.09
95th Percentile TTI	d/c	49.60	4.37
	ILHL	0.89	0.62
	HrsRain05	0.56	0.56
99th Percentile TTI	d/c	102.60	37.17
	ILHL	0.71	0.71

It is revealing that the mid-day models do not include the effect of either incidents or rain. This is a period typically showing very little overall congestion and reduced demand. The fact that events do not show up as statistically relevant may be an indication that demand (volume) is low enough so there is enough buffer to absorb the effect of most events.

The importance of demand and capacity to predicting reliability measures cannot be overstated. Examination of the Type I (sequential) and Type III (marginal) sums of squares for the peak models reveals the relative contribution of the independent variables. (Type I sums of squares estimate the contribution of adding the variables in sequence. Type III sums of squares shows the additional contribution of a variable given that the other variables are already in the model. Higher values indicate greater contribution to the model's explanatory power.) For the 80th, 95th, and 99th percentile TTIs, the Type III sums of squares all show that the marginal contribution of the d/c ratio is higher than the other factors.

7.3.2 Second Stage Models

Estimating d/c Ratio

The demand used in developing the models is the volume that occurred for the entire length of the study period, adjusted for any potential queuing affects as discussed in Section 4.6. Because the data were continuously collected for an entire year, the 99th percentile demand volume was selected. This was done to correspond to the usual way that traffic data are developed for highway capacity analysis, as follows. For the peak hour, the 99th percentile demand volume is close to the volume determined by the traditional K-factor, 30th highest hour of the year. Table 7.8 shows a comparison of these values for detectors (stations) in Atlanta for 2008. Note that the 99th percentile hourly volume is taken from a distribution of the actual peak hour volumes (weekday, nonholiday) for the year, i.e., developed from all weekdays. The 30th highest hourly volumes (K-Factor volumes) are derived in the usual way by rank ordering all hours in the year.

Table 7.8 Comparison of 99th Percentile Hourly Volumes and K-Factor Volumes

Station ID	Hourly Volume		Ratio
	99th Percentile	30th Highest	
200511	8,558	7,756	0.91
200512	6,115	5,698	0.93
200516	8,067	7,697	0.95
200517	8,095	7,600	0.94
200520	2,524	2,986	1.18
750502	11,931	11,278	0.95
750503	14,848	14,385	0.97
750505	11,377	11,631	1.02
750506	11,210	11,612	1.04
750508	12,119	11,987	0.99
750509	11,795	11,955	1.01
750510	8,939	9,542	1.07
750511	9,325	10,020	1.07
750512	8,613	8,907	1.03
750513	9,298	9,435	1.01
750515	8,446	8,730	1.03
750516	8,548	8,833	1.03
750517	6,791	6,342	0.93
750518	9,904	9,864	1.00
750519	10,012	10,001	1.00
750520	10,457	10,188	0.97
750521	10,081	10,037	1.00
750522	9,582	9,296	0.97
750523	7,846	7,490	0.95
750524	9,882	9,646	0.98
750526	6,930	6,968	1.01
751472	5,706	6,439	1.13
751473	5,872	6,073	1.03
751475	8,458	8,209	0.97
751476	8,176	8,184	1.00
751477	8,327	8,181	0.98
751479	9,380	9,805	1.05
751480	10,096	9,510	0.94
751481	9,000	9,669	1.07
751482	9,390	9,476	1.01
751484	9,750	10,185	1.04
751486	9,880	9,926	1.00
751487	9,775	10,075	1.03
751488	9,873	9,648	0.98
751491	12,394	12,369	1.00
751495	14,396	14,027	0.97
751496	12,494	12,551	1.00
2850002	4,110	3,880	0.94

Station ID	Hourly Volume		Ratio
	99th Percentile	30th Highest	
2850003	8,028	7,945	0.99
2850004	12,823	12,634	0.99
2850005	10,688	10,585	0.99
2850008	9,552	9,129	0.96
2850009	9,649	9,290	0.96
2850010	10,308	10,094	0.98
2850011	10,270	10,069	0.98
2850012	10,063	9,935	0.99
2850013	10,112	10,015	0.99
2850014	12,370	12,046	0.97
2850015	10,309	10,048	0.97
2850016	10,345	10,077	0.97
2850017	8,897	8,684	0.98
2850020	6,813	6,880	1.01
2850021	8,399	9,692	1.15
2850023	9,529	9,257	0.97
2850024	7,736	8,314	1.07
2850025	8,307	8,589	1.03
2850026	9,402	9,820	1.04
2850028	7,930	9,056	1.14
2850029	7,911	8,384	1.06
2850031	8,020	8,707	1.09
2850032	7,935	8,503	1.07
2850033	8,256	8,748	1.06
2850034	8,233	8,960	1.09
2850035	8,786	9,633	1.10
2850036	9,130	9,348	1.02
2850042	3,705	3,983	1.08
2851004	4,457	4,796	1.08
2851005	5,204	5,330	1.02
2851006	8,343	8,027	0.96
2851007	11,484	11,980	1.04
2851008	13,046	13,553	1.04
2851009	9,424	9,916	1.05
2851010	8,815	8,831	1.00
2851011	11,198	11,305	1.01
2851012	11,023	11,141	1.01
2851013	11,389	10,942	0.96
2851014	10,371	10,352	1.00
2851015	11,536	10,472	0.91
2851016	10,581	10,564	1.00
2851018	12,597	12,155	0.96
2851020	10,428	10,278	0.99
2851021	9,930	9,743	0.98

Station ID	Hourly Volume		Ratio
	99th Percentile	30th Highest	
2851022	11,255	11,096	0.99
2851023	9,545	8,975	0.94
2851026	12,935	13,354	1.03
2851027	8,847	10,051	1.14
2851028	9,190	9,746	1.06
2851029	9,879	10,410	1.05
2851030	9,842	9,817	1.00
2851031	9,131	9,647	1.06
2851033	8,118	7,999	0.99
2851034	10,065	10,960	1.09
2851035	9,107	9,673	1.06
2851036	8,440	8,899	1.05
2851037	8,451	8,925	1.06
2851038	8,441	9,101	1.08
2851039	9,017	9,402	1.04
2851041	9,123	8,579	0.94
2851043	3,687	3,815	1.03
		Average	1.01

The lengths of the time periods are different: the peak hour is one-hour long, the mid-day period is three hours long (11:00 a.m. to 2:00 p.m.), and the peak period is variable as defined in Section 4.5. To develop demand volume, users should rely on local data to the extent possible, using the guidance above. In the absence of local data, the following default procedure is offered, based on the assumption that the 99th percentile of the peak-hour volumes is equivalent to the K-factor volumes. Figure 7.15 shows the relationship between the peak period d/c and the product of peak-hour d/c times the length of the peak period assembled from the urban freeway study sections. A linear regression was performed on the data and produced the following equation:

$$(d/c)_{pp} = \{(d/c)_{ph} * PeakPeriodLength\} * 0.01648 \qquad [57]$$

Where: $(d/c)_{pp}$ = d/c for the peak period

(d/c)ph = *d/c for the peak hour*

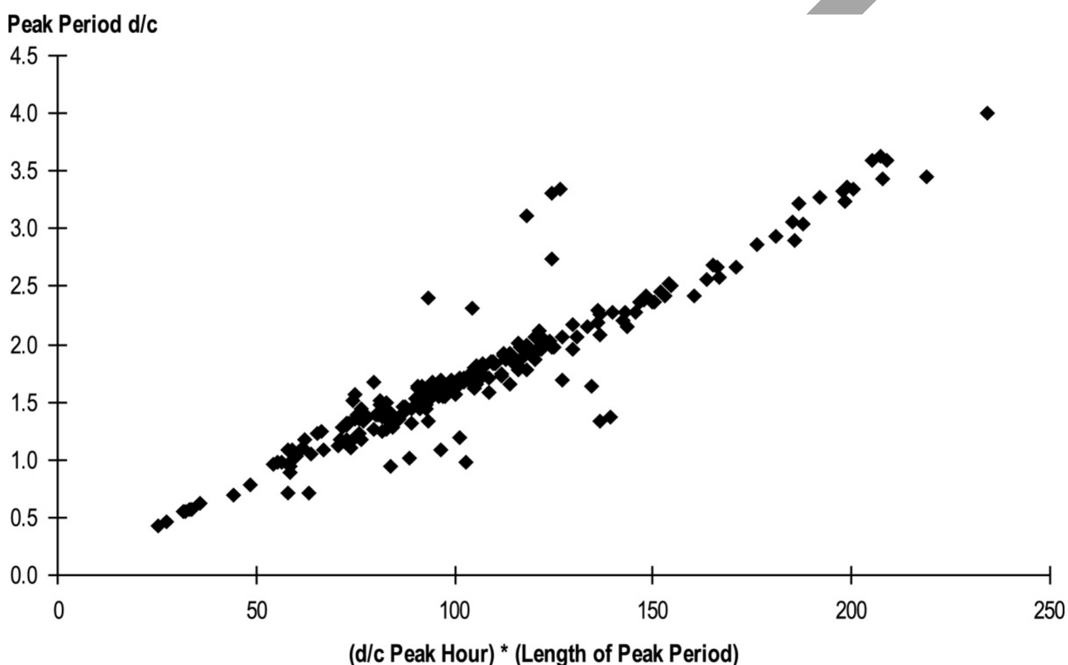
= peak hour v/c ratio

PeakPeriodLength = length of the peak period, minutes (see Section 4.5)

RMSE = 0.220; alpha level of coefficient < 0.0001

The maximum peak period length in the data was 200 minutes. Therefore, it is recommended that this equation be used only for peak period lengths up to 200 minutes.

Figure 7.15 Predicting Peak Period d/c Ratio



The peak hour v/c ratio is computed either from empirical (factored daily traffic) data or model output. A typical way to compute it from empirical data is:

*v/c = (AADT * K-factor * D-Factor)/HourlyCapacity* [58]

Where: *AADT* is the annual average daily traffic

K-factor is the 30th highest hour of traffic in a year

D-factor is the directional split of traffic in the 30th highest hour

HourlyCapacity is calculated using the *HCM*

The weekday and mid-day time periods likewise use the 99th percentile demand volume. Local values for these are preferred, but if these are not available, then the following factors developed from the Atlanta study sections can be used.

Weekdays

99th percentile weekday demand = AADT * 1.251 [59]

Mid-day (11:00 am to 2:00 p.m.)

99th percentile mid-day demand = AADT * 0.234 [60]

The "capacity" term in the d/c ratio as defined in the analysis is the ***hourly*** capacity is the determined from the Highway Capacity Manual. It should include the effect of weaving sections and merge areas, as appropriate.

Estimating Lane-Hours Lost

Total lane-hours-lost (annual) is the sum of lane-hours lost due to incidents (ILHL) and work zones. Work zone lane-hours lost must be estimated with local knowledge of the extent and characteristics of planned work zones. Incident lane-hours lost are calculated as follows.

$$ILHL = NumberIncidents * LanesBlocked * IncidentDuration \quad (61)$$

NumberIncidents = Number of annual incidents (Incident rate and VMT should be computed for the particular time slice under study, e.g., the peak period.)

$$= IncidentRate * VMT \quad (62)$$

LanesBlocked = Lanes blocked per incident

IncidentDuration = Average incident duration (hours), defined as the time between when the incident started and the last lane or shoulder has been cleared.

