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San Diego Case Study Validation: Travel Time Reliability Monitoring

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1. MONITORING SYSTEM

STUDY DESCRIPTION

This case study is the first of five, performed by the project team in order to validate the approaches to travel time reliability monitoring described in the Travel Time Reliability Monitoring Guidebook. The goal of each case study is to illustrate how agencies apply best practices for: monitoring system deployment; travel time reliability calculation methodology; and agency use and analysis of the system. To accomplish this goal, the team is implementing prototype travel time reliability monitoring systems at each of the five sites. These systems take in sensor data in real-time from a variety of transportation networks, process this data inside a large data warehouse, and generate reports on travel time reliability for agencies to help them better operate and plan their transportation systems. This case study consists of the following sections:

- Monitoring System
- Methodological Advancement
- Use Case Analysis
- Lessons Learned

These sections map to the master system components, as shown below in Figure 1.1.

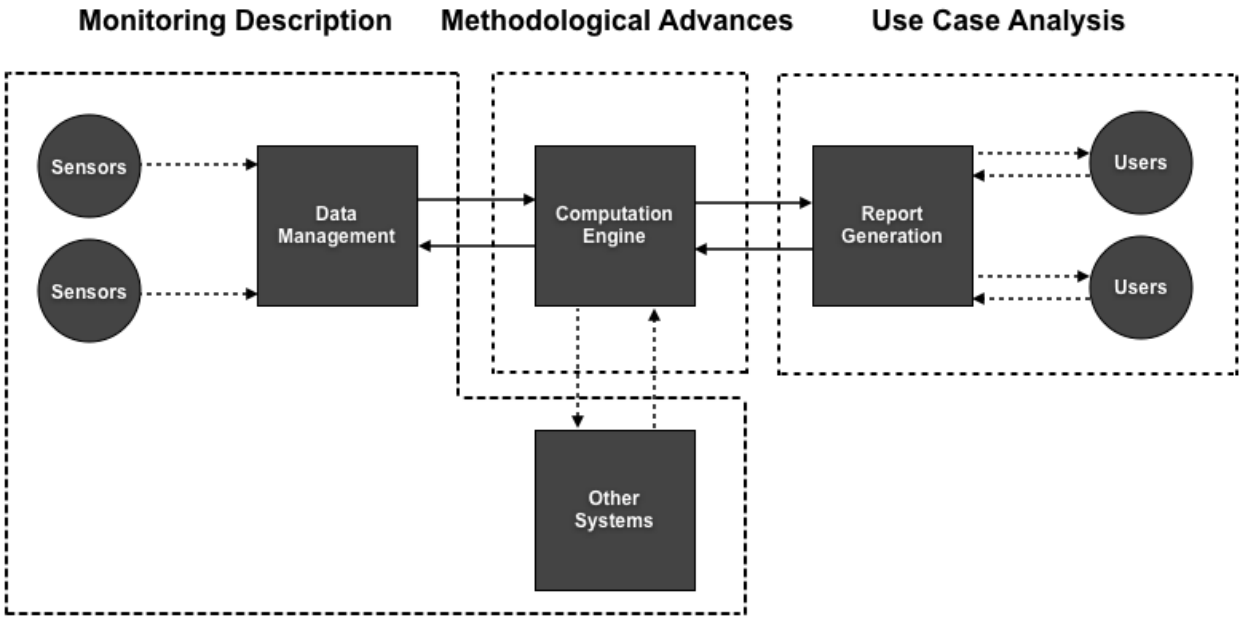

Figure 1.1: Travel Time Reliability System Description

This *monitoring system description* section details the reasons for selecting San Diego as a case study and gives an overview of the region. It briefly summarizes agency monitoring practices, discusses the existing travel time sensor network, and describes the software system that the team used to analyze use cases. The section also details the development of travel time reliability software systems, and their relationships with other systems.

The section on *methodology* is the most experimental and least site specific. It is dedicated to an ongoing investigation, spread across all five case studies, to test, refine, and

implement the Bayesian travel time reliability calculation methodology outlined in this project's Task 7 document. For this section, the team is using, as appropriate, site data and other data in order to investigate this approach. The goal of each case study methodology section is to advance the team's understanding of the theoretical framework and practical implementation of the new Bayesian methodology.

Use cases are less theoretical, and more site specific. Their basic structure is derived from the user scenarios described in the Task 2/3 document, which are the results of a series of interviews with transportation agency staff regarding agency practice with travel time reliability.

Lessons learned summarizes the key findings from this case study, with regards to all aspects of travel time reliability monitoring: sensor systems, software systems, calculation methodology, and use. These lessons learned will be integrated into the final guidebook for practitioners.

SITE OVERVIEW

The team selected San Diego as an exemplar of the leading edge of the state of the practice for using conventional monitoring systems within an urbanized metropolitan area. Led by its Metropolitan Planning Organization, the San Diego Association of Governments (SANDAG), and the California Department of Transportation, the San Diego region has developed one of the most sophisticated regional travel time monitoring systems in the United States. This system is based on an extensive network of sensors on freeways, arterials, and transit vehicles. It includes a data warehouse and software system for calculating travel times automatically. Regional agencies utilize this data in sophisticated ways to make operations and planning decisions.

In California, the San Diego Metropolitan Area encompasses all of San Diego County, which is approximately 4,200 square miles and the fifth most populous county in the United States. The county, bordered by Orange and Riverside Counties to the north, Imperial County to the east, Mexico to the south, and the Pacific Ocean to the west, contains over 3 million people. Approximately 1.3 million of these people live within the City of San Diego, with the rest concentrated within the southern suburbs of Chula Vista and National City, the beach-side cities of Carlsbad, Oceanside, and Encinitas, the northern, in-land suburbs of Escondido and San Marcos and the eastern suburb of El Cajon. The metropolitan area also includes significant rural areas within and to the east of the Coastal Range Mountains, with the Sonoran Desert and the Cleveland National Forest on the far eastern edge and the Anza-Borrego Desert State Park in the northeast corner of the county. The county has a large military presence, containing numerous Naval, Marine Corps, and Coast Guard stations and bases. Tourism also plays a major role in the regional economy, behind the military and manufacturing, particularly during the summer months.

Over the past several years, transportation agencies operating within the San Diego region have, through partnerships between SANDAG, Caltrans, local jurisdictions, transit agencies, and emergency responders, been updating and integrating their traffic management systems, as well as developing new systems, under the concept of Integrated Corridor Management (ICM). The goal of ICM is to improve system productivity, accessibility, safety, and connectivity by enabling travelers to make convenient and informed shifts between corridors and modes to complete trips. The partnering agencies selected I-15 from SR-52 in San Diego to SR-78 in Escondido as the corridor along which to implement an ICM pilot project using Federal ICM Initiative funding. A Concept of Operations document for this pilot project was completed in

March of 2008, and San Diego was selected for the Demonstration Phase of the ICM Initiative early in 2010.

Because of this effort and others, San Diego has a sophisticated travel time monitoring software infrastructure. Among the systems that will share data as part of the planned Integrated Corridor Management System (ICMS) are the Advanced Transportation Management System (ATMS), Performance Measurement System (PeMS), Ramp Meter Information System (RMIS), Lane Closure System (LCS), the managed lane closure and congestion pricing systems on I-15, the Regional Arterial Management System (RAMS), and the Regional Transit Management System (RTMS).

SENSORS

Freeway

The California Department of Transportation (Caltrans District 11) manages San Diego's freeway network. District 11 (D11) encompasses San Diego and Imperial County, though only the managed portion of the freeway system in San Diego County will be considered as part of this case study. Within San Diego County, D11 is responsible for 2,000 centerline miles of monitored freeways, 64 lane-miles of which are Managed HOV/HOT lane facilities.

A number of major interstates pass through the district, including Interstate 5, which passes through many major cities on the west coast between Mexico and Canada, Interstate 8, which connects Southern California with Interstate 10 in Arizona, and Interstate 15, which connects San Diego with Las Vegas. Within the county, I-5 connects downtown San Diego with the Mexican Border at Tijuana to the south, and the North County beach-side suburbs and Orange County to the north. I-8 connects the north part of the City of San Diego with El Cajon and the southern California desert. I-15 connects downtown San Diego with the inland suburbs of Rancho Bernardo and Escondido, then travels up through the Los Angeles suburbs in Riverside County. Other major freeways include Interstate 805, which parallels I-5 on the inland side between the Mexican border and its intersection with I-5 between La Jolla and Del Mar. State Route 163 connects I-5 in downtown San Diego with I-15 near the Marine Corps Air Station in Miramar. State Route 94 links I-5 downtown with eastern suburbs, paralleling I-8 to the south. State Route 78 is the major east-west freeway in North County, connecting Oceanside and Carlsbad with Escondido, and traveling further east into the mountainous regions of the county. A map of San Diego's freeway network is shown in Figure 1-1.

To monitor its freeways, District 11 has 3,592 ITS traffic sensors deployed at 1,210 locations that collect and transmit data in real-time to a central database. 2,558 of these sensors are in the freeway mainline lanes, 20 are in HOV lanes, and the rest are located at on-ramps, off-ramps, or interchanges. These sensors are a mixture of loop detectors and radar detectors. Approximately 90% of the ITS detection is owned by Caltrans, with the remainder owned by NAVTEQ/Traffic.com. San Diego County has had freeway detection in place since 1999, with the number of detectors steadily increasing over time.

Detectors are spaced relatively frequently on major freeway facilities. Most monitored freeways have an average detector station spacing of between ½ mile and 1 mile. The number and average spacing of detector stations for each monitored mainline facility in the County are indicated in Table 1-1.