If incident rate is unavailable locally, it may be estimated by multiplying the crash rate by 4.545, which assumes that crashes are 22 percent of all incidents; this factor was developed from analyzing the incident data in the analysis dataset.

If lanes blocked per incident is unavailable locally, it can be estimated using the following factors, developed from two years of incident data from Atlanta:

- 0.476 if a usable shoulder is present and it is local policy to move lane-blocking incidents to shoulder as rapidly as possible. (This is the policy in Atlanta. A usable shoulder is capable of safely storing the disabled vehicle and emergency vehicles.)
- 0.580 if lane-blocking incidents are not moved to the shoulder. (Developed by considering lane-blocking incidents that were moved to the shoulder, and reassigning them back to lane-blocking status.)
- 1.140 if usable shoulders are unavailable.

Average incident duration is largely a function of incident management actions and policies. However, developing a statistical relationship from the data available has proven to be elusive. We had originally hoped to use the Traffic Incident Management Self-Assessment scores as a way of capturing quantitatively the myriad of factors that comprise incident management programs. As it turned out, these scores were available for only a few of the locations. As a means of guidance to practitioners, we offer the following characteristics of the study locations (Table 7.9).

Table 7.9 Peak Period Incident Characteristics for Study Locations

Urban Area	Average Incident Duration (Minutes)	Quick Clearance Law?	PDO-Move-to-Shoulder Law?	Fatality Removal Without Medical Examiner?
Atlanta	43.5	Yes	Yes	Yes
Houston	43.2	Yes	Yes	Yes
Jacksonville	32.1[a]	Yes	Yes	Yes
Los Angeles	51.5	No	Yes	No
Minneapolis	47.3	No	No	No
San Diego	52.0	No	Yes	No

Note: Average Incident Duration is defined as the time between when the incident started and the last lane or shoulder has been cleared.

[a] End time defined as when lane is cleared (incident may still be active on shoulder).

Estimating Hours of Rainfall >= 0.05 Inches

The National Weather service maintains hourly records of weather conditions that should be used to calculate this factor.

Graphical Display of Equations

Figures 7.16 through 7.18 graphically show the behavior of selected equations for predicting the 95th percentile TTI.

Figure 7.16 Peak-Hour Equations
D/C Critical versus 95th Percentile TTI

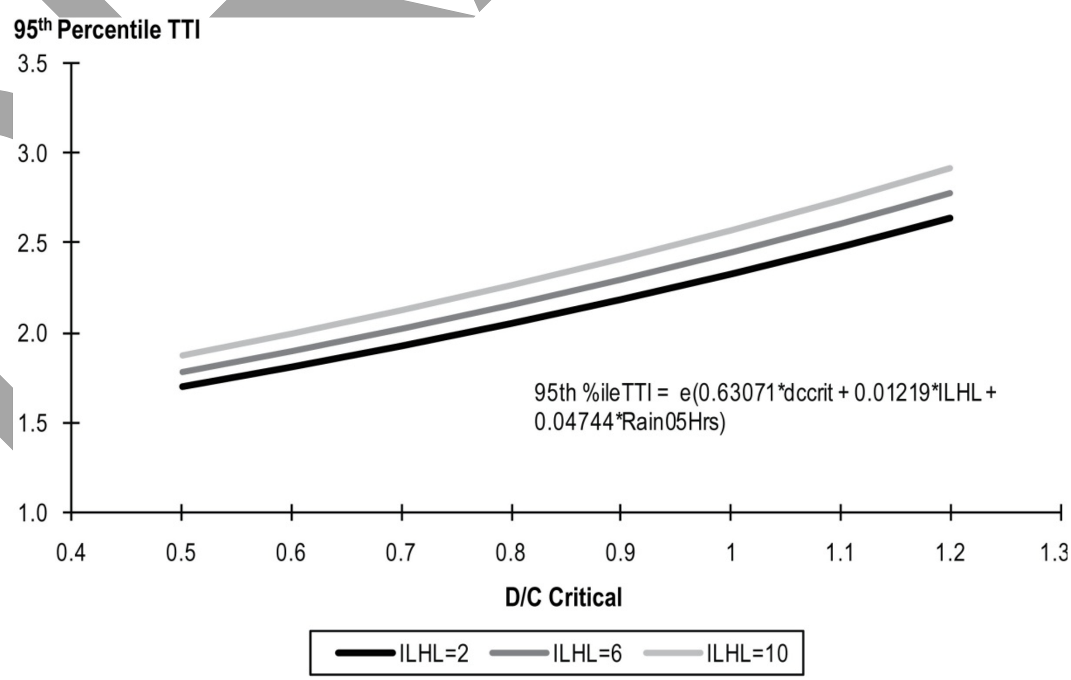


Figure 7.17 Peak-Period Equations
D/C Critical versus 95th Percentile TTI

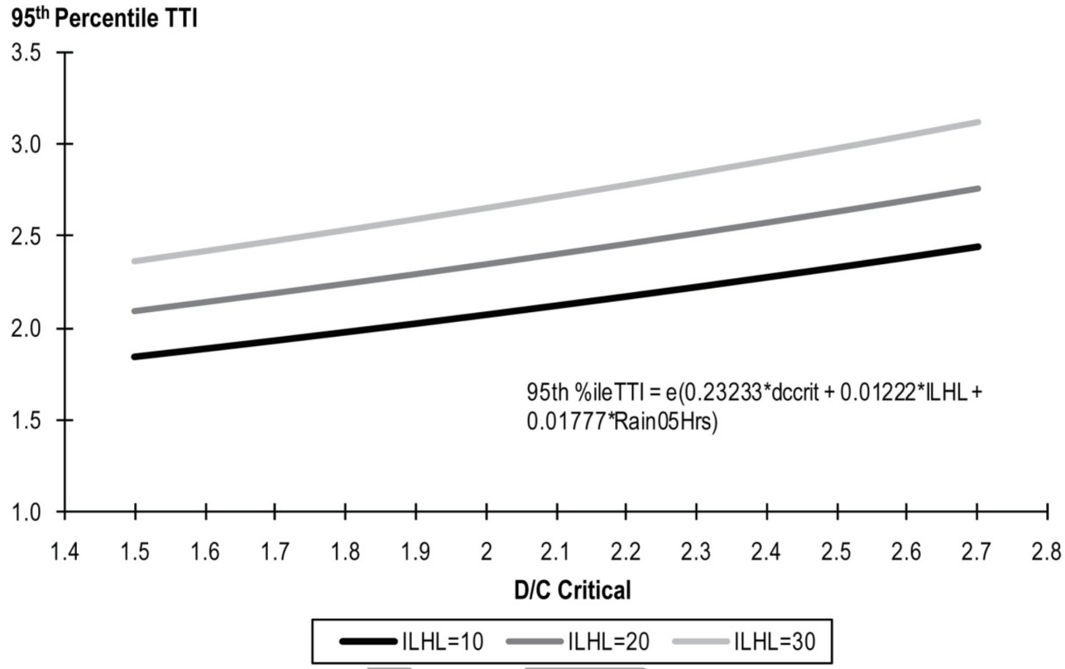
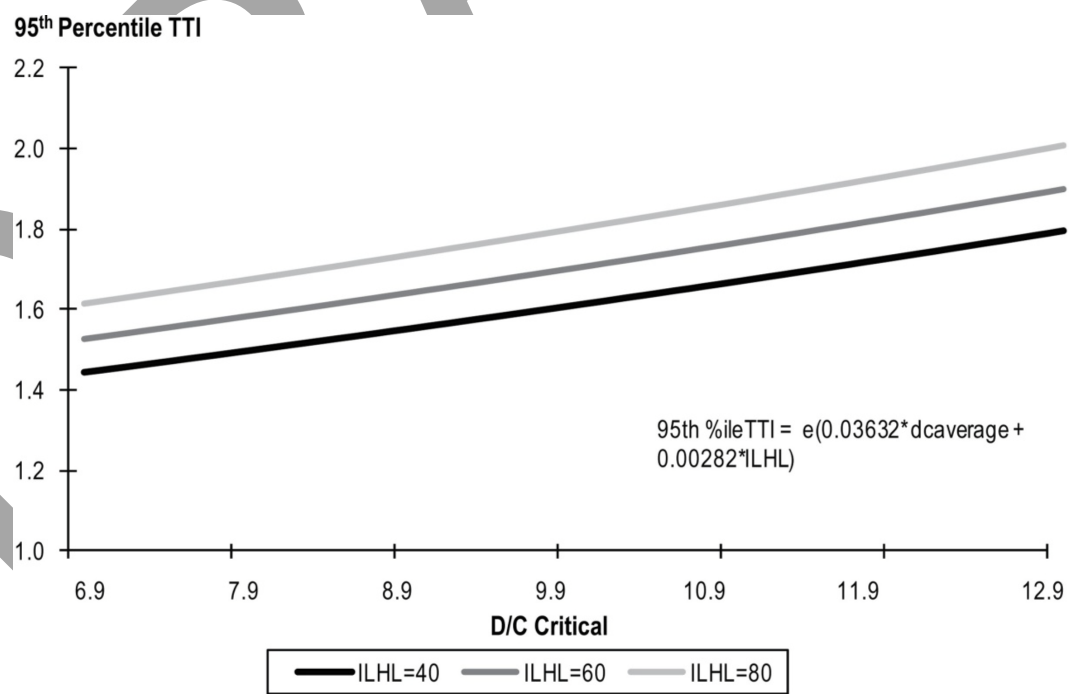


Figure 7.18 Weekday Equations
D/C Critical versus 95th Percentile TTI



7.4 Validation of Statistical Models

Data from the Seattle area, which was used in the congestion-by-source analysis in Section 5.0, was used to validate the data-rich and data-poor statistical models. The actual travel-time metrics were compiled directly from the Seattle detector data. Lane-hours lost information was compiled directly from the Seattle incident data base. Data on demand and capacity were compiled from Highway Performance Monitoring System data for the Seattle study sections.

The results for the data-rich model comparison appear in Tables 7.10 and 7.11. For peak periods, the models tend to over-predict the key metrics when actual congestion is fairly low, and under-predict when actual congestion is high (e.g., mean TTIs greater than 2.5). Low congestion during the peak period was rare in the data on which the models were fit, so a recommendation for their application would be to apply the peak period models only in situations where at least a modest amount of congestion exists. (The rainfall factor was set to four hours for peak hour and eight hours for the peak period.)

For weekdays (all 24 hours), the models tend to under-predict Seattle conditions, especially the 95th percentile TTIs. This may be due to the lack of a weather/rain variable in the weekday models, which proved to be insignificant for the model dataset, but rain was shown in Section 5.0 to be an extremely important factor in Seattle congestion. Without testing another city, it is not known if Seattle is an exception or if rainfall has a universal influence on total weekday congestion. The problem may lie in the fact that Seattle weekday 95th percentile TTIs do not behave in the same way as those of the other cities. Table 7.12 shows the prediction of the 95th percentile TTI from the mean TTI using the data-poor model. The predicted 95th percentiles are consistently lower than the predicted ones, yet the data-poor relationship had an excellent goodness-of-fit. We are not sure why the 95th percentile TTIs in Seattle are so much higher compared to their means, but this indicates that further validation of the models with data from other cities is warranted.