Figure 1-1: San Diego freeway network

Table 1-1: San Diego County freeway detection

Freeway	Monitored lane-miles	Detector stations	Average spacing	HOV
I5-N	61.8	98	0.65	X
I5-S	60.8	89	0.70	X
18-E	26.3	45	0.60	
18-W	26.3	46	0.60	
I15-N	39.1	50	0.80	X
I15-S	37.9	45	0.85	X
I805-N	28.7	49	0.60	
I805-S	28.7	46	0.60	
I905-W	3	2	1.50	
SR52-E	14.8	17	0.90	
SR52-W	14.8	16	0.90	
SR54-E	7	3	2.30	
SR54-W	6.8	3	2.30	
SR56-E	5.7	3	1.90	
SR56-W	5.7	3	1.90	
SR78-E	20.2	17	1.20	

SR78-W	20.2	23	0.90	
SR94-E	11.1	14	0.80	
SR94-W	11.6	20	0.60	
SR125-N	10.8	13	0.85	
SR125-S	10.7	13	0.80	
SR163-N	11.1	15	0.75	
SR163-S	11.1	15	0.75	

District 11 also owns and maintains almost 2,000 census count stations. All of these stations report data on traffic volumes and 20 additionally provide vehicle classification and weight information. These stations do not report conditions in real-time, but are obtained and input into the PeMS database via an offline batch process.

In San Diego County, real-time flow, occupancy, and- at some locations- speed data is collected in the field by controller cabinets wired to the individual sensors. Data is transmitted from these controller cabinets to the Caltrans D11 Traffic Management Center (TMC) via a Front End Processor (FEP). The TMC's Advanced Transportation Management System software (ATMS) parses the raw, binary field data from the field and writes outputs into a TMC database. These values (measured flow and occupancy values for every 30-second time period at every detector) are then transmitted to the PeMS Oracle database in real-time via the Caltrans Wide Area Network (WAN). PeMS then performs a number of database routines on the data, including detector diagnostics, imputation, speed calculations, performance measure computations, and aggregation. These processing steps are fully described in Chapter 11 of the Guidebook.

Arterial

Although San Diego's arterial facilities are managed by the cities in which they are physically located, SANDAG assists these local agencies in implementing the Regional Arterial Management System, a region-wide traffic signal integration system that allows for inter-jurisdictional management and coordination of freeway/arterial interchanges. As part of a project to evaluate technologies for monitoring arterial performance, SANDAG installed an arterial travel time monitoring system along four miles of Telegraph Canyon Road and Otay Lakes Road between I-805 and SR-125 in Chula Vista, a suburb in San Diego's South Bay. The corridor has 18 sensor locations (9 in each direction of travel). The sensors deployed along this corridor are wireless magnetometer dots, which directly measure travel times by re-identifying unique vehicle magnetic signatures across detector locations. In order to read a vehicle's magnetic signature, the dots need to be deployed in series of 5 at each location. Consequently, a total of 90 wireless magnetometer sensors have been deployed along this corridor.

After a vehicle passes over a sensor location, each set of five sensors wirelessly transmits the vehicle's magnetic signature information to an access point on the side of the roadway. If the sensors are located further than 150 feet from the access point, a battery-operated repeater is needed to transmit the data from the sensor to the access point. The access point collects the sensor data then transmits it via Ethernet or a high-speed cellular modem to a data archive server in the TMC. At the TMC, the magnetic signatures are matched between upstream and downstream sensor stations and travel times are computed.

Transit

The largest share of San Diego County's transit service is operated by the San Diego Metropolitan Transit System (MTS). MTS operates bus and light rail service (through its subsidiary, San Diego Trolley) in 570 square miles of the urbanized area of San Diego, as well as rural parts of the East County, totaling 3,420 square miles of service area. To monitor its transit fleet, MTS has equipped over one-third of its bus fleet with Automatic Vehicle Location (AVL) transponders and over one-half of its fleet with Automated Passenger Count (APC) equipment. The AVL infrastructure allows for the real-time polling of buses to obtain real-time location and schedule adherence data. The APC data is not available in real-time, but can be used for off-line analysis to report on system utilization and efficiency.

DATA MANAGEMENT

Freeway

The primary data management software system in the region is PeMS. All Caltrans districts use PeMS for data archiving and performance measure reporting. PeMS integrates with a variety of other systems to obtain traffic, incident, and other types of data. It archives raw data, filters it for quality, computes performance measures, and reports them to users through the web at various levels of spatial and temporal granularity. It reports performance measures such as speed, delay, percentage of time spent in congestion, travel time, and travel time reliability. These performance measures can be obtained for specific freeways and routes, and are also aggregated up to higher spatial levels such as county, district, and state. These flexible reporting options are supported by the PeMS web interface, which allows users to select a date range over which to view data, as well as the days of the week and times of the day to be processed into performance metrics. Since PeMS has archived data for San Diego County dating back to 1999, it provides a rich and detailed source of both current travel times and historical reliability information.

In Southern California, PeMS obtains volume and occupancy data for every detector every 30 seconds from the Caltrans ATMS, which governs operations at the District TMCs. The ATMS is used for real-time operations such as automated incident detection and for handling special event traffic situations. ATMS data transmitted to the PeMS Oracle database supports the majority of transportation performance measures reported by PeMS and serves as the primary source of data for the travel time system validations discussed in this case study.

PeMS integrates, archives, and reports on incident data collected from two different sources: the California Highway Patrol (CHP) and Caltrans. CHP reports current incidents in real-time on its website. PeMS obtains the text from the website, uses algorithms to parse the accompanying information, and inserts it into the PeMS database for display on a real-time map, as well as for archiving. Additionally, Caltrans maintains an incident database, called the Traffic Accident Surveillance and Analysis System (TASAS), which links to the highway database so that incidents and their locations can be analyzed. PeMS obtains and archives TASAS incident data via a batch process approximately once per year. Incident data contained in PeMS has been leveraged to validate use cases associated with how different sources of congestion impact travel time reliability.

PeMS also integrates data on freeway construction zones from the Caltrans Lane Closure System (LCS), which is used by the Caltrans districts to report all approved closures for the next seven days, plus all current closures, updated every 15 minutes. PeMS obtains this data in real-time from the LCS, displays it on a map, and lets users run reports on lane closures by freeway, county, district, or state. Lane closure data in PeMS was used in the validation of the use cases associated with how different sources of congestion impact travel time reliability.

Arterial

Arterial travel time systems are an emerging concept in San Diego. As described in the Sensors subsection, San Diego currently only has detection for arterial travel time support on one corridor in the suburb of Chula Vista. The system used to evaluate arterial travel times in San Diego is the Arterial Performance Measurement System (A-PeMS), an arterial extension of PeMS that collects and stores arterial data. A-PeMS receives a live feed of travel times and volume data from a server at Sensys Networks (the manufacturer of the arterial sensors deployed on this corridor) and stores them in the PeMS database. Within PeMS, this data is integrated with information on each intersection's signal timing, which allows for the computation of arterial performance measures. As part of the San Diego A-PeMS deployment, cycle-by-cycle timing plan information is parsed from time-of-day signal timing plans. A-PeMS can also integrate real-time signal timing cycle lengths and phase green times from traffic signal controllers. The performance reporting capabilities within A-PeMS are similar to those within PeMS. Users can view arterial-specific performance measures such as control delay and effective green time, as well as general performance measures such as travel times.

Outside of the reliability and performance monitoring aspects of arterial operations, the various agencies operating within San Diego County, led by SANDAG, are working toward development of a Regional Arterial Management System (RAMS). This system has relevance to this project since its signal timing plan data could eventually be used to support the widespread monitoring of travel time variability on county arterials. This would facilitate a greater understanding of how different arterial facilities interact with one another, with transit service, and with freeway operations.

Transit

District 11 also uses a transit extension of PeMS, the Transit Performance Measurement System (T-PeMS), to obtain schedule, AVL, and APC data from its existing real-time transit management system, compute performance measures from this data, and aggregate and store them for further analysis.

2. METHODOLOGICAL ADVANCES

OVERVIEW

One objective of the case studies is to test and refine the methods developed in Phase 2 for defining and identifying segment and route regimes for freeway and arterial networks. The team's research to date has focused on identifying operational regimes based on individual vehicle travel times and determining how to relate these regimes to system-level information on average travel times. Since individual vehicle trip travel times on freeways are not available in the San Diego metropolitan region, data from the Berkeley Highway Laboratory (BHL) was used in this analysis.

ANALYSIS SETTING AND DATA

The Berkeley Highway Laboratory (BHL) is a 2.7-mile section of Interstate 80 in west Berkeley and Emeryville. The BHL includes fourteen surveillance cameras and sixteen directional dual inductive loop detector stations dedicated to monitoring traffic for research purposes. The sensors are a unique resource because they provide individual vehicle measurements. The system collects individual vehicle actuations from all 164 loops in the BHL every 1/60th of a second and archives both the actuation data and a large set of aggregated data, such as volumes and travel times. The loop data collection system is currently generating approximately 100 megabytes of data per day. A suite of loop diagnostic tests has been developed over the last 2 years, which continuously tests the data stream received from the loops and archives the test results.

The BHL loop data is unique because it provides event data on individual vehicle actuations, accurate to 1/60th of a second. Most other loop detector systems collect only aggregated data over periods of 20 seconds or longer. Collecting the individual loop actuations allows the generation of data sets which are not found elsewhere, such as vehicle stream data, which can be used for headway studies, gap analysis, and merging studies. The BHL loops also provide individual vehicle length measurements, allowing for the classification of freeway traffic. Rich data sets of individual vehicle travel times are also available on the BHL, stemming from research that developed a vehicle re-identification algorithm to calculate travel times between successive loop stations. A final benefit of the BHL data is that the corridor was temporarily instrumented with two Bluetooth reader stations (BTRs) along eastbound I-80. These stations record the timestamps and MAC addresses of Bluetooth devices in passing vehicles. Travel times can be derived from the matching of MAC addresses between two readers. A map of the BTR locations is shown in Figure 2-1.