Table 7.10 Peak Period Data-Rich Model Validation
Seattle Data

	Mean TTI			80th Percentile TTI			95th Percentile TTI		
Section	Actual	Predicted	Percent Error	Actual	Predicted	Percent Error	Actual	Predicted	Percent Error
I-405 Bellevue Northbound	1.346	1.810	34.5%	1.507	2.301	52.7%	2.314	3.369	45.6%
I-405 Eastgate Northbound	1.667	1.835	10.0%	1.981	2.372	19.7%	2.720	3.740	37.5%
I-405 Eastgate Southbound	2.728	1.955	-28.4%	3.227	2.575	-20.2%	4.209	4.091	-2.8%
I-405 Kennydale Southbound	1.898	1.677	-11.6%	2.313	2.077	-10.2%	3.376	2.958	-12.4%
I-405 Kirkland Northbound	1.995	2.019	1.2%	2.408	2.640	9.6%	3.132	3.827	22.2%
I-405 Kirkland Southbound	1.766	1.748	-1.0%	2.147	2.189	2.0%	2.673	3.119	16.7%
I-405 North Northbound	1.609	1.654	2.8%	1.876	2.031	8.3%	2.236	2.822	26.2%
I-405 North Southbound	2.820	1.792	-36.4%	4.090	2.254	-44.9%	6.272	3.161	-49.6%
I-405 South Northbound	2.578	1.609	-37.6%	3.080	1.960	-36.4%	3.756	2.707	-27.9%
I-405 South Southbound	1.522	1.607	5.6%	1.797	1.957	8.9%	2.406	2.703	12.3%
I-5 Everett Northbound	1.872	1.976	5.5%	2.777	2.570	-7.5%	4.294	3.740	-12.9%
I-5 Everett Southbound	1.520	1.843	21.2%	1.850	2.348	26.9%	2.590	3.387	30.8%
I-5 Lynnwood Northbound	1.443	1.722	19.4%	1.667	2.163	29.8%	3.539	3.198	-9.6%
I-5 Lynnwood Southbound	1.898	1.829	-3.6%	2.448	2.338	-4.5%	3.968	3.481	-12.3%
I-5 South Northbound	1.764	2.084	18.2%	2.313	2.782	20.3%	3.184	4.318	35.6%
I-5 South Southbound	1.762	1.964	11.5%	2.350	2.576	9.6%	3.251	3.969	22.1%
I-5 Tukwila Northbound	1.502	1.819	21.1%	1.811	2.054	13.4%	2.582	2.840	10.0%
I-5 Tukwila Southbound	1.205	1.858	54.2%	1.265	2.111	66.8%	1.933	2.926	51.3%
I-90 Bellevue Westbound	1.307	1.609	23.1%	1.453	1.961	35.0%	1.998	2.716	35.9%
I-90 Bridge Eastbound	1.414	1.636	15.7%	1.868	2.008	7.5%	2.622	2.832	8.0%
I-90 Bridge Westbound	1.739	1.687	-3.0%	2.608	2.091	-19.8%	3.483	2.960	-15.0%
I-90 Issaquah Westbound	1.476	1.679	13.8%	1.880	2.090	11.2%	2.635	3.051	15.8%
SR 167 Auburn Northbound	1.685	1.615	-4.2%	2.057	1.976	-3.9%	2.567	2.795	8.9%
SR 167 Auburn Southbound	1.961	1.681	-14.3%	2.693	2.082	-22.7%	4.162	2.958	-28.9%
SR 167 Renton Northbound	1.623	1.689	4.0%	1.744	2.100	20.4%	3.361	3.026	-10.0%
SR 167 Renton Southbound	1.637	1.675	2.3%	2.029	2.078	2.4%	3.357	2.991	-10.9%
			4.8%			6.7%			7.2%

Table 7.11 Weekday Data-Rich Model Validation
Seattle Data

Section	Mean TTI			80th Percentile TTI			95th Percentile TTI		
	Actual	Predicted	Percent Error	Actual	Predicted	Percent Error	Actual	Predicted	Percent Error
I-405 Bellevue Northbound	1.186	1.130	-4.7%	1.285	1.127	-12.3%	1.865	1.606	-13.9%
I-405 Eastgate Northbound	1.177	1.177	0.0%	1.232	1.158	-6.0%	1.964	1.867	-4.9%
I-405 Eastgate Southbound	1.369	1.190	-13.1%	1.399	1.181	-15.5%	2.432	1.959	-19.4%
I-405 Kennydale Southbound	1.357	1.119	-17.5%	1.642	1.113	-32.2%	2.491	1.544	-38.0%
I-405 Kirkland Northbound	1.196	1.133	-5.3%	1.123	1.146	2.1%	2.227	1.633	-26.7%
I-405 Kirkland Southbound	1.162	1.123	-3.3%	1.133	1.128	-0.4%	2.000	1.572	-21.4%
I-405 North Northbound	1.135	1.124	-0.9%	1.137	1.116	-1.9%	1.784	1.568	-12.1%
I-405 North Southbound	1.105	1.136	2.8%	1.318	1.137	-13.8%	2.121	1.640	-22.7%
I-405 South Northbound	1.476	1.121	-24.1%	1.933	1.110	-42.6%	2.967	1.549	-47.8%
I-405 South Southbound	1.270	1.122	-11.6%	1.446	1.112	-23.1%	1.904	1.556	-18.3%
I-5 Everett Northbound	1.192	1.119	-6.1%	1.031	1.129	9.5%	2.514	1.553	-38.2%
I-5 Everett Southbound	1.054	1.122	6.4%	1.012	1.134	12.1%	1.216	1.570	29.1%
I-5 Lynnwood Northbound	1.134	1.112	-2.0%	1.085	1.106	1.9%	1.730	1.504	-13.1%
I-5 Lynnwood Southbound	1.165	1.116	-4.2%	1.100	1.113	1.2%	1.978	1.528	-22.7%
I-5 South Northbound	1.117	1.142	2.3%	1.033	1.155	11.8%	1.859	1.684	-9.4%
I-5 South Southbound	1.154	1.127	-2.3%	1.061	1.129	6.3%	2.123	1.592	-25.0%
I-5 Tukwila Northbound	1.111	1.117	0.6%	1.066	1.118	4.8%	1.680	1.536	-8.5%
I-5 Tukwila Southbound	1.060	1.114	5.1%	1.043	1.112	6.6%	1.207	1.517	25.7%
I-90 Bellevue Westbound	1.101	1.076	-2.2%	1.000	1.076	7.6%	1.516	1.330	-12.3%
I-90 Bridge Eastbound	1.118	1.078	-3.6%	1.075	1.074	-0.1%	1.876	1.335	-28.8%
I-90 Bridge Westbound	1.161	1.080	-7.0%	1.053	1.078	2.4%	1.547	1.346	-13.0%
I-90 Issaquah Westbound	1.077	1.062	-1.4%	1.043	1.056	1.3%	1.454	1.260	-13.4%
SR 167 Auburn Northbound	1.168	1.084	-7.2%	1.248	1.078	-13.6%	1.759	1.363	-22.5%
SR 167 Auburn Southbound	1.189	1.084	-8.8%	1.265	1.078	-14.7%	1.954	1.365	-30.1%
SR 167 Renton Northbound	1.201	1.093	-9.0%	1.213	1.087	-10.4%	1.916	1.406	-26.6%
SR 167 Renton Southbound	1.123	1.090	-3.0%	1.144	1.083	-5.4%	1.581	1.392	-12.0%
			-4.6%			-4.8%			-17.2%

Table 7.12 Application of Data-Poor Model to Seattle Data
Weekdays

Section	Mean TTI	80th Percentile TTI Actual	80th Percentile TTI Predicted	80th Percentile TTI Percent Error	95th Percentile TTI Actual	95th Percentile TTI Predicted	95th Percentile TTI Percent Error
I-405 Bellevue Northbound	1.186	1.285	1.262	-1.8%	1.865	1.379	-26.0%
I-405 Eastgate Northbound	1.177	1.232	1.249	1.4%	1.964	1.358	-30.8%
I-405 Eastgate Southbound	1.369	1.399	1.536	9.8%	2.432	1.807	-25.7%
I-405 Kennydale Southbound	1.357	1.642	1.516	-7.7%	2.491	1.776	-28.7%
I-405 Kirkland Northbound	1.196	1.123	1.277	13.8%	2.227	1.402	-37.1%
I-405 Kirkland Southbound	1.162	1.133	1.228	8.4%	2.000	1.327	-33.6%
I-405 North Northbound	1.135	1.137	1.188	4.5%	1.784	1.269	-28.9%
I-405 North Southbound	1.105	1.318	1.146	-13.0%	2.121	1.207	-43.1%
I-405 South Northbound	1.476	1.933	1.702	-11.9%	2.967	2.083	-29.8%
I-405 South Southbound	1.270	1.446	1.385	-4.2%	1.904	1.568	-17.7%
I-5 Everett Northbound	1.192	1.031	1.271	23.3%	2.514	1.393	-44.6%
I-5 Everett Southbound	1.054	1.012	1.075	6.2%	1.216	1.105	-9.1%
I-5 Lynnwood Northbound	1.134	1.085	1.188	9.5%	1.730	1.268	-26.7%
I-5 Lynnwood Southbound	1.165	1.100	1.232	12.1%	1.978	1.334	-32.5%
I-5 South Northbound	1.117	1.033	1.163	12.6%	1.859	1.232	-33.7%
I-5 South Southbound	1.154	1.061	1.217	14.6%	2.123	1.311	-38.3%
I-5 Tukwila Northbound	1.111	1.066	1.154	8.2%	1.680	1.218	-27.5%
I-5 Tukwila Southbound	1.060	1.043	1.083	3.8%	1.207	1.116	-7.6%
I-90 Bellevue Westbound	1.101	1.000	1.140	14.0%	1.516	1.199	-20.9%
I-90 Bridge Eastbound	1.118	1.075	1.164	8.3%	1.876	1.233	-34.3%
I-90 Bridge Westbound	1.161	1.053	1.226	16.4%	1.547	1.324	-14.4%
I-90 Issaquah Westbound	1.077	1.043	1.107	6.1%	1.454	1.150	-20.9%
SR 167 Auburn Northbound	1.168	1.248	1.236	-1.0%	1.759	1.339	-23.9%
SR 167 Auburn Southbound	1.189	1.265	1.267	0.1%	1.954	1.385	-29.1%
SR 167 Renton Northbound	1.201	1.213	1.284	5.9%	1.916	1.412	-26.3%
SR 167 Renton Southbound	1.123	1.144	1.172	2.4%	1.581	1.244	-21.3%
				5.5%			-27.4%

8.0 Application Guidelines

8.1 Introduction

The predictive models that can be used in transportation modeling and analysis applications are of three kinds:

1. Adjustment factors (percent reduction) derived from the before/after studies;
2. Relationships between the mean Travel Time Index (TTI) and reliability metrics (i.e., the simple or "data-poor" model); and
3. Direct prediction of reliability metrics as a function of demand, capacity, and disruption characteristics (i.e., the statistical or "data-rich" model).

The section provides general guidance on how to apply these relationships. Implementation of the methods within a specific application (e.g., the *Highway Capacity Manual (HCM*) will require greater adaptation to the requirements of those methods.

8.2 Selecting the Appropriate Relationship

The most direct relationships developed for the impact of improvements on reliability are the adjustment factors from the before/after studies. However, as with adjustment factors for other forms of transportation analysis (e.g., safety analysis), care must exercised in their application. Specifically, the base conditions for the before/after case studies should roughly match the conditions for the situation at hand. Therefore, the analyst should examine the details provided in Appendix B for the improvement type of interest and decide if the conditions of the case study are relevant. Only then can the adjustment factors be applied.

For many planning level applications, the data-poor models can be used to generate reliability statistics. Because the relationships are based on first knowing the overall (grand) mean TTI, i.e., the average TTI over the course of a year that includes all possible sources of variation (both recurring and nonrecurring), the analyst must identify how many nonrecurring events are included in the estimate of the overall TTI produced by their model. Usually, the overall TTI from planning models includes only recurring congestion, so the adjustment provided in Section 7.0 (Equation 9) can be used directly.

The basic response variable used in this research is the TTI. In some cases, analysts will want different response metrics. The TTI can be converted to other measures if the section length and free-flow speed are known. (For urban freeways, the free-flow speed was set at 60 mph in this research.) TTI is the result of dividing the actual travel time by the travel time at the free-flow speed. For example consider a section 1.5 miles in length with a TTI of 1.3. The free-flow travel time (at 60 mph) is 1.5 minutes and the actual travel time is 30 percent higher, or 1.95 minutes. The travel rate is therefore 1.95 divided by 1.5, or 1.3 minutes per mile.

8.3 Linking Improvements to Model Variables

The final stage of model application is to develop linkages between improvement types and the variables in data-rich model. Table 8.1 presents a general discussion for how the improvements are to be considered and how their effects are to be accommodated by the models. Basically, the effect of improvements is traced to the changes in the independent variables and their determinants. Within the models, improvements can affect:

- Demand (volume for the time period considered).
- Capacity (physical capacity, as determined by the *HCM*).
- Lane-hours lost due to incidents and work zones. Work zone lane-hours-lost must be entered directly. Incident lane-hours lost can be entered directly or as changes to:
  - Incident frequency, a function of both:
    - Incident rate; and
    - VMT (demand).
  - Lanes blocked per incident, a function of:
    - Presence of shoulders; and
    - Local policy concerning moving lane-blocking incidents to the shoulder.
  - Average incident duration.

Note that in the model structure, improvements/strategies that affect demand are accounted for twice: in the demand-to-capacity (d/c) ratio and in the incident frequency calculations.

The research team also undertook a review of recent studies of reliability improvements. While none of them deal directly with estimating reliability, they can still be used in the modeling framework presented above (Tables 8.2 to 8.4). In some cases, we have provided a recommendation on how to adapt these results to the modeling framework. In others, we have not provided a recommendation but the results are presented because some practitioners might find them useful. As new research becomes available, especially other SHRP 2 research projects currently underway, their results can be adapted to the modeling framework in a similar manner.

Table 8.1 General Linkages between Improvements and Model Variables

Actions to Improve Reliability	Effect on Reliability	Model Variables Affected by Action
Add Capacity		
Add new through lanes	Increases design capacity.	d/c ratio
Other geometric improvements (lane widening, shoulders, lower grades, etc.)	Increases design capacity.	d/c ratio
Modify interchange (new configuration, longer, or additional ramps)	Increases design capacity.	d/c ratio
Access control, median barriers	Modest design capacity increase, significant reduction in the probability of incidents (collisions).	d/c ratio; primary incident rate
Add managed lane (truck climbing lanes, HOV lanes, and HOT lanes)	Increases capacity in unmanaged lanes by removing trucks, HOVs, toll payers from stream. Improves reliability for vehicles able to switch to managed lanes (d/c of managed lanes will usually be lower than for unmanaged lanes).	d/c ratio
Add auxiliary lanes	Increases capacity by allowing nonthrough vehicles to use auxiliary lanes.	d/c ratio
Add new interchange	Change demand by changing access to facility. Minor effect on design capacity.	d/c ratio
Add turn lanes	Increases capacity by shifting demand out of through lanes and increasing design capacity of through lanes.	d/c ratio
Convert two-way to one-way streets	Reduces demand by shifting one direction of demand to other streets. Increases design capacity for remaining allowed direction.	d/c ratio
Safety improvements (median barriers, eliminate visual obstructions, lighting, wider lanes, etc.)	Reduces likelihood of collisions, therefore, reduces incident frequency.	Primary crash rate
Operational Improvements		
Incident Management		
Improved equipment for incident detection and verification (CCTV)	Reduces incident duration.	Average incident duration
Improved interagency communications for incident detection and verification	Reduces incident duration.	Average incident duration
Improved equipment and service for incident response	Reduces incident duration.	Average incident duration
Improved interagency incident management coordination	Reduces incident duration.	Average incident duration
Improved responder training	Reduces incident duration.	Average incident duration
Incident command system	Reduces incident duration.	Average incident duration
Crash investigation sites	Reduces lane blockage.	Shoulder usability factor (in the lanes blocked per incident calculation)
Weather Management		
More effective deployment of snow/ice resources	Reduces impact of weather events on pavement and crashes.	Capacity reduction not as severe; primary crash rate

Actions to Improve Reliability	Effect on Reliability	Model Variables Affected by Action
Snow/ice pretreatment	Reduces impact of weather events on pavement and crashes.	Capacity reduction not as severe; primary crash rate
Microlevel weather forecasting	Reduces impact of weather events on pavement and crashes.	Primary crash rate
Weather monitoring	Reduces crash rates due to better traveler information.	Primary crash rate
Fog warning system	Reduces crash rates due to better traveler information.	Primary crash rate
Work Zone Management		
Scheduling (accelerated schedules, night time activities)	Reduces work zone duration.	Work zone duration
Use of more durable materials	Reduces frequency of work zone occurrence.	Work zone duration
Improved signing	Increases design capacity; decreases crashes.	d/c ratio; primary crash rate
Increased enforcement	Decreases crashes.	Primary crash rate
Full road and lane closures	Decreases design capacity but reduce work zone duration.	d/c ratio; work zone duration
Traffic control plan development	Increases design capacity.	d/c ratio
Active Traffic Management		
Traffic signal coordination	More green time/cycle increases capacity.	d/c ratio
Traffic adaptive signal control	Through capacity is increased as demand increases.	d/c ratio
Ramp metering (fixed time, traffic responsive)	Increases design capacity.	d/c ratio
Integrated corridor management	Problematic; current FHWA research may reveal impacts; probably reduces demand and/or increases capacity (d/c ratio).	
Traveler information system improvements (pretrip, roadside, and in-vehicle)	Problematic; probably reduces demand.	d/c ratio
Variable speed limits	Increases design capacity.	d/c ratio
Lane controls	Increases design capacity.	d/c ratio
Queue warning	Increases design capacity.	d/c ratio
Truck lane restrictions	Increases design capacity of nontruck lanes.	d/c ratio
"Hard shoulder running" during peak	Increases design capacity, but increases incident impacts.	d/c ratio; shoulder usability factor
Access management	Increases design capacity.	d/c ratio
Traveler Information		
511	Reduces demand on event-stricken facilities.	d/c ratio
VMS	Reduces demand on event-stricken facilities.	d/c ratio
In-vehicle guidance	Reduces demand on event-stricken facilities.	d/c ratio
Demand Management		
Telecommuting	Reduces demand.	d/c ratio
Alternative work hours	Shifts demand (changes temporal traffic distribution).	d/c ratio
Land use controls	Reduces demand.	d/c ratio
Road pricing	Reduces demand on priced facility.	d/c ratio
Parking pricing	Reduces demand.	d/c ratio
Shifts to nonauto modes	Reduces demand.	d/c ratio

Table 8.2 Incident Management Impacts

Improvement	Impact
Incident Management: Improving from no formal IM program to a program that includes detection, verification, and service patrols	Atlanta – Average time between first report and incident verification was reduced by 74% – Average time between verification and response initiation reduced by 50% – Average time between incident verification and clearance of traffic lanes reduced by 38% – The maximum time between incident verification and clearance of traffic lanes was reduced by 60% (*1*). Houston – Average 30-minute incident duration reduction *(2).* *IDAS Model recommends a default reduction in incident duration of 9% for incident detection, 39% for incident response systems, and 51% for combination incident detection and response systems* (*3*). Georgia (Navigator) – Reduced incident clearance time by an average of 23 minutes, incident response time reduced by 30% (*4*). Maryland (CHART) – Reduced the blockage duration from incidents by 36%. This translates to a reduction in highway user delay time of about 42,000 hours per incident (*5*). 15% to 38% reduction in all secondary crashes, 4% to 30% reduction in rear-end crashes, and 21% to 43% reduction in severe secondary crashes (*4*).
RECOMMENDATION	*Based on CHART, reduce incident lane-hours lost by 36%.*
Improved equipment for incident detection and verification (CCTV)	Brooklyn – Average time required to clear incident from roadway has been reduced by 66% (*6*). San Antonio (TransGuide) – 20% improvement in response time (21% reduction for major incidents and 19% for minor incidents) (*7*).
RECOMMENDATION	*Based on TransGuide and assuming that incident response time is 20% of incident duration time, reduce incident duration by 4%.*
Improved interagency communications for incident detection and verification	Minneapolis/St. Paul (Highway Helper) – Automatic tow truck dispatch program is credited with a 20-minute reduction in incident response and removal times (85% improvement) (*8*).
RECOMMENDATION	*Assuming that response time is 20% of incident duration time, reduce incident duration by 17%.*
Improved equipment and service for incident response	Hayward, California – 38% reduction in incident duration – 57% reduction in breakdown duration (*9*). Northern Virginia – Reduction in duration for all incidents is 2 to 5 minutes for cell phone in response vehicles, 2 to 5 minutes for CAD screens in response vehicles, and 4 to 7 minutes for GPS location for response vehicles (*10*). Oregon – The duration of delay-causing incidents decreased by approximately 30% on Highway 18, and 15% on Interstate 5 (service patrol addition) (*11*). Pittsburgh – Service patrol reduced response time to incidents from 17 to 8.7 minutes (*12*). Washington State – Average freeway incident clearance time for large trucks reduced to 1.5 hours from 5 to 7 hours without the incident response team (*13*).
RECOMMENDATION	*For the implementation of service patrols, reduce incident duration by 38%.*