Analysis was performed on a day's worth of BHL data, collected on Tuesday, 11/16/2010. One data file was obtained for each of the two BTRs, with each file containing every MAC address captured by that sensor on that day. Some MAC address IDs were repeated within the file, due to the fact that passing devices can be sampled multiple times by a single reader. Since the BTRs are located along the eastbound side of the freeway, the majority of MAC address re-identifications were for eastbound traffic, though some westbound vehicles were also captured. There was a one-hour gap in the data between 4:30 AM and 5:30 AM due to a bug in the BHL database. Additionally, some of the initial time-stamps in the file for the midnight hour were negative, possibly due to clock error. Six files of loop detector actuation data were also obtained. Together, these files contain all of the vehicles records at all of the BHL stations on this day.

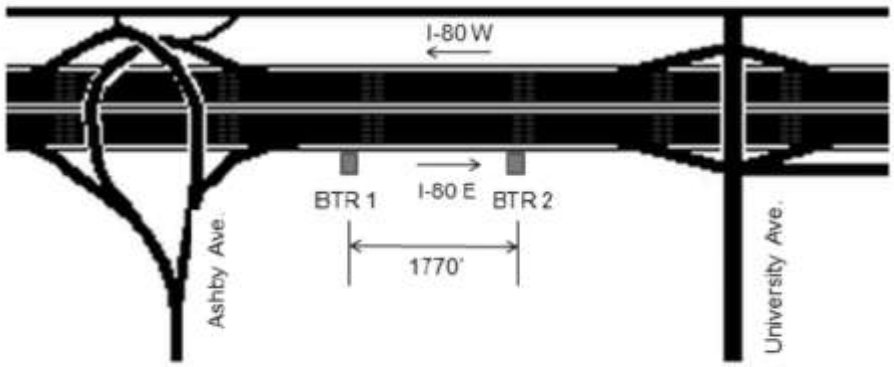

Figure 2-1: Bluetooth reader locations, I-80E

METHODOLOGICAL USE CASES

Overview

Five concepts are important in this analysis:

Concept 1: Regardless of the data source, the methodology must always generate afull travel time probability density function (PDF). All reliability measures can be generated from the PDF.

Concept 2: We need to distinguish between two types of PDFs:

- Those pertaining to the distribution of travel times derived from *individual travelers* along a segment or route; this accounts for travel time variability (for a route or a segment) among individual travelers and over time.
- Those pertaining to the distribution of the mean travel time along a segment or route; this accounts for variations in the mean travel time (for a segment or a route) over time.

Concept 3: It is desirable (and we think possible) to generate individual traveler travel time PDFs directly from some data sources (for example, Bluetooth or GPS) and indirectly from others (for example, loop detectors or video).

Concept 4: The travel time PDFs can be reasonably characterized by a Shifted Gamma Distribution with parameters (α, β, δ) as follows:

- α: the shape of the density function, with $\alpha > 1$ implying that it has a “log-normal” type shape
- β: the spread in the density function, with larger values implying more spread
- δ: the offset of the “zero-point” from the value of zero, or, in this context, the smallest possible travel time

Concept 5: A finite number of traffic states, or regimes, describe all possible travel time PDFs for a route or a segment. Regime PDFs can be continuously updated using real-time data.)

For use cases that serve motorists in need of traveler information, the development of reliability statistics from individual travel time PDFs is ideal. The use cases examined in this chapter are shown in Table 2-1. They are intended to provide information on recommended trip start times (ST) for constrained trips, subject to certain arrival time performance criteria.

Table 2-1: Use cases MC1, MC2, and MC3

Use Case	Description	What is known?	Desired Deliverable	Metrics
MC1	User wants to know *in advance* what time to leave for a trip and what route to take—planning level analysis	Origin position, Destination position, Day of Week, Desired Arrival Time at Destination	A list of alternative routes, their mean travel time and required start time on each route to ensure meeting arrival time 95% of the time	Average O-D travel time by path, planning time
MC2	User wants to know *immediately* what route to take and time to leave for a trip to arrive on time at destination—real time analysis	Origin position, Destination position, Desired Arrival Time at Destination	A ranked list of alternative routes, their mean travel time based on current conditions and required start time on each route to ensure meeting arrival time 95% of the time	Average O-D travel time by path, planning time
MC3	User wants to know *the extra time needed* for a trip to arrive on time at destination with a certain probability	Origin position, Destination position, Prob. arriving on time, day of week, time of day	Map of the route with lowest travel time meeting the threshold, the route average travel time, selected % travel time and buffer time.	Buffer time, % travel time, average travel time for O-D pair

In this discussion, the analysis is focused on developing the probability density function of travel times for those *individual travelers* who depart an origin in a pre-specified time interval in order to meet a pre-specified arrival time at the destination within an acceptable – and specified- level of risk. The size of the time interval is selected in such a way as to ensure stationary travel conditions within the interval as well as to capture a sufficient sample of travelers to characterize or update the developed travel time distribution.

It is hypothesized that the *route travel time distribution can be "stitched" from the distribution of segment travel times which make up the route*. This hypothesis is still subject to testing and validation using field data. Furthermore, it is assumed that there is a finite number of travel time PDFs (or regimes) that can fully characterize the travel time distribution between an origin and a destination on a given route over a full year. Figure 2-2 illustrates an example that

uses four PDFs and a transition PDF (labeled T) , where each cell color represents a unique travel time regime based on historical travel time data for a given origin-destination pair on a given route.

It is further hypothesized that the individual auto travel times on links or routes can be characterized by a 3-parameter shifted Gamma distribution (α, β, and δ) of the form:

$$g_{\alpha,\beta,\delta}(t) = \frac{\beta^{\alpha}}{\Gamma(\alpha)}(t-\delta)^{\alpha-1}e^{-\beta(t-\delta)} \quad for\ t \geq \delta, o.e.w$$

For α=1, the Gamma distribution degenerates into the shifted exponential distribution. Figure 2-3 shows a diagram of the distribution for α > 1.0. There is a unique set of distribution parameters associated with each origin-destination pair, route, and PDF regime

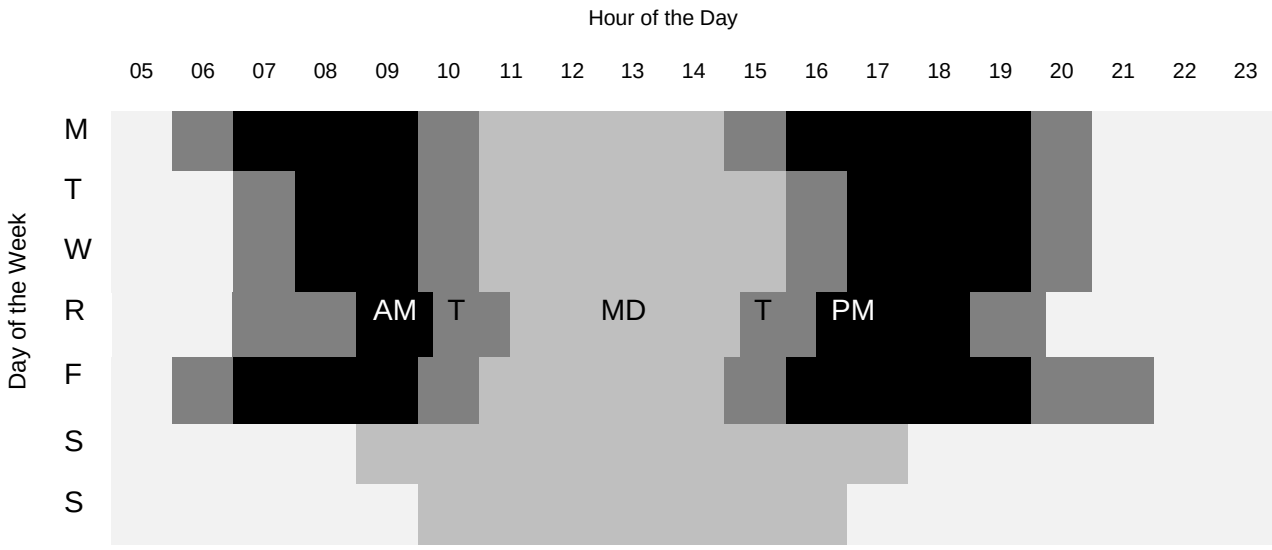

Figure 2-2: Historical route travel time PDFs by time of day and day of week

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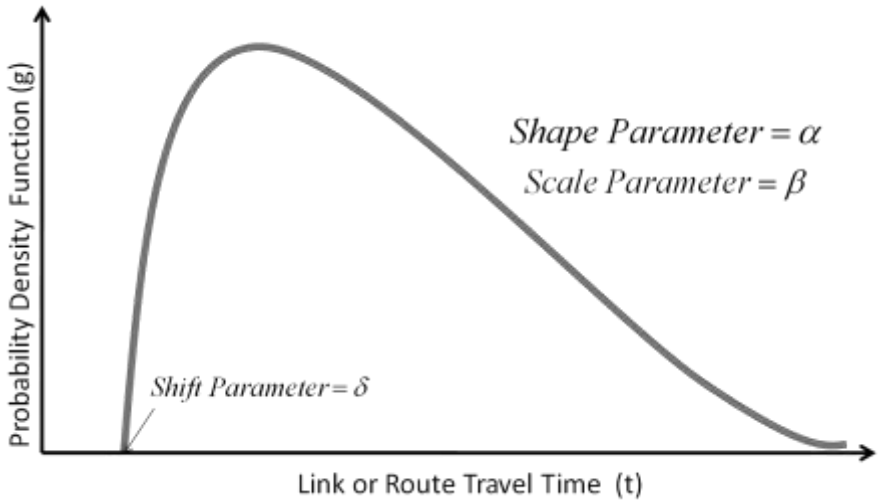


Figure 2-3: Shifted gamma distribution of travel times

Use Case MC1: User wants to know *in advance* what time to leave for a trip and what route to take

The procedure for validating use case MC1 is depicted in Figure 2-4. The top-right corner represents user-driven input, such as origin-destination (O-D) selection, desired arrival time at destination, and possible routes to be evaluated. The top-left corner represents field data collection of travel times to develop and update off-line historical travel times PDFs which follow the shifted Gamma distribution described in the previous section. The bottom section represents the actual algorithm to determine the computed user start time (ST) in order to meet the desired arrival time (DAT) criterion.

The outcomes, shown in the table in Figure 2-4, match the use case MC1 results requirement specified in Chapter 3 of the Guidebook, which is to generate "… *A list of alternative routes that displays the required start time to arrive on-time 95% of the time and the required start time based on the average travel time".* Based on this example, the entry time PDF consistent with the desired arrival time (DAT) of 8:40 AM is the 8:00-10:00 entry time.

An example application of the procedure using hypothetical travel time parameter values is shown in Figure 2-5. The procedure works as follows:

- User enters origin, destination, and a DAT of 8:40 at the destination on a Thursday.
- The user or the system identifies (or retrieves from a route library) a finite number of routes connecting the input O-D (or nearby locations). Let the first route be labeled Route 1.
- The system identifies the relevant time-dependent PDF (the AM peak) consistent with the user-inputted DAT and DOW. It represents all travel times for entry times between 8:00 AM and 10:00 AM on Thursdays.
- Based on the retrieved PDF, achieving a 95% on-time arrival requires a planned 30 minute travel time, compared to the average travel time of 23 minutes.
- Thus the recommended start time ST is 8:10 AM. Other DAT scenarios and outcomes are also shown in the table in Figure 2-4.

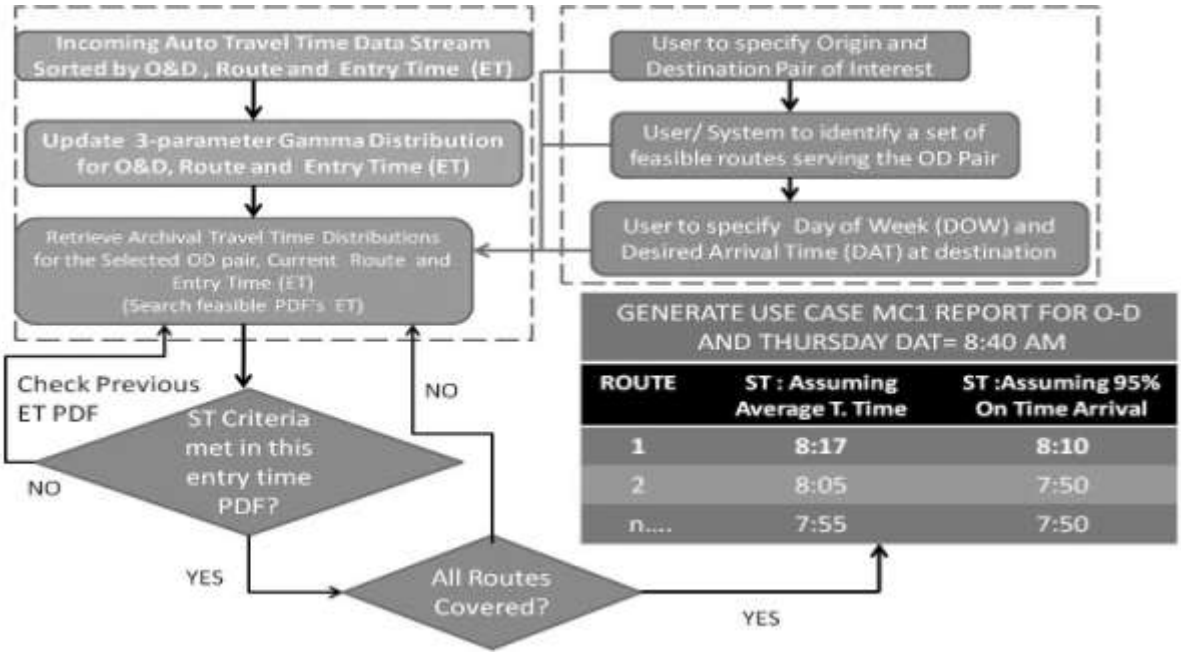


Figure 2-4: Validation process for Use Case MC1

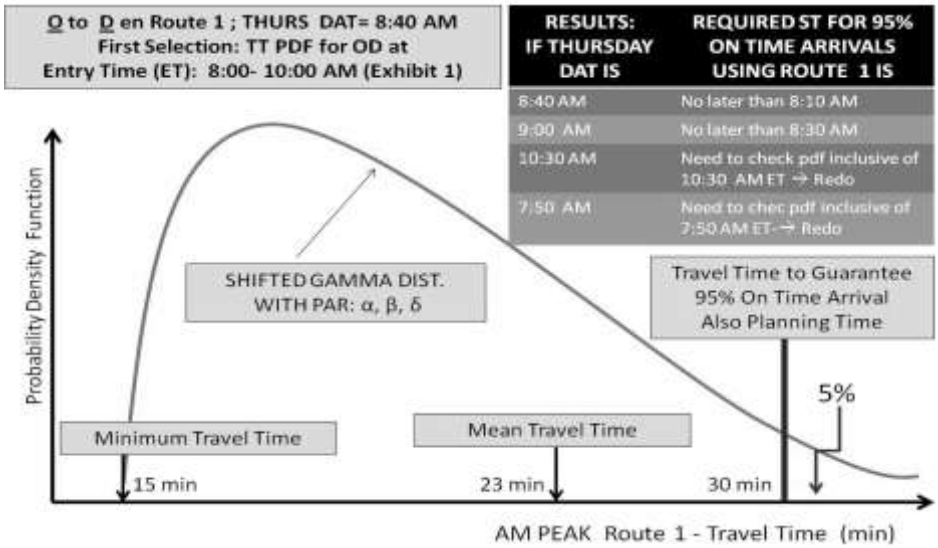
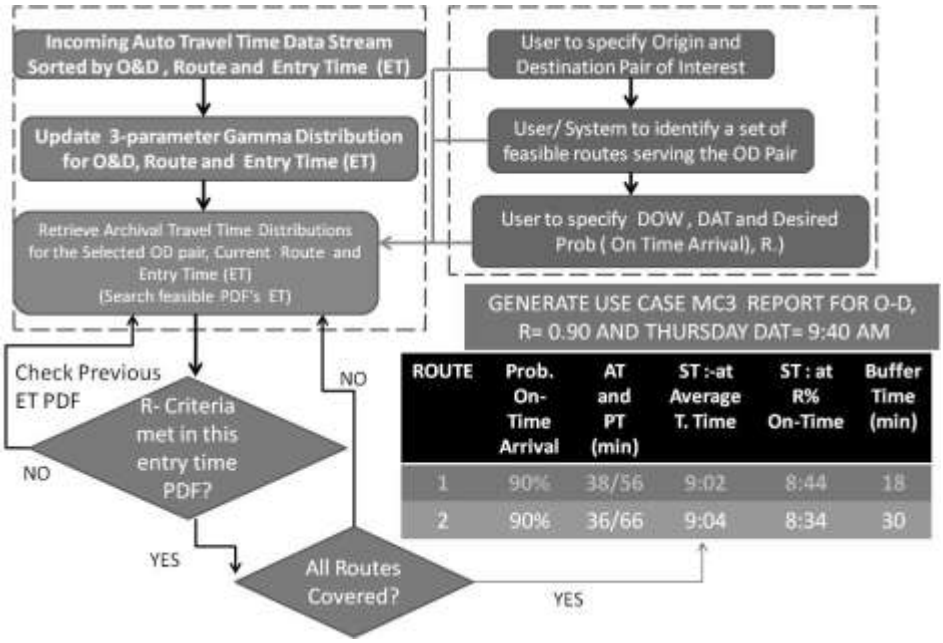


Figure 2-5: Example application of Use Case MC1

Use Case MC3: User wants to know *the extra time needed* for a trip to arrive on time at destination with a certain probability

This use case represents a simple variation of use case MC1 and is therefore discussed before the real-time use case, MC2. Here, the user is interested in identifying, for a known O-D,

DAT, and DOW, a route, average travel time (AT) and planned travel time (PT) that will ensure his or her on-time arrival R% of the time. The algorithm for MC1 is adjusted slightly to meet these new requirements, as shown in Figure 2-6. The hypothesized PDFs for the two candidate routes are shown in Figure 2-7. These are designed to highlight the contrast between a shorter route (Route 2) and a more reliable route (Route 1). In this case, the system would recommend the selection of Route 1 and a departure time of no later than 8:44 AM in order to guarantee arrival at the destination by 8:40 AM with 90% certainty. The user would have to depart 10 minutes earlier on Route 2 to achieve the same probability of on-time arrival. This is confirmed by comparing the buffer times between the two routes.