Table 8.3 Weather Management Impacts

Improvement	Impact
More effective deployment of snow/ice resources	U.S. Route 12 (Idaho DOT) – Mobile anti-icing operations – The average winter accident frequency has reduced by 83% compared to the past three years (*14*).
Snow/ice pretreatment	Finland – The Finnish National Road Administration – The duration of slippery road condition has been estimated to shorten 10 to 30 minutes per deicing activity, which decreases the chance for accidents caused by slipperiness. The estimated average time saved was 23 minutes per deicing activity (*15*).
	Minneapolis – I-35W and Mississippi River Bridge – The 2000-2001 season had a 50% reduction in total number of crashes over the comparison season (1996-1997), even with an increase in ADT of 9.3%(*16*).
Microlevel Weather Forecasting	
Weather monitoring	Idaho Storm Warning System – Mean speeds in southbound lanes drop from 47.0 mph without DMS to 41.2 mph with DMS warnings – or by roughly 12 percent. When high winds occurred with snow-cover pavement, mean speeds in southbound lanes dropped 35 percent from 54.7 mph to 35.4 mph compared to a 9 percent decline from 48.4 to 44.1 mph in northbound lanes (*17*).
Fog warning system	M25 London Orbital Motorway – When the fog messages were switched on, there was a statistically significant overall net reduction in mean vehicle speeds of about 1.8 mph. These speed reductions indicate that the fog warning messages do alert drivers to the presence of fog ahead (*18*).
	I-215, Utah Fog Warning System – The average vehicle speed measured during fog events increased from 54 miles per hour (mph) to 62 mph after the system was deployed. The increase in speed was partly attributable to the reduction in excessively slow drivers during fog events (*19*).
	Salt Lake Valley – 15% increase in speeds and 22% decrease in standard deviation of those speeds under foggy conditions (*20*).
No recommendations made for weather strategies' impacts on reliability	

Table 8.4 Active Traffic Management Impacts

Improvement	Impact
Traffic signal coordination	Phoenix – 6.2% to 8% average increase in trip speeds (*21*).
	IDAS Model recommends a capacity increase of 14 to 20%. Actual increase value is sensitive to traffic variability and frequency of retiming (*3*).
RECOMMENDATION	*Decrease MeanTTI by 7%.*
Traffic adaptive signal control	Los Angeles (ATSAC) – Travel time reduced by 12% to 18%, delay reduced by 44%, speed increased by 16% (*22*).
	Minneapolis (SCOOT) – Installation in 56 intersections showed 19% reduction in delay during special events, 8% during peaks (*12*).
	Oakland County, Michigan (SCATS) – Corridor travel time reduced from 7% to 32% over optimized foxed-time signal control. Average travel-time reduction of 8% (average speed increased from 25 to 27 mph) (*12*).
	IDAS Model recommends a default capacity increase of 8 to 14%. Actual increase value is sensitive to traffic variability. Assumes upgrade from coordinated pre-set timing (*3*).
	Dallas (North Central Expressway) – 15% increase in speed, 15% decrease in delay (*23*).
RECOMMENDATION	*Reduce MeanTTI by 12%.*
Ramp metering (fixed time)	Portland – 25% increase in volume (*24*).
	Portland – 43% reduction in peak-period accidents (13).
	Houston – 29% increase in speed (*25*).
	IDAS Model recommends a default mainline capacity increase of 9.5% offset by a ramp capacity decrease of 33%. IDAS also suggests a reduction in accidents of 30% on ramp and adjacent freeway links (*3*).
	Minneapolis/St. Paul – Metering results in 14% average increase in throughput and a 7% increase in corridor speed (*26*).
	Minneapolis/St. Paul – Metering decreased peak period accidents by 26% on metered corridors *(26)*.
	Denver – 19% increase in volume *(24)*.
	Seattle (I-405 in 1997) – 5 to 6% increase in volume *(24)*.
	IDAS Model recommends a default mainline capacity increase of 13.5% offset by a ramp capacity decrease of 28%. IDAS also suggests a reduction in accidents of 30% on ramp and adjacent freeway links (*3*).
RECOMMENDATION	*None. Use Before/After adjustment factors.*
VMS/DMS	Austin – 7 to 12% reduction in upstream lane volumes of an incident (*13*).
RECOMMENDATION	*For peak hour and period only, reduce demand volume by 3.5% (assumes 9% reduction in volumes during an incident and that incidents comprise 40% of total delay).*

8.4 Relationship between Incident Management Efficiency and Model Variables

The incident management factors in Table 8.2 relate primarily to the technological (physical) aspects of incident management, i.e., equipment deployed to detect, verify, and respond to incidents. However, effective incident management depends not only on equipment but how efficiently the equipment is used and how well responders work together on the incident scene; the institutional arrangements and programmatic aspects will determine the level of efficiency. Quantifying these attributes for inclusion in a statistical model is a challenging task, although it is thought that they would influence primarily incident duration. Originally it was thought that the Traffic Incident Management (TIM) Self-Assessment scores – which rank the level of sophistication and/or aggressiveness of incident management programs – could be used for this purpose.

However, these were only available from three of the cities used in the urban freeway analysis. A few other key aspects of incident management programs were identified and these were available for six locations. Table 8.5 presents the results; cities are not identified because in order to obtain this information the research team had to maintain anonymity. There appears to be a loose relationship between the Self-Assessment scores and incident duration: higher scores, which indicate greater sophistication or aggressiveness, generally correspond to lower incident duration. However, the sample size here is so small that it is impossible to say with certainty that a mathematical relationship exists. It does suggest that additional work based on including many more locations is warranted in this area.

Table 8.5 Institutional and Programmatic Characteristics on Incident Management Programs in Study Locations

	TIM Self-Assessment							
Urban Area	Overall Score	Program and Institutional	Operational	Communications and Technology	Quick Clearance Law	PDO Move to Shoulder law	Fatality Removal[a]	Average Peak Period Incident Duration
Area 1	85.9	27.5	32.1	26.3	Yes	Yes	Yes	32.1
Area 2	82.0	25.5	32.1	24.4	Yes	Yes	Yes	43.5
Area 3	74.0	21.3	29.3	23.4	Yes	Yes	Yes	45.0
Area 4					No	No	No	47.3
Area 5					No	Yes	No	52.0
Area 6					No	Yes	No	61.5

[a] Can a fatality be moved with medical examiner present?

8.5 INDUCED DEMAND EFFECTS OF IMPROVEMENTS

It has long been observed that transportation improvements, primarily related to capacity expansion, that reduce travel times become a victim of their own success: lower travel times spur increased demand for the now improved facility. This phenomenon is known as induced demand and has both short-run and long-run components. In the short-run, trips will divert from nearby congested facilities to take advantage of the lower travel times. Also, travelers who previously avoided a congested peak period will be drawn back to the peak. In the long-run, reductions in travel time are thought to increase the amount of travel (VMT) as lower congestion allows both longer and more trips to be made. (Longer trips result from the location decisions for place of residence and business.) The converse is that congestion suppresses these aspects of travel.

Short-run induced demand can be studied via the travel demand models which account for diversion of traffic from parallel facilities to an improved highway, for shifts of travelers from other modes, and (depending on how the models are applied) the role of improved highways in causing people to shift the destinations of their trips. However, the models usually do not account for the effects of highway improvements on the total number of trips made and shifts in the locations of households, businesses, and other activities.

In previous studies of induced demand, the induced demand effect is quantified as elasticities of VMT with respect to highway travel time or lane miles. Travel-time elasticities have been used in sketch planning analyses to estimate the aggregate response of travelers to transportation system improvements that provide time savings. The elasticities indicate the percentage change in VMT expected to result from a one percent change in travel time or lane miles. Cohen provided a summary of these studies (Table 8.6) (*27*). The results of Barr and Gorina/Cohen are especially relevant because of the use of travel time as the causal factor. Their elasticities were in the -0.1 to -0.4 range, indicating that at 10 percent decrease in travel rate would cause a one to four percent increase in household VMT. These increases in VMT include the effects of modal diversion, trip distribution (substituting longer trips for shorter trips in this case), and increases in the total number of person trips made.

Table 8.6 Summary of Elasticities Used for Induced Demand

Study	Primary Data Sources	Long Run Elasticity of VMT with respect to Travel Time	Long Run Elasticity of VMT with respect to Lane Miles	Comment
Barr and Gorina/Cohen	1990 and 1995 NPTS	-.3 to -.5		Elasticities may be overstated because of the tendency for longer trips to have higher average speeds than shorter trips. Reanalysis suggests elasticities of -.1 to -.4.
SACTRA	Fuel price elasticities	-1.0		Elasticity may be overstated because of differences in opportunities available to motorists to reduce travel time and fuel costs.
Noland	Highway Statistics		-0.8	Elasticity may be overstated because of: 1) shifts of VMT and lane miles among highway systems; and 2) highways that are widened have more VMT/lane mile than other highways.
Strathman	1995 NPTS, TTI Urban Mobility Study data set		-0.32	Elasticity includes direct effects of lane miles on household VMT and indirect effects due to changes in density.
Marshall	TTI Urban Mobility Study data set		-0.76 to -0.85	Elasticity may be overstated because of roadway classification issues and diversion from outside urban areas.

For an individual facility, it would be expected that time savings would cause a greater increase in VMT than that suggested by the above elasticities. This is because traffic increases on individual facilities include not only the three effects noted above (modal diversion, trip distribution, and trip frequency), but also route diversion (in which travelers shift the routes they use but do not alter their origins or destinations).

These previous studies did not include the effect of reliability on induced demand, just changes in the average travel time. However, it has been noted that travel-time reliability has additional value to travelers beyond consideration of average or typical conditions (*28*). To the extent this is true, improvements in reliability may have an additional effect on induced demand. One approach may be to convert reliability improvements to equivalent travel-time units. For example, Bates measured variability as the standard deviation of travel time and found the value of variability reductions to be equal to 0.8 to 1.3 times the value of mean travel-time reductions (*29,* pp. 191-229). Brownstone and Small measured variability as the difference between the 90th and 50th percentile travel times and found the value of variability reductions to be roughly equal to the value of mean travel-time reductions (*30*).

However, the merit of adding a reliability factor to the changes in mean travel time may be dubious. If elasticities are based on empirical data collected over a sufficiently long period of time so that they include the effect of disruptions, then adding a reliability factor would be double counting. That is, to the extent that the observed travel times are the overall mean travel times that include both recurring and nonrecurring sources, then the relationships identified in Section 7.0 indicate that an improvement in the overall mean also means that reliability has improved. Therefore, if this is the case, the reliability effect is already imbedded in the observed increases in travel activity.

The situation is further clouded because no empirical studies have been done on the induced demand effect of operational treatments. Unlike capacity expansions (the basis of previous elasticity work) which improve recurring congestion every day, operational treatments only affect those conditions when disruptions occur (e.g., incidents and wok zones). While the effect of operational treatments can be tracked to a reduction in overall mean travel times, which in theory should have an induced demand effect, it is still not known if the improvement in travel times on a few days affects travel behavior in the same way as for improvements ***every*** day.

These issues are sufficiently complex to warrant additional study. This project did not attempt to address these issues, but focused on the immediate/first order impacts of improvement strategies on reliability. As new research becomes available that quantifies induced demand effects, it can be incorporated with the relationships developed herein. The process would involve two steps:

1. Estimate the first order change in mean travel-time and reliability measures.
2. Increase demand using elasticities from new research. The pivot point formulation is a convenient way to implement elasticities, for example:

   $V = V_0 * (T / T_0)^{\beta}$

   Where: V = new volume, including induced demand

   V_0 = original volume, before the improvement

   T = travel time after the improvement

   T_0 = travel time before the improvement

   β = elasticity
3. Re-estimate the mean travel-time and reliability measures using the new (increased) demand values.