ROUTE	Prob. On-Time Arrival	AT and PT (min)	ST :-at Average T. Time	ST : at R% On-Time	Buffer Time (min)
1	90%	38/56	9:02	8:44	18
2	90%	36/66	9:04	8:34	30

Figure 2-6: Validation process for Use Case MC3

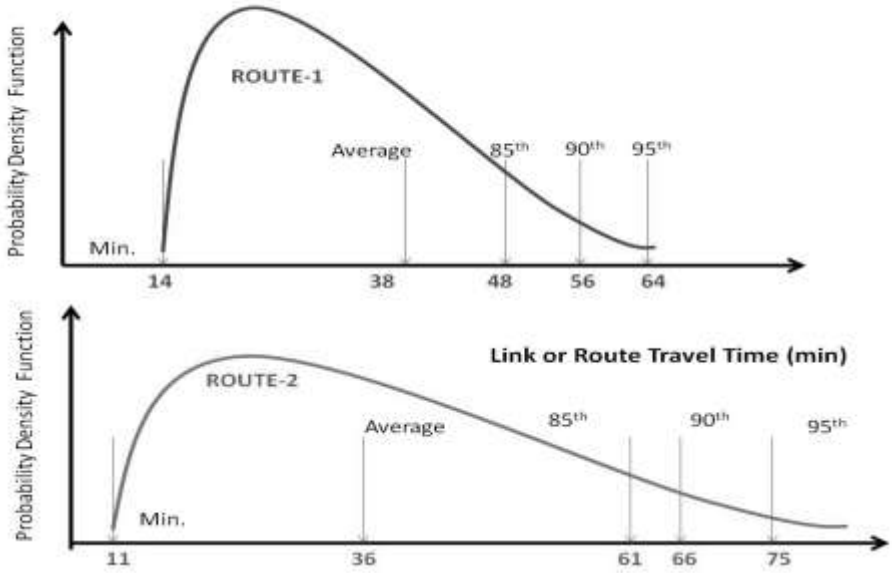


Figure 2-7: Illustration of a reliable route PDF (top) and a faster average route PDF (bottom)

Use Case MC2: User wants to know *immediately* what route to take and what time to leave for a trip to arrive on time at a destination

This use case is different and much more challenging to validate than MC1 or MC3. It also represents the application with the highest utility from the driver's perspective since it will provide real-time information on the recommended trip start time, including the effects of incidents or other events not explicitly accounted for in historical travel time PDFs. The principal issue, therefore, is how to combine the historical and real-time data streams in order to provide up-to-date travel time estimates and predictions based on current conditions. As an example, during major weekend road construction projects, the more accurate distribution may be the weekday AM peak profile, rather than the historical weekend travel time PDF.

Several stipulations are important to note:

- It is possible that there are no feasible solutions to the current user request. A departure at the earliest departure time may not guarantee the user's DAT at the specified probability R on some or all of the feasible routes.
- While historical PDFs are still important, they are not appropriate for use in a real time context. The system must be able to detect which PDF regime each link or route is operating in, based on the real-time data stream.
- The PDF regime selection process is akin to the "plan selection" algorithm that is used in many urban traffic signal control systems. Those algorithms collect traffic data (typically key link volumes and occupancies) to be matched with the signal plans most appropriate for the collected data patterns.
- In a real time context, where computational speed is of the essence, the number of PDFs to be considered should be kept to a minimum. Each link or route could theoretically be considered to operate in four regimes: uncongested, transition from uncongested to congested, congested, and transition from congested to uncongested.

The procedure for Use Case MC2 is shown in Figure 2-8. It assumes that there are three feasible alternate routes, and that the earliest departure time is 8:15 AM, while the DAT is 9:40 AM. The system checks which of the routes is feasible, and determines the required start time assuming average and 95th percentile travel times. In this case, Route 3 is deemed infeasible, while Routes 1 and 2 are both feasible. Work is underway to apply Bayesian techniques to match real-time travel data to historical regime-based PDFs and to develop the simplified four PDF regimes described earlier in this section.

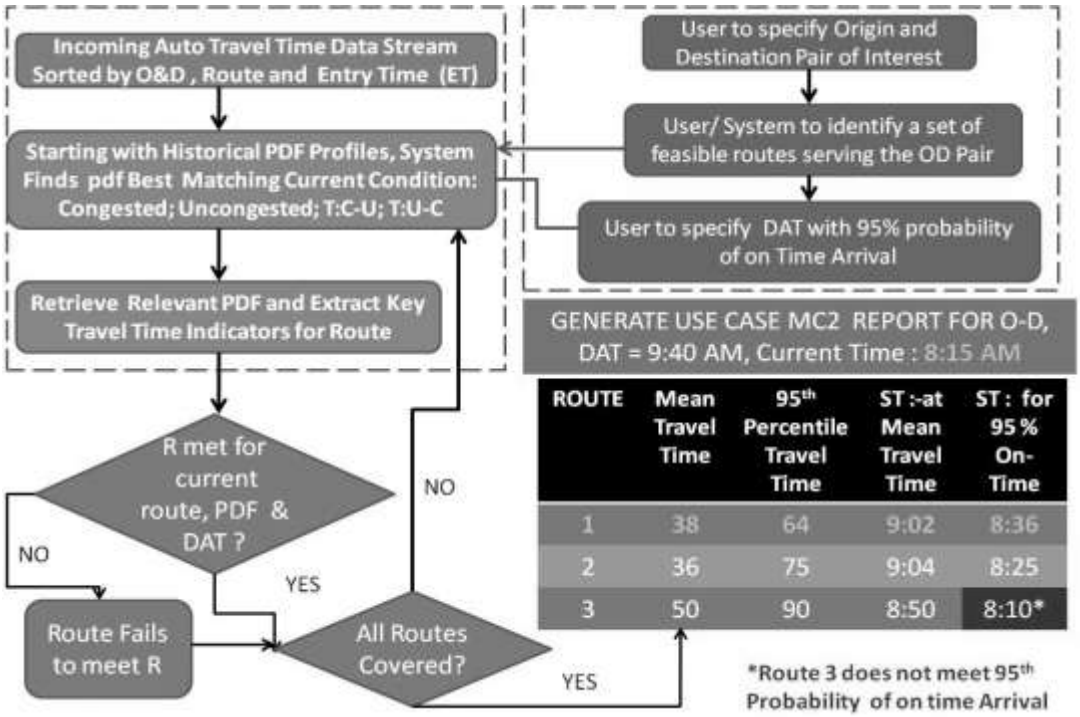


Figure 2-8: Validation process for Use Case MC2

Route Selection Criteria

An interesting byproduct of the use case analyses is the possibility of developing additional route selection criteria that can account for the differential utilities of early and late arrivals. Thus far, the selection between routes has been made on the basis of the route yielding the latest trip start time while ensuring a pre-specified on time arrival probability (for example, Route 1 in Figure 2-8). Specifying different penalty functions for late and early arrivals could change the selection.

ANALYSIS OF BLUETOOTH TRAVEL TIMES

To support the methodologies presented in use cases MC1, MC2, and MC3, Bluetooth data from the BHL was analyzed to see what could be learned about individual vehicle travel times and the probability density functions.

The raw data were filtered to remove MAC addresses with six or more timestamps on either reader. Contiguous timestamps from the same vehicle were averaged to obtain an estimate of when the vehicle was adjacent to the sensor. The filtering process resulted in a data set of 5,028 travel time measurements. These were then filtered a second time to remove

observations where the speed between the readers was below 5 mph. This resulted in 5,012 final measurements. These travel times are plotted in Figure 2-9 and Figure 2-10.