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9.0 Conclusions and Recommendations

9.1 Findings and Products of the Research

9.1.1 Dataset Compilation and Usage

A large and comprehensive dataset was compiled in order to conduct the research. The dataset will be of use for future research and the SHRP 2 data archive being constructed with the L03 dataset as its core. The dataset includes many different levels of aggregation and summarization. The traffic data from urban freeways is the largest portion of the dataset and includes the original measurements from roadway detectors (five-minute intervals by lane), numbering in the hundreds of millions of records. The traffic data also is summarized at several spatial and temporal aggregation levels. The most summarized portion of the dataset is the one used for the cross-sectional statistical analysis: every record is an annual summary of traffic and reliability characteristics, with annual event characteristics and roadway features merged into it. The data processing included new procedures that the Research Team created specifically for the project (see the next section).

The sources of the data were primarily from state DOTs; data included continuous traffic measurements, incidents, work zones, ITS equipment, operating policies, and geometric characteristics. In addition, we purchased a limited amount of private vendor vehicle probe data for rural freeways and signalized arterials; the rural freeway data was adequate to establish reliability but the signalized arterial data did not appear to have enough samples, and local signal timing data was not available for the time period of the probe data. Incident data from a second private vendor also was available without fee; these provided the needed lane blockage data in several locations where public agencies did not collect this type of information.

Fusion/integration of the various data proved to be a daunting and time-consuming task. The data sets had different georeferencing which complicated the matching of traffic data, incidents, improvements, and geometric characteristics. A good deal of the matching had to be done manually. A large amount of testing, quality control, and development of new processing procedures had to be conducted.

The utility of the dataset as a research resource was proven several times during the project. Often, the team needed to investigate new areas or compute factors and these were easily accomplished because the data was “analysis already.” We expect future researchers to appreciate this feature.

In addition to supporting research, the dataset represents an excellent model for practitioners to use in developing performance monitoring systems for congestion and reliability. Specifically, the different levels of temporal and spatial aggregation can be used to support many local requirements. The fusion of traffic, event, and geometric data provide the basis for not only tracking reliability trends but also includes the data required to explain those trends (e.g., demand and events). The data processing methods which supported the research also should be strongly considered for state and local congestion/ reliability monitoring systems. Data processing for performance monitoring is not trivial and many different methods and assumptions can be used. The L03 research provides a basis for standardizing those procedures.

9.1.2 Exploratory Analyses

A large variety of exploratory analyses were undertaken prior to the main analyses in order to test assumptions, develop data processing methods, and as an aid in understanding reliability in general. The highlights of these exploratory analyses include:

- **Recommended Reliability Metrics.** Based on empirical tests, it was found that the performance metrics defined in the early stages of the research are sensitive to the effects of improvements. However, it was noticed that the 95^{th} percentile travel time or TTI may be too extreme a value to be influenced significantly by operations strategies and that the 80^{th} percentile was more sensitive to these improvements. As a result, the 80^{th} percentile was added to the list of reliability performance metrics for the remainder of the research. The final set of reliability metrics, which also are appropriate for general practice, appear in Table 9.1. While the 95^{th} percentile was used most often in the analyses in this report, it is recommended that practitioners use multiple metrics, depending on their applications.

Table 9.1 Recommended Reliability Metrics

Reliability Performance Metric	Definition	Units
Buffer Index (BI)	The difference between the 95^{th} percentile travel time and the average travel time, normalized by the average travel time. The difference between the 95^{th} percentile travel time and the median travel time, normalized by the median travel time.	Percent
Failure/On-Time Measures	Percent of trips with travel times <: • (1.1 * Median Travel Time); and • (1.25 * Median Travel Time). Percent of trips with space mean speed <: • (50 mph, 45 mph, and 30 mph).	Percent
Planning Time Index	95^{th} percentile Travel Time Index.	None
80^{th} Percentile Travel Time Index	Self-explanatory.	None
Skew Statistic	The ratio of (90^{th} percentile travel time minus the median) divided by (the median minus the 10^{th} percentile).	None

Misery Index (Modified)	The average of the highest five percent of travel times divided by the free-flow travel time.	None

- **Travel-Time Distributions.** Development of travel-time distributions is the starting point for defining reliability metrics and a convenient way to visualize general congestion and reliability patterns for a highway section or trip. Examination of the distributions from the study section used in this research reveals several characteristics:
  - The shape of the travel-time distribution for congested peak times (weekdays, nonholidays) is much broader than the sharp spike evident in uncongested conditions. The breadth of this broad "shoulder" of travel times decreases as congestion level decreases.
  - Likewise, the tails of the distributions (to the right) appear more exaggerated for the uncongested time slices. However, note that the highest travel times occur during the peaks.
  - Despite the fact that peaks have been defined, there are still a number of trips that occur at close to free-flow; more in the peak period than in the peak hour. This is probably due to the fact the peak times actually shift slightly from day-to-day as traffic demand can be shifted by events. Also, there are probably some days where overall demand is lower than other days.
- **Data Requirements for Establishing Reliability: How Much Data is Enough?** Because reliability is defined by the variability of travel conditions (travel time), it must be measured over a substantial portion of time to allow all of the influences of random events to be exerted. Tests showed that an absolute minimum of six months of data is required to establish reliability within a small error rate, in areas where winter weather is not a major factor. A full year of data is preferred.
- **Trends in Reliability.** A study was undertaken using the Atlanta study sections tracking performance for 2006, 2007, and 2008. Between 2006 and 2007, average congestion increased and reliability decreased, where reliability was measured by both the Planning Time Index and the Buffer Index. However, between 2007 and 2008, average congestion levels fell on all study sections as demand fell due to the reduction in overall economic activity; this corresponded to many anecdotal stories and other analyses about congestion in 2008. However, on most study sections, the Buffer Index showed an increase or a very marginal decrease, which would indicate that reliability worsened in most cases. In contrast, the Planning Time Index decreased on all sections. This raised doubts about the use of the Buffer Index as the primary metric for tracking trends in reliability. The problem comes from way the Buffer Index is calculated: it is the "buffer time" (difference between the 95th percentile and the mean) normalized by the mean. What happened in this experiment is that the 95th percentile decreased less than the mean, resulting in a higher Buffer Index. In other words, the

decreased demand affects all points on the travel-time distribution, not just the upper tail. We believe the mechanism for these changes is that reduced demand led to across-the-board decreases in congestion, including days with and without roadway events (disruptions). However, conditions on the worst days, which are primarily a result of severe disruptions, were improved to a lower degree than "typical" or average conditions. We would expect operations strategies to have a more pronounced effect on the times influenced by severe events.

The end result of this experiment is that the Buffer Index is considered to be too erratic/unstable for use as the primary reliability metric for tracking performance trends or for studying the effects of improvements. However, as a secondary metric, it does provide useful information and should not be discarded but rather should be included in a suite of reliability performance metrics. In the case of Atlanta from 2007 to 2008, it might be said that from the perspective of the user, the new conditions of 2008 are indeed less reliable, if one assumes that the 2008 average congestion is the base level: the worst days (as measured by the 95th percentile are still out there). If, however, one considers the base level of congestion to be 2007, then it is clear that overall, the user's experience has been improved.

- **Defining the Peak Hour and Peak Period.** Most previous studies of reliability and congestion define fixed time periods for the peak hour and peak period. However, for the research, we decided that the most appropriate method would be to define them specifically for each study section. Several methods were tested with the best using a definition based on the most typical start and end times of continuous congestion. The resulting time slices were reviewed against local anecdotal knowledge and required very little adjustment.
- **Estimating Demand in Oversaturated Conditions on Freeways.** Because the study took an empirical approach to studying reliability, the team had to deal with the thorny issue of how to measure demand given that measured volumes under congested flow are actually less than capacity on freeways. A method for assigning the demand stored in queues during periods of flow breakdown was developed and used throughout the remainder of the research, particularly in defining the demand-to-capacity ratio for the statistical modeling.
- **Reliability Breakpoints on Freeways.** It was shown that travel-time reliability on a freeway is NOT a function of counted traffic volumes until a "breakpoint volume" is reached. At that breakpoint, the travel-time reliability decreases abruptly. Once the breakpoint volume is exceeded, the decrease in travel-time reliability (increase in the variance) is so extreme and abrupt as to suggest it is a vertical function, with a nonsingular relationship to further volume increases. The breakpoint volume varies significantly between facilities and even within the same freeway facility (by location and direction of travel on the same facility). The breakpoint volume does not

appear to be a fixed ratio of the theoretical capacity of the subject section of the facility. The breakpoint in reliability generally occurs at a counted volume significantly lower than the theoretical capacity of the facility computed per the *Highway Capacity Manual* (HCM). This is partly because the breakpoint volume computed in this analysis is the average hourly volume counted over a peak period and not the peak 15-minute demand as used in the HCM capacity.

But this peaking effect does not entirely explain the difference. Part of the reason that the breakpoint volume is significantly lower than the theoretical capacity is because most sections of freeway are upstream of a bottleneck and, thus, are impacted by downstream congestion backing up into the subject section long before the subject section's HCM capacity is reached. Further, the effect of traffic-influencing events – especially incidents – effectively lower capacity when they occur and over time, cause reliability to degrade. This effect manifests itself in lower breakpoint volumes than for capacity related strictly to physical features. Finally, even for bottlenecks, the data suggests that the reliability breakpoint occurs long before the theoretical HCM capacity of the bottleneck is reached.

- **Sustainable Service Rates on Freeways.** Just as travel times vary over time, it has been noted that capacity is not a fixed value but also varies over time. The same factors that influence reliability also affect capacity variability. Incidents and work zones reduce overall roadway capacity by blocking lanes and shoulders and by affecting driver behavior (lower speeds and variable following distances due to "rubbernecking"). Weather conditions also affect driver behavior in similar ways. Capacity probably is not affected by the amount of demand (volume) as is reliability, but it is affected by the nature of that demand. That is, at a microlevel when volumes are very close to theoretical capacity, variability in driver behavior, small bursts of demand at merge areas (e.g., on-ramps), and the distribution of trucks at specific places and times all probably cause flow to breakdown at different demand levels. The research did not specifically tease out these factors, but all of them are imbedded in the final capacity distributions. The team developed a large set of capacity distributions that look roughly like travel-time distributions but reversed: the tail of the distribution is skewed to the left (lower capacity values) rather than to the right. Because these distributions were developed from year-long data measurements, they include the effect of the influencing factors, resulting in capacity values that could be used in a stochastic framework to model congestion and reliability. It also is a useful construct for accounting for reliability within future versions of the *Highway Capacity Manual*.

- **Travel-Time Distributions on Urban Freeways, Signalized Arterials, and Rural Freeways.** An analysis of travel-time distributions for different time slices and congested levels revealed the following characteristics:

- All distributions feature a tail that is skewed to the right (i.e., higher travel times). Most of these abnormally high travel times can be attributed to one or more of the sources of congestion, that is, they occur in the presence of an event(s) and/or high demand.
- Uncongested periods are characterized by a sharp peak of travel-time frequencies near the free-flow speed.
- When congestion dominants the time slice (e.g., peak hour, peak period), the travel-time distribution becomes more broad and less peaked.
- Travel-time distributions on signalized arterials are uniformly broad in shape, even for relatively low levels of congestion, presumably because of signal delay at even low volumes and interference from side traffic.
- As trips become longer, the travel-time distributions assume the typical uncongested shape.