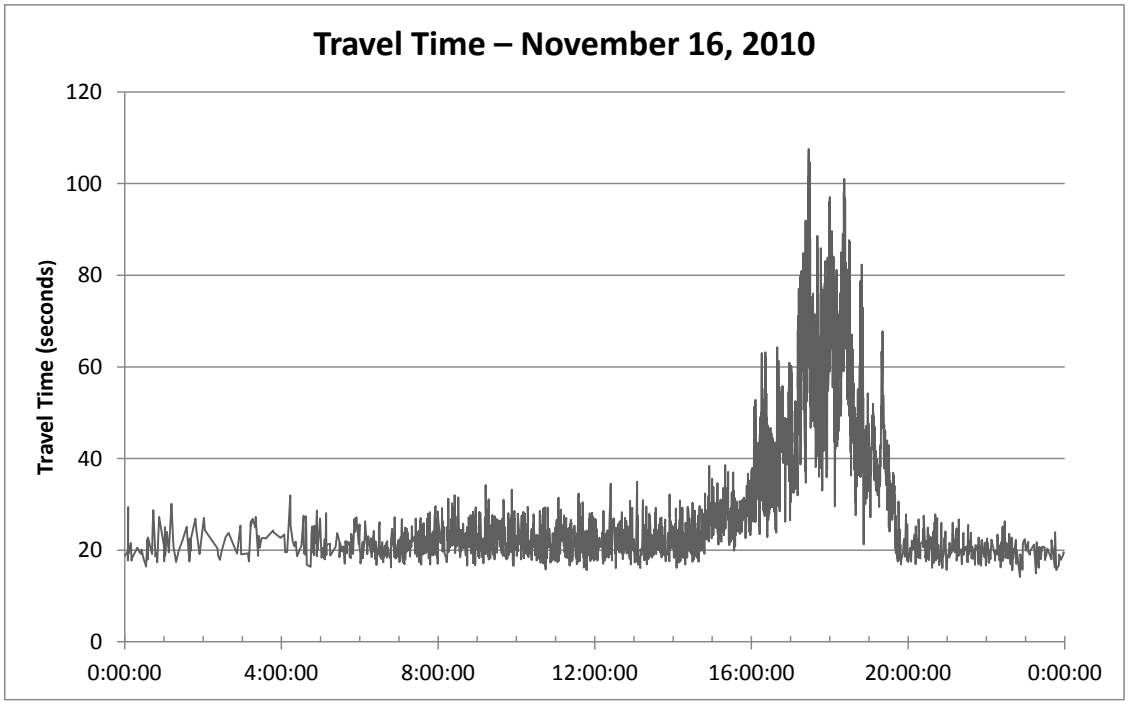


Figure 2-9: BHL Bluetooth-measured travel times, 11/16/2010

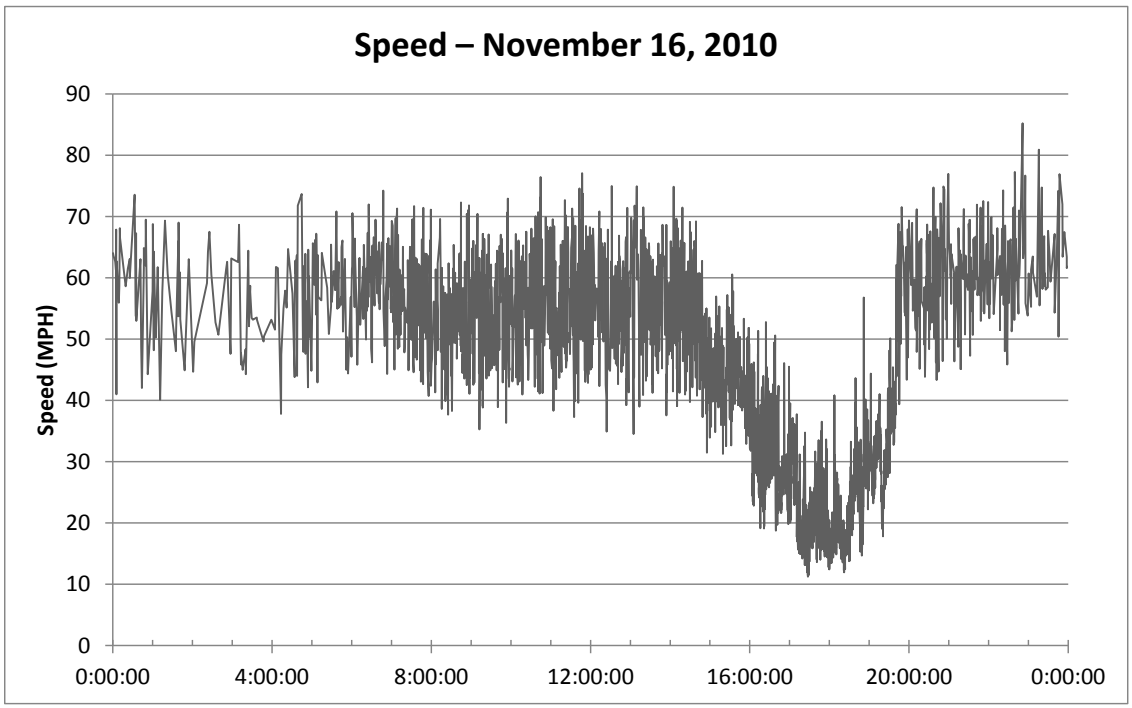


Figure 2-10: BHL Bluetooth-measured speeds, 11/16/2010

By inspection, three time periods of operative regimes were identified as follows:

- Free flow: 0:00:00-14:30:00 and 19:45:00-23:59:59
- Transition: 14:30:00-15:45:00 and 19:30:00-19:45:00
- Congested: 15:45:00 -19:30:00

The resulting distribution of the Bluetooth travel time observations is shown in Table 2-2.

The data were then analyzed using EasyFit software to see how different probability density functions fit the data and to estimate the parameters for each density function. Table 2-3, Table 2-4, and Table 2-5 present the goodness of fit results down to the 3-parameter Gamma distribution (Gamma(3p)), sorted by the Anderson-Darling statistic. Figure 2-11, Figure 2-12, and Figure 2-13 show the resulting plots of the Gamma(3p) density functions. The Gamma(3p) fits relatively well for the Free Flow and Congested conditions. It is likely that there will be multiple transition regimes, and Gamma(3p) fit may be improved for stratified transition regimes.

Table 2-2: Bluetooth data regime classifications

Category	Flag	Observations
Free flow	1	2679
Transition	2	484
Congested	3	1849

Table 2-3: Goodness-of-fit results for the free-flow regime

Distribution	**Kolmogorov Smirnov**		**Anderson Darling**		**Chi-Squared**	
	Statistic	**Rank**	**Statistic**	**Rank**	**Statistic**	**Rank**
Pearson 5 (3P)	0.01352	1	1.0731	1	6.7917	1
Pearson 6 (4P)	0.01377	2	1.0875	2	7.2844	2
Dagum	0.01795	4	1.4442	3	13.684	3
Burr (4P)	0.02118	6	2.1326	4	22.291	5
Gen. Logistic	0.01975	5	2.3254	5	23.294	6
Log-Logistic (3P)	0.02309	9	2.4624	6	25.444	8
Frechet (3P)	0.02139	7	2.726	7	23.419	7
Gen. Extreme Value	0.02174	8	2.9185	8	27.343	9
Burr	0.02749	11	3.748	9	30.88	10
Lognormal (3P)	0.0172	3	5.798	10	16.413	4
Frechet	0.03534	15	7.4445	11	44.274	13
Gen. Gamma (4P)	0.02908	12	11.258	12	51.262	14
Inv. Gaussian (3P)	0.03043	13	11.749	13	36.427	11
Fatigue Life (3P)	0.03055	14	11.915	14	38.129	12
Log-Logistic	0.04617	19	12.611	15	117.0	18
Pearson 5	0.03864	17	13.959	16	69.484	15
Gamma (3P)	0.03686	16	18.252	17	84.176	16

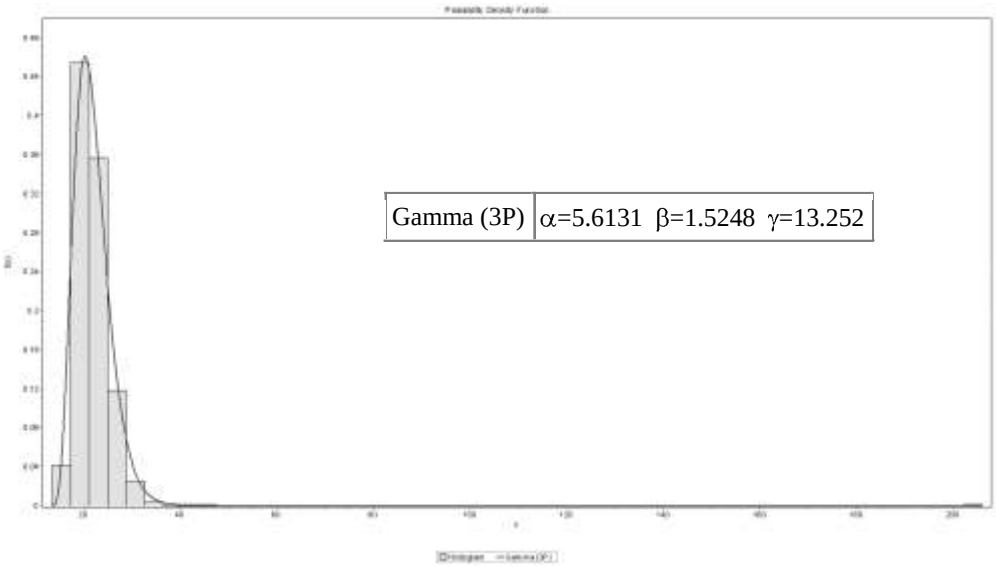


Figure 2-11: 3-Parameter Gamma distribution for the free-flow regime

Table 2-4: Goodness-of-fit results for the transition regime

Distribution	**Kolmogorov Smirnov**		**Anderson Darling**		**Chi-Squared**	
	Statistic	**Rank**	**Statistic**	**Rank**	**Statistic**	**Rank**
Burr	0.02676	1	0.81555	1	16.645	1
Burr (4P)	0.02709	2	0.82053	2	19.224	2
Johnson SU	0.03208	4	0.95065	3	22.543	10
Dagum (4P)	0.03373	6	0.97157	4	21.446	6
Dagum	0.03512	7	1.0092	5	21.472	7
Gen. Extreme Value	0.03317	5	1.0168	6	22.294	8
Frechet	0.02965	3	1.058	7	20.188	5
Frechet (3P)	0.03808	10	1.1188	8	22.351	9
Log-Logistic (3P)	0.03514	8	1.1732	9	19.289	3
Gen. Logistic	0.03904	12	1.2923	10	19.714	4
Pearson 5 (3P)	0.04297	13	1.3807	11	23.961	11
Pearson 6 (4P)	0.04478	14	1.5089	12	25.479	12
Lognormal (3P)	0.05205	15	2.0513	13	29.111	13
Inv. Gaussian (3P)	0.05956	16	2.5343	14	33.83	14
Fatigue Life (3P)	0.06274	18	2.8342	15	37.124	16
Gen. Gamma (4P)	0.06117	17	3.0654	16	36.792	15
Log-Pearson 3	0.03856	11	5.3555	17	N/A	
Pearson 5	0.08043	21	5.4889	18	47.002	17