- **Vulnerability to Flow Breakdown.** Examination of the five-minute data at individual stations (groups of detectors in a direction on a highway segment) reveals that just 20 to 45 minutes before the start of what is considered the normal peak period, there is an upsurge in the 95th percentile travel times. This upsurge begins prior to the uptick in average travel times and indicates that this window of time is vulnerable to flow breakdown. These windows are extremely important for operators to focus on as breakdowns during this time will strongly influence the duration and severity of the peak.
- **Reliability of Urban Trips Based on the Reliability of Links.** For extended travel on urban freeways ("trips" of 10 to 12 miles in length), the reliability of the entire trip can be predicted as a function of the reliability of the links that comprise the trip. While not specifically tested, it should be possible to construct trip reliability for trips that include other types of highways in addition to freeways, subject to the issue of time dependency for long trips.

9.1.3 Before/After Studies on Selected Study Sections

The primary goal of the research was to develop relationships for predicting the change in reliability due to improvements. The best way to accomplish this is with controlled before/after studies. However, such analyses are substantially more challenging than what is typically done because of the data requirements: to establish reliability empirically, 6 to 12 months of data is required, with 12 months being the preferred data collection period. This means a long period of continuously collected data is required both before and after the improvement. So, instead of designing traditional before/after experiments, the team concentrated on collecting continuous traffic data from areas we knew from previous experience had quality data, "interesting" congestion, and good records of event data. At a minimum, this would provide the best data for developing cross-sectional statistical relationships. As it turned out, we were able to identify 17 cases of improvements that coincided with the data we had identified, although the types of improvements was somewhat limited.

The analysis produced reliability adjustment factors that can be applied to the various improvements. The adjustment factors for a specific type of improvement vary slightly, presumably because background (baseline) conditions are somewhat different. Users are directed to the detailed descriptions of the studies in Appendix B to select the conditions most appropriate for their situation.

A global finding from the before/after analyses is that ***ALL*** forms of improvements – including capacity expansion – affect ***BOTH*** average congestion and reliability in a positive way (i.e., average congestion is reduced and reliability is improved). Conceptually, this makes sense: one of the seven sources of congestion/reliability identified earlier was the amount of base capacity. All things being equal, more capacity (in relation to demand) means that the roadway is able to "absorb" the effects of some events that would otherwise cause disruption. The size of this effect was greater than we had originally anticipated. (See Section 8.1.6 for a more complete discussion.) What this means for the profession is that, to the extent that reliability is valued above and beyond typical/average travel time, a large part of the benefits of capacity expansion projects has been missed in historical analyses.

9.1.4 Cross-Sectional Statistical Modeling

Going into the project, the team realized that only a limited number of before/after studies would be possible. Therefore, much of the effort for the study went into the creation of a cross-sectional dataset from which statistical models could be developed. The final analysis data set for the statistical modeling is highly aggregated: each record represents reliability, traffic, and event data summarized for a section for a year. This structure must be used: reliability is measured as the variability in travel times over the course of a year. As such, the cross-sectional model is a macroscale model. It does not seek to predict what the travel time for a particular set of circumstances. (For example, what is the expected travel time if incident and demand characteristics for a given day are known.) Rather, it seeks to predict the overall travel-time characteristics of a highway section in terms of both mean and reliability performance. It is, therefore, appropriate for adaptation to many existing models and applications that seek to do the same, and can serve as the basis for conducting cost/benefit analysis. It is not appropriate for real-time travel-time prediction.

Two model forms were developed: simple and complex. The simple model form relates all of the reliability metrics to the mean TTI for all three highway types studied (urban freeways, rural freeways, and signalized arterials). These relationships are convenient for many applications that produce mean travel-time-based measures as output (e.g., traditional travel demand forecasting models, the *Highway Capacity Manual*). Because the mean TTI developed from the research data includes the effects of all the possible influences of congestion, which produces a mean value greater than model results which usually are for "typical" (non-extreme) conditions, an adjustment factor was developed to convert model output to the overall mean TTI so that the relationships can be applied.

A more detailed model form also was developed that related reliability measures to the factors that influence reliability. It has long been theorized that reliability is determined by demand, capacity, incidents, weather, and work zones. In fact, that is what we found from the analyzing the research dataset. A tiered predictive model was developed that related the reliability metrics over highway sections (multiple links, usually four to five miles long) for different time slices to:

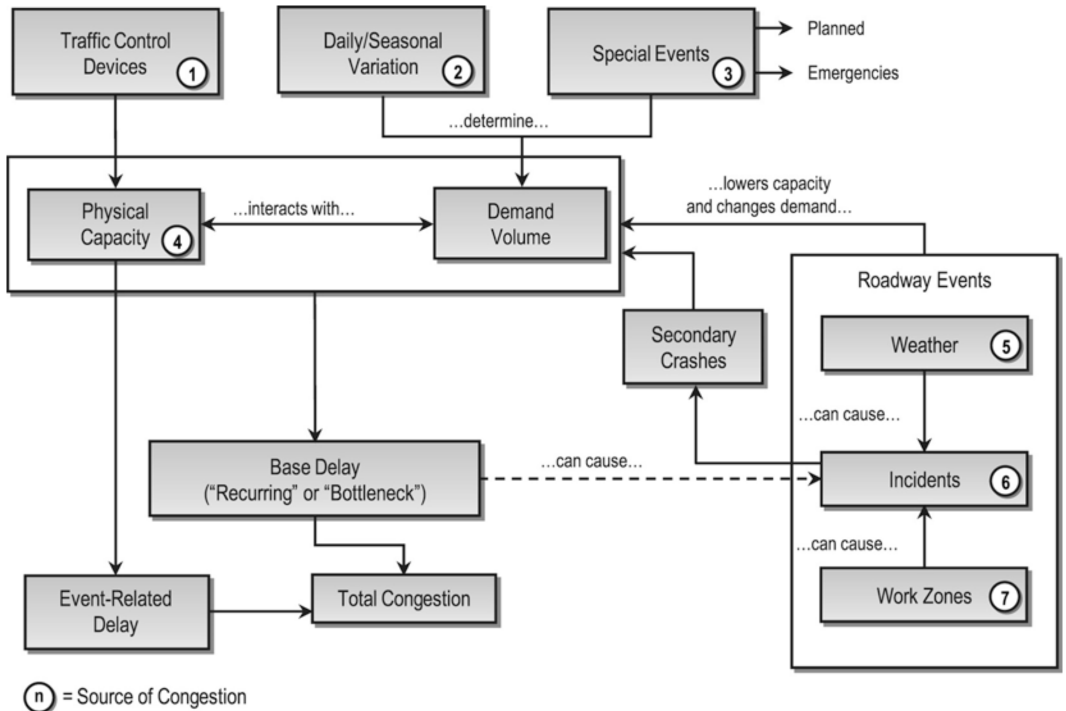
- The critical demand-to-capacity ratio (maximum from the individual links);
- Lane-hours lost due to incidents and work zones combined (annual); and
- Number of hours where rainfall was >= 0.05" (annual).

The rainfall variable must be computed using weather records directly. Guidance was developed for how to develop the demand-to-capacity ratio. Lane-hours lost was decomposed into a series of subrelationships that can be estimated using easily obtained data.

9.1.5 Congestion-by-Source

As part of earlier projects, the research team had previously conducted congestion-by-source analyses but we realized that the data available for those studies were incomplete. The L03 research offered an opportunity to assemble the data more carefully and to incorporate other data sources. The goal was to capture the contributions of the factors influencing congestion and reliability, as shown in Figure 9.1.

Figure 9.1 A Model of Congestion and Its Sources



The analysis was conducted at a microlevel; data at the five-minute level was analyzed for possible effects by the sources.

An assignment of congestion causality was made for the measured delay in the Seattle data. Taken at face value, the analysis supports the commonly heard statement that "incidents and crashes cause between 40 and 60 percent of all delay." In reality, a considerable portion of the delay associated with incidents and crashes also is "caused" by large traffic volumes. Therefore, the amount of delay "caused" by incidents is actually less than can be reasonably assigned by simply observing the occurrence of events. There were numerous examples in the analysis data set of significant crashes and other incidents that caused little or no congestion because of when they occurred. These showed that without sufficient volume, an incident causes no measurable change in delay.

In the Seattle area, many incidents take place during peak periods, causing already existing congestion to grow worse, the result of the interwoven effects of incidents, bad weather, and traffic volumes on travel times. In addition, all types of disruptions to normal roadway performance (rain, crashes, non-crash incidents) cause congestion to start earlier and last longer during the peak period, while increasing travel times during the normally congested times. Incidents and other disruptions also can cause congestion to form during times of the day that are normally free from congestion. However, congestion only forms when the disruption lowers functional capacity below traffic demand. Thus volume, relative to roadway capacity, is a key component of congestion formation, and in urban areas it is likely to be the primary source of congestion.

Disruptions then significantly increase the delay that the basic volume condition creates.

The fact that traffic volume is the basis of congestion also has an impact on how various traffic disruptions affect travel patterns. Not only does traffic volume affect whether an incident causes congestion, but it affects how long that congestion lasts once the primary incident has been removed. The Seattle data showed that in the morning peaks, disruptions have a more noticeable effect on the timing of the end of the peak period, while in the evening the opposite is true.

In summary, analysis of 42 roadway segments in the Seattle area showed that a majority of travel delay in the region is the direct result of traffic volume demand exceeding available roadway capacity. Whenever they occur, incidents, crashes, and bad weather add significantly to the delays that can be otherwise expected. The largest of these disruptions play a significant role in the worst travel times that travelers experience on these roadways. However, the relative importance of any one type of disruption tends to vary considerably from corridor to corridor.

In peak periods, incidents add only marginally (percentage-wise) to total delay, but they do SHIFT when and where those delays occur, as well as who suffers from those delays. That is, many incidents shift where a normally occurring bottleneck occurs, freeing up some roadway sections, while causing others to suffer major increases in congestion. But taken as a total, if it is already "normally congested," the added delay from incidents is modest (at least in Seattle) compared to the daily delay from simply too many vehicles for the available physical capacity.

In congested urban areas, traffic incidents are often more about causing more unreliable traffic patterns than they are about causing increases in total delay. While the total delay value does goes up, the big change is often that shift in ***WHO*** gets delayed. For an individual severe incident, many of travelers may value the extra (unplanned) delay very highly, and are very likely to remember these extreme cases. Some of that (total) delay is offset by other travelers who reach their destination early – their trip is downstream of the incident-caused bottleneck and volume has probably been metered by that bottleneck.