Wakeby	0.03568	9	5.4998	19	N/A	
Gamma (3P)	0.08052	22	5.6067	20	53.894	20

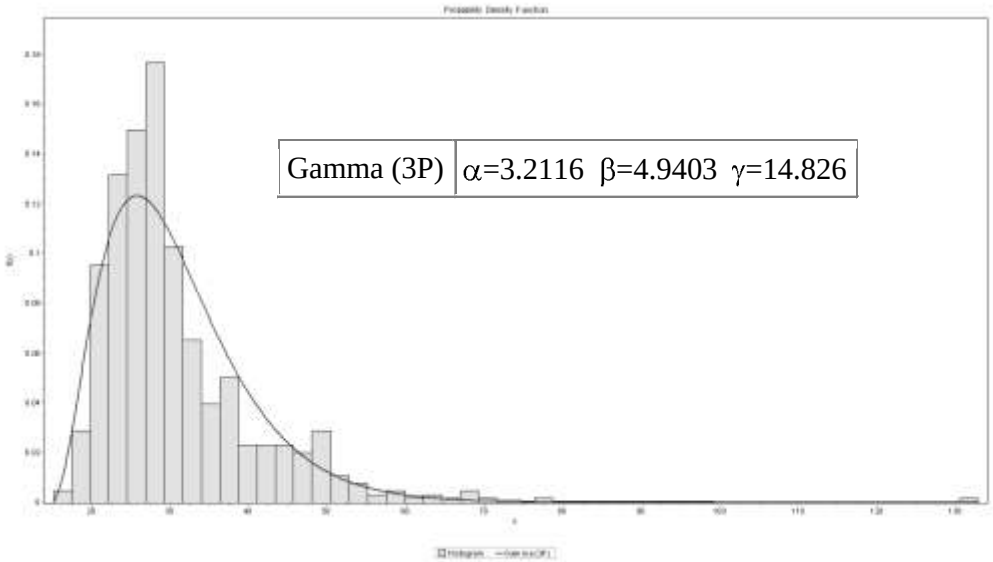


Figure 2-12: 3-Parameter Gamma distribution for the transition regime

Table 2-5: Goodness-of-fit results for the congested regime

Distribution	**Kolmogorov Smirnov**		**Anderson Darling**		**Chi-Squared**	
	Statistic	**Rank**	**Statistic**	**Rank**	**Statistic**	**Rank**
Fatigue Life (3P)	0.02266	3	0.9031	1	13.229	4
Inv. Gaussian (3P)	0.02297	4	0.94129	2	13.141	3
Gamma (3P)	0.02734	10	1.0359	3	13.408	5

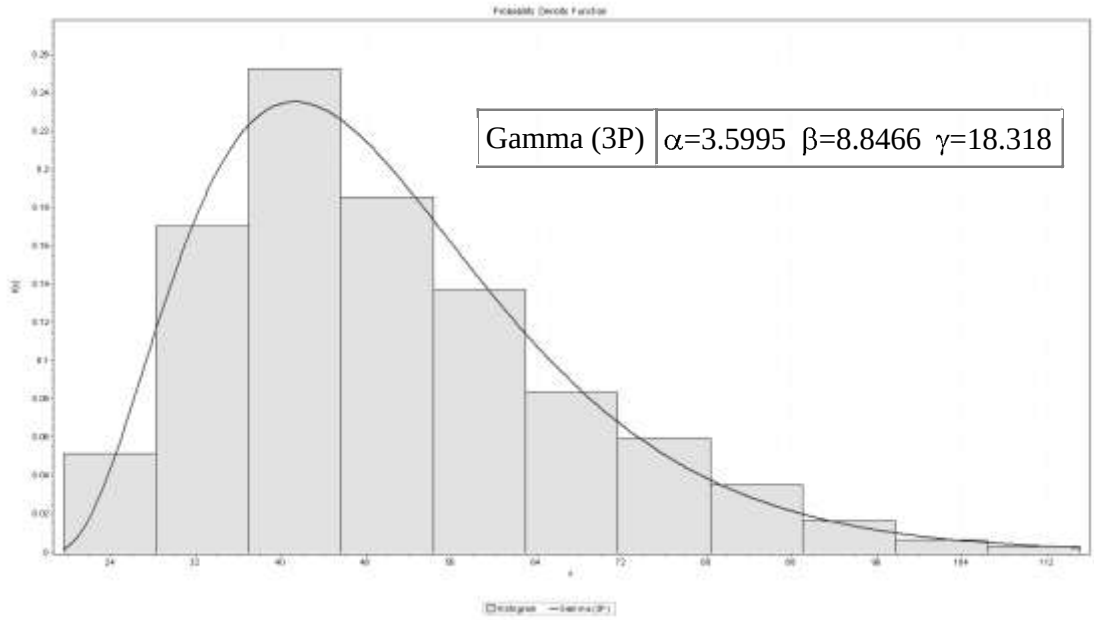


Figure 2-13: 3-Parameter Gamma distribution for the congested regime

The three PDFs are superimposed in Figure 2-14. It is apparent that the free-flow PDF has a lower mean travel time, a smaller standard deviation, and the lowest 95th percentile value. The congested PDF is at the other end of this extreme, with the largest mean, the largest standard deviation, and the highest 95th percentile value. Not unexpectedly, the PDF for the transition regime lies between these two. The numerical values are presented in Table 2-6.

Table 2-6: 3-Parameter Gamma distribution means, standard deviations, and 95th percentiles

Condition	Mean (sec)	StdDev (sec)	95th Percentile (sec)
Uncongested	21.8	3.57	28.3
Transition	30.4	9.11	47.7
Peak	50.0	17.0	83.5

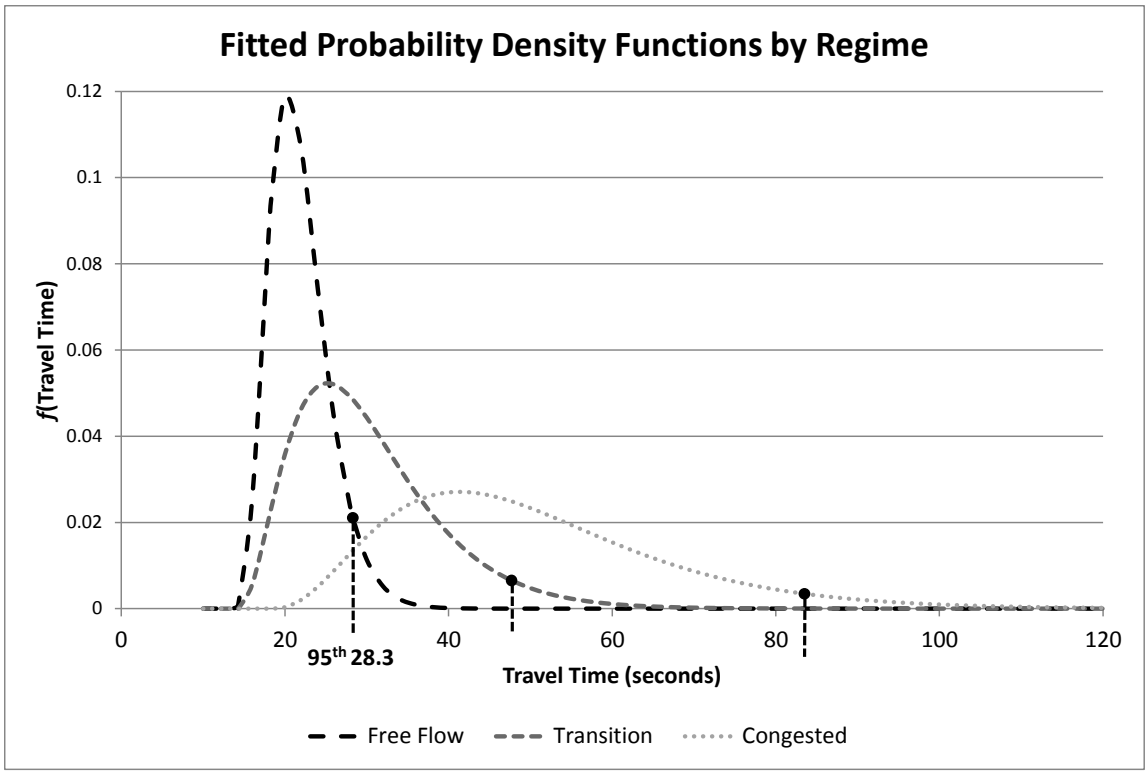


Figure 2-14: 3-Parameter Gamma distributions for all three regimes

CONCLUSIONS

This analysis examined data from the Berkeley Highway Lab to see if operative regimes for individual vehicle travel times can be identified from Bluetooth data. The research team concluded that this can, indeed, be done. Based on more than 5,000 observations of individual travel times, three different regimes can be identified: (1) off-peak or uncongested; (2) peak or congested; and (3) transition between congested and uncongested. All three can be characterized by 3-parameter Gamma density functions. More specifically, the PDF for the free flow condition has the lowest mean, the smallest standard deviation, and the lowest 95th percentile. The congested PDF is at the other extreme; and the transition PDF is in between.

Further investigation is needed into the individual vehicle PDFs and the parameters that describe them, but the efficacy of the concepts seems sound. Two issues that need to be explored in the very near future are: (1) how the PDFs for individual vehicle travel times relate to mean travel times (for example, those computed from loop detectors) during the same time periods and (2) whether there are ways to retrieve information from loop detectors that would be help to infer the PDFs that describe individual vehicle travel times.

3. USE CASE ANALYSIS

OVERVIEW

Chapters 3 through 6 of the Guidebook present dozens of use cases intended to satisfy the myriad ways that different classes of users can derive value from a reliability monitoring system. For the San Diego case study, a number of these use cases were combined to form six high-level use cases that broadly encompass the types of reliability information that users are most interested in and that were suited for validation using the San Diego data sources. These six use cases, their primary user groups, and the guidebook use cases that they encompass, are shown in Table 3-1.

Table 3-1: Validated use cases in San Diego

Use Case	Primary users	Guidebook sub-use cases
Freeways		
Conducting offline analysis on the relationship between travel time variability and the seven sources of congestion	Planners and Roadway Managers	MC4, PE1, PE2, PE3, PE4, PE5, PE11, PP1
Using planning-based reliability tools to determine departure time and travel time for a trip	Motorists	MC1, MC2, MC3
Combining real-time and historical data to predict travel times in real-time	Operations Managers	MM1, MM2, MC5
Transit		
Using planning-based reliability tools to determine departure time and travel time for a trip	Transit Riders	TP1, TS2, TO2, TC4
Conducting offline analysis on the relationship between travel time variability and the seven sources of congestion	Transit Planners and Managers	PE1, PE2, PE3, PE4, PE5, PE11, PP1
Freight		
Using historical data to evaluate freight travel time reliability	Drivers and Freight Carriers	FP1, FP3, FP4, FP6

In line with the use case divisions shown in the table, the remainder of this chapter is broken up into three sections: Freeways, Transit, and Freight. Each section presents the analytical results of validating the use cases with reliability monitoring system data and methods.