9.1.6 The Significance of Demand for Reliability Estimation

A major result of the research was the finding that demand (volume) is an extremely important determinant of reliability, ***especially in terms of its relation to capacity***. As shown in Figure 9.1, demand's interaction with physical capacity is the starting point for determining congestion. Conceptually, the research team initially postulated that the effect of most events are determined by the level of demand under which they occur. (If an incident or work zone blocks a traffic lane, the impact will only be felt if volumes are high enough to be affected by the loss capacity.) However, we did not expect demand to have as strong an effect as the analyses indicated. Throughout the different analyses we conducted for the L03 research, demand kept emerging as a significant factor. The case for the strong effect of demand/volume is summarized as follows:

- The Atlanta trend analysis revealed that roughly a three percent drop in demand significantly improved both average congestion level and reliability between 2007 and 2008.
- The before/after studies of capacity improvements produced a strong improvement in reliability, not just average congestion. We believe the mechanism for this improvement is capacity in relation to demand simultaneously (the demand-to-capacity or volume-to-capacity ratios), so a change in either will produce the same effect. (This was subsequently verified in the cross-sectional statistical models.)
- The Seattle congestion-by-source analysis which revealed that a substantial portion of delay could not be attributed to an event, even with careful consideration of off-section conditions and special events. This leaves only demand as the sole cause. The Seattle analysis also shows that incidents during low demand periods have only a small effect on congestion.
- The mid-day cross-sectional models did not show lane-hours lost due to incidents and work zones as a statistically significant independent variable, indicating that under low volume conditions (i.e., conditions where volumes are low relative to the available physical capacity), the annual effect of disruptions is small. Extreme disruptions – multiple lane closures – clearly will have an effect on an individual day, but over the course of a year these events are rare and do not appear to "move" the annualized reliability metrics very much at all.
- The peak-hour and peak-period cross-sectional models showed that the demand-to-capacity ratio was a stronger contributor to the model than lane-hours lost.

The influence of demand is probably related not only to sheer volume of traffic but its characteristics. As volumes approach theoretical capacity, traffic flow becomes unstable and increasingly susceptible to breakdown due to small changes. These small changes can occur at a point substantially less than theoretical capacity and when they occur near potential bottleneck areas such as on-ramps, weaving areas, and lane-drops, we postulate that their effect is enhanced.

In addition to variations in demand as a source of unreliable travel times, evidence also exists that physical capacity also is variable. The research team observed that throughout the course of a year, due to disruptions and other factors that can occur on a highway segment. However, the work of Brilon and preliminary research conducted by other SHRP 2 contractors suggest that ***capacity varies even in the absence of disruptions.***

Why would physical capacity vary? We believe that fluctuations in traffic conditions at a microscale are the most likely causal factors. These small changes could be related to:

- **Driver Behavior –** One or a few vehicles can behave aberrantly (e.g., sudden unexplained stops);
- **Truck Presence –** A small increase in trucks in the traffic stream at a given point in time and space could have a detrimental effect; and
- **"Microbursts of Merging Traffic" –** A small but intense influx of vehicles from an on-ramp could be enough to cause flow breakdown.

There are several implications of the finding that demand and capacity will strongly influence travel-time reliability:

- The mechanism for demand's and capacity's influence on travel-time reliability can be seen in the before/after studies. Consider the distribution of travel times that occur on a routinely congested highway segment over the course of a year. In terms of the distribution, they will reduce nearly all the travel times in the congested portion of the distribution. Capacity additions and demand reductions will improve congestion on nearly all days; they are always present in the roadway environment. Strategies geared to disruptions (e.g., incident management) will only affect congestion when those disruptions appear, and they will not appear during every congested period of every day. In other words, only selected travel times in the congested portion of the distribution will be reduced.
- It is clear that traditional capacity projects improve reliability, and failure to account for this effect in economic analyses has excluded benefits to users.
- Demand management strategies, such as pricing, also will lead to improvements in reliability.
- Accounting for volumes in relation to available capacity can provide a tool for efficiently allocating operations strategies, particularly incident management. That is, times and locations that are most vulnerable to flow breakdowns can be targeted.

9.1.7 Reliability as a Feature of Congestion

The intertwined relationship between demand, capacity, and disruptions documented in the L03 research leads to another major conclusion: ***reliability is a feature or attribute of congestion, not a distinct phenomenon.*** Because any influence on congestion will lead to unreliable travel, reliability cannot be considered in isolation. Going into the research, the project team's thinking – and that of the profession in general – was that reliability related primarily to disruptions and the operational treatments aimed at those disruptions. Our analysis showed that even in the absence of disruptions, a substantial amount of variability (i.e., unreliability) in travel times exists for recurring-only (bottleneck-related) conditions. Therefore, the most inclusive view of travel-time reliability is that it is part of overall congestion. Just as congestion can be defined by extent and severity, it can also be defined as how it varies over time. Operational treatments are clearly effective in dealing with unreliable travel, but so are other congestion relief measures.

9.2 Recommendations for Future Research

Based on our research, the team also offers the following suggestions for future research.

- **Detailed Examination of Reliability Causes and Prediction on Signalized Arterials.** Because of data limitations in the number of signalized arterials with continuous travel-time data collection, the amount of data on those that did, lack of continuous volume data to match against the available travel-time data, and no information on incident and work zone characteristics, only simple analyses using travel-time data could be undertaken for this study. However, since we completed the data collection for the research, it is very clear that data availability is about to increase dramatically. Private vendors of vehicle probe data have improved their data processing methods and increased the sources of travel-time data in just the past 18 months. As a result, many states already have purchased private vendor probe data statewide primarily for traveler information applications. As with freeway detector data, these data have value in developing performance measures and supplying research studies after the fact. We expect the trend to continue as new sources – perhaps even those from consumer sources – continue to be added to their products. In addition, new and relatively inexpensive technologies for collecting travel times on signalized highways – such as Bluetooth readers and vehicle signature detectors – offer great potential for new forms of traffic management applications by public agencies.
- **Determine How Demand (Volumes) Can Be Effectively Collected Systemwide.** The study was fortunate that traditional urban freeway detectors collect both speed and volumes. However, if the other sources of speed/travel-time data discussed above become widespread, there will be no companion volume measurements until the number of vehicles that are detected approach 100 percent. The L03 research has shown that demand is a very important determinant of reliability. Further, from an operations viewpoint, emerging methods such as active traffic management (ATM) are likely to require more, not less, data (travel times and volumes) to feed their control processes.
- **Consistency in Data Collection for Incidents and Work Zones.** The study labored mightily to find and process incident and work zone data to match against the traffic measurements. The duration of blockages – recognizing that the nature of blockages can change over the course of a single event – is

the critical piece of data required. Also, consistency in geocoding of events, traffic detectors, and roadway features would greatly enhance future research. An extra complication is the fact that private vendors (at least the two we used in the research) use the Traffic Message Channel standard for geolocation, a standard that is almost never used by public agencies. To avoid the large amount of manual intervention endured by the study – which would be even more onerous for public agencies trying to deal with the issues systemwide rather than on selected study sections – some consideration should be given to how all of these data should be collected, organized, and related to each other. This may require the development of new standards or the extension of existing ones.

- **Development of Alternative Reliability Concepts for Extreme Events.** As developed in this research, the concept of reliability is part of the urban congestion problem. That is, it has been studied on highways that experience routine congestion from both recurring and nonrecurring sources. The working definition used was that reliability is a description of how travel times vary over time. It was noted that extreme events (disruptions) such as major snow/ice storms, hurricane evacuations, and full highway closures do not have a statistical significance in trying to predict reliability, which, by definition, occurs over the course of a year. Because they are so rare, they only shift the annual travel-time distribution by a small amount. However, these extreme events are extremely important to both transportation agencies and travelers, even if their occurrence is rare. If the urban congestion-based reliability concepts cannot describe these events, then an alternative should be explored.
- **Standard Processing Methods for Developing Congestion and Reliability Performance Measures.** In order to conduct the research, data processing procedures had to be developed to develop reliability performance metrics. These metrics are likely to be used on their own in many other transportation applications. However, a large amount of leeway exists in how the metrics can be developed from field data. As congestion performance monitoring becomes more widespread, and perhaps even Federally mandated, the need to produce consistent metrics will become critical.
- **Improved Methods for Microlevel Weather Data Collection.** The weather data used in the study was admittedly crude in terms of location. The assumption is that the closest National Weather Service station observations apply to the study sections, when they could be several miles apart. This probably led to misallocation of rainfall occurrence for at least some cases, but major weather fronts are most likely accounted for in the data. However, we believe that better methods can be explored. In lieu of deploying weather stations at regular intervals which would be prohibitively expensive, one method that seems to have promise is the automated processing of time-lapse radar information to obtain precipitation data.

- **Reliability of Trips.** At the beginning of the study we selected the "extended highway section" as the basic unit of analysis: a relatively homogenous highway section in terms of geometrics covering several miles, typically four to five miles, for urban sections. (Much longer sections were used for the few rural freeway sections.) The reasons for this were related to both practicality and usability: this is the level at which the data were available and can be used by many existing applications. However, the reliability of entire trip is likely to be quite different due to a number of factors. First, the study section was selected because they had relatively high volumes and were at least moderately congested during peak times (Jacksonville's sections were less congested). So, in terms of an entire trip that a user might make, they represent the worst conditions that can be encountered. This means that a trip-based travel-time distribution is likely to gravitate towards one that shows less congestion and better overall reliability. An additional complication is the scheduling component: if a "trip" can start within a window of time as opposed to a specific time, users can in theory improve the travel time and reliability of their trip. Research is needed on these subjects and specifically how they impact investment decisions. That is, the facility focus as suggested by the L03 perspective leads to a certain set of investments (improvements). If we change the focus to the entire trip (that is, we manage trips in addition to facilities), how do the investment decisions change?

- **Before/After Studies for Demand Management, Active Traffic Management, and Institutional Aspects of Incident Management.** Reliability style (long before and after periods) should be undertaken as these types of projects are deployed. In addition to observing changes in congestion and reliability, these studies also should report the changes in the independent variables for the L03 cross-sectional statistical models (demand, capacity, and the characteristics of incidents and work zones). The study also noted that various degrees of institutional arrangements and policies related to incident management should have a positive effect on incident duration, which can then be related to reliability via the statistical models. The idea is that, beyond the deployment of equipment, the success of incident management will be determined by how agency agreements and policies translate to reductions in incident duration in the field.

- **Real-Time Predictive Models.** A potentially useful corollary to the macrolevel reliability relationships developed in the L03 effort is the development of models that relate congestion level ***on a specific day*** to the contributing factors. This is not really reliability – it is travel-time prediction for a given set of circumstances – but it would provide useful tool for traffic managers. The L03 dataset could be used as a starting point for this research, although based on our experiences with the congestion-by-source analysis, more microlevel data on traffic flow and events might be necessary (e.g., 30-second to 1-minute volumes and speeds. Specifically, the microlevel examination of traffic flow breakdown would provide great insight into the causes of congestion.

- **Expand on the Concept of Whole Year Capacity.** The L03 research demonstrates that capacity varies substantially. The concept of whole year capacity, touched on in the L03 exploratory analyses, is worth pursing further. Because many predictive models, including travel demand forecasting, macroscopic and mesoscopic simulation models use the concept of capacity as a starting point for determining congestion, using whole year capacity may an entry point for incorporating reliability into these models. That is, instead of using a fixed capacity, model runs can use whole year capacity distributions stochastically. Because the whole year capacity distributions developed from empirical data include all of the possible influencing factors, they represent a more realistic picture of how capacity actually behaves.

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