FREEWAYS

Use Case 1: Conducting offline analysis on the relationship between travel time variability and the seven sources of congestion

Summary

This use case aims to quantify the impacts of the seven sources of congestion: (1) incidents; (2) weather; (3) lane closures; (4) special events; (5) traffic control; (6) fluctuations in demand; and (7) inadequate base capacity, on travel time variability. To perform this analysis, methods were developed to create travel time probability density functions (PDFs) from large data sets of travel times that occurred under each event condition. From these PDFs, summary metrics such as the median travel time and planning travel time were computed to show the variability impacts of each event condition.

Users

This use case has broad applications to a number of different user groups. For planners, knowing the relative contributions of the different sources of congestion toward travel time reliability helps them to better prioritize travel time variability mitigation measures on a facility-specific basis. For example, if unreliability on a particular route is predominantly caused by the frequent occurrence of incidents, planners may want to consider measures such as freeway service patrol tow truck deployments to help clear incidents faster. If unreliability on a route has a high contribution from special event traffic impacts, planners may want to consider providing better traveler information before events to inform travelers of alternate routes.

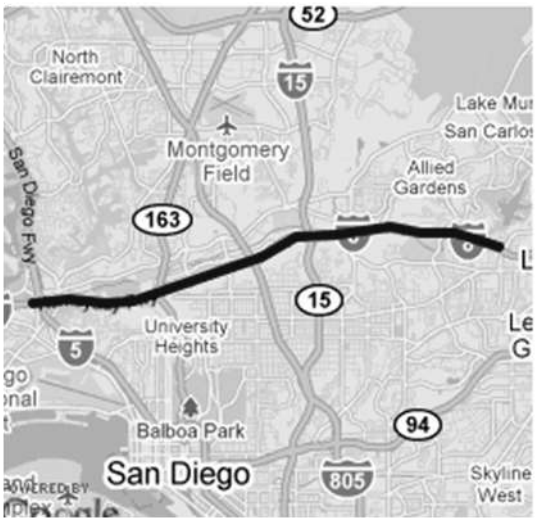
The outputs of this use case are also of value to operators, providing them with information on the range of operating conditions that can be expected on a route given certain source conditions. Knowing the historical impacts of the different sources of congestion helps operators better manage similar conditions in real-time by, for example, changing ramp metering schemes to mitigate congestion or posting expected travel times on variable message signs. It is important for operators to have outputs from this use case at a time-of-day specific level. For example, on some facilities, incidents may significantly impact reliability during one or more peak hours, but may have little impact during the midday due to lower baseline traffic volumes. On some facilities, weather may have a major impact at all times of the day, since all vehicles may need to slow to safely travel in the conditions. Understanding the time-dependency of variability impacts would help operators more effectively manage events as they occur.

Finally, the outputs of this use case have value to travelers, by providing better predictive travel times under certain event conditions that could be posted in real-time on variable message signs or on traveler information websites. This information would help users better know what to expect during their trip, both during normal operating conditions and when an external event if occurring.

Sites

Two routes were selected for the evaluation of this use case, to highlight the varying contributions of congestion factors to travel time reliability across different facilities, days of the week, and times of the year. These routes are shown in Figure 3-1. The first route analyzed is a 10 mile stretch of westbound Interstate-8 beginning at Lake Murray Boulevard in the eastern suburb of La Mesa and ending at Interstate-5 north of the San Diego International Airport. This route was selected because it provides access to Qualcomm Stadium, located at the major interchange of I-8 and I-15, which hosts San Diego Chargers football games as well as college football bowl games, concerts, and other events. Because this route is a major commute route, the impacts of the sources on travel time variability were investigated for weekdays between the months of November and February (when Qualcomm Stadium regularly hosts events and when San Diego experiences the most inclement weather).

The second route is a 27 mile stretch of northbound I-5 beginning just south of the I-805 interchange in San Diego and ending north of SR-78 in the northern suburb of Oceanside. This route was selected because it has a significant amount of congestion and incidents, and it sees special event traffic impacts during the summer months due to the San Diego County Fair and Del Mar horse races. The route also has significant traffic congestion on weekends. For this reason, travel time variability and its relationship with the sources of congestion were evaluated over a year-long period on Saturdays and Sundays.



Westbound I-8

Northbound I-5

Figure 3-1: Freeway Use Case 1 routes

Methods

These routes were analyzed to determine the travel time variability impacts caused by five sources of congestion: (1) incidents; (2) weather; (3) special events; (4) lane closures; and (5) fluctuations in demand. Traffic control contributions were not investigated as ramp metering location and timing data could not be obtained. The impacts of inadequate base capacity were also not considered due to the difficulty of quantifying this factor.

For each route, five-minute travel times were gathered from PeMS for each day in the time period of analysis (four months of weekdays for the westbound I-8 route and one year of weekends for the northbound I-5 route). To ensure data quality, five-minute travel times computed from more than 20% imputed data were discarded from the data set.

To link travel times with the source condition active during their measurement, each 5-minute travel time was tagged with one of the following sources: (1) baseline; (2) incident; (3) weather; (4) special event; (5) lane closure; or (6) high demand. A travel time reliability monitoring system that supports this use case would ideally integrate data on external sources of freeway congestion such as incidents, weather, lane closures, special events, and demand levels. The PeMS system operational in San Diego integrates statewide incident data from Caltrans' Traffic Accident and Surveillance Analysis System (TASAS) and statewide lane closure data from Caltrans' Lane Closure System. PeMS also reports peak-period vehicle-miles-travelled data for freeway routes. This PeMS data was used to evaluate the relationship between travel time variability and incidents, lane closures, and demand. Hourly weather data from the Automated Weather Observing System (AWOS) station at the San Diego International

Airport was obtained from the NOAA National Data Center. Special event data was collated manually from various sport and event calendars for venues adjacent to the study routes.

- **Baseline**: A travel time was tagged with “baseline” if none of the factors was active during that five-minute time period.
- **Incident**: Incident data was obtained from the PeMS system operational in San Diego, which integrates statewide incident data from Caltrans’ Traffic Accident and Surveillance System (TASAS). A travel time was tagged with “incident” if an incident was active anywhere on the route during that five-minute time period. Incident start times and durations reported through PeMS were used to determine when incidents were active along the route. Incidents with durations shorter than 15 minutes were not considered.
- **Weather**: A travel time was tagged with “weather” if the weather station used for data collection reported precipitation during that hour.
- **Special Event**: A travel time was tagged with “special event” if a special event was active at a venue along the route during that time period. Special event time periods were determined from the start time of the event and the expected duration of that event type. For example, if a football game at Qualcomm Stadium had a start time of 6:00 PM and was scheduled to end around 9:00 PM, the event was considered active between 4:00 PM and 6:00 PM and between 8:30 PM and 10:00 PM, as this is when the majority of traffic would be accessing the freeways surrounding the venue.
- **Lane Closure**: A travel time was tagged with “lane closure” if a lane closure (scheduled or emergency) was active anywhere along the route during that time period.
- **High Demand**: Finally, a travel time was tagged with “high demand” if the vehicle-miles-travelled measured during that time period were more than 10% higher than the average vehicle-miles travelled for that time period. This approach was adapted from the SHRP2 L03 project, which considered high demand to be any time period where demand was 5% higher than the average for that time period. 10% was selected in this research effort because a 5% increase in demand had no measureable impact on travel times on either of the selected corridors.
- **Multiple Factors**: There were a few time periods within each data set where more than one factor was active during a single 5-minute period; in these cases, the travel time was tagged with the factor that was deemed to have the larger travel time impact (for example, when an incident coincided with light precipitation, the travel time was tagged with “incident”).

Tagged travel times were then divided into different categories based on the time of the day, since the impacts of the congestion sources are time-dependent. For the westbound I-8 route, which was analyzed for weekdays, two different time periods were evaluated: (1) AM Peak, 7:00 AM-9:00 AM and (2) PM Peak, 4:00 PM-8:00 PM. For the northbound I-5 route, which was analyzed for weekends, two different time periods were evaluated: (1) Morning, 8:00 AM-12:00 PM and (2) Afternoon, 12:00 PM-9:00 PM.

Finally, within each time period, travel time probability density functions (PDFs) were assembled separately for all travel times and for those occurring during each source condition. The PDFs were plotted and summarized in various ways to give a thorough description of how the sources of congestion impact travel time variability and conditions on a route.

Route 1 (I-8) Results

For the westbound I-8 route, travel time variability and its contributing factors were investigated for weekdays during the four month period between November 2008 and February

2009. Data on incidents, weather, lane closures, special events, and demand fluctuations was collected from PeMS and external sources as described in the Methods section. Due to the preference of scheduling freeway lane closures during overnight, weekend hours, no lane closures were active on the route during the selected hours and date range. As a result, the contribution of lane closures to travel time variability on this route is zero. Analysis of vehicle-miles-travelled for the demand fluctuations component showed that demand is very steady and consistent on this corridor. Only three days were identified as having a demand level not otherwise attributable to a special event that exceeded 10% of the average weekday demand level. All of these hours of high demand were during the PM period.

AM Peak. Figure 3-2 illustrates the distribution of 5-minute travel times in the AM period (7:00 AM-9:00 AM), divided by source condition. The AM period is the peak period for commute traffic on this route, since it begins in the eastern suburbs and terminates near downtown San Diego. As such, it is the time period with the most travel time variability. As evidenced by the plot, there is a wide distribution of travel times during the morning hours, ranging from approximately 8.5 minutes free-flow to 25 minutes at a maximum, a travel time measured when there was an incident. The only source conditions active during the weekday AM period over the four month study period were incidents and precipitation; no special events or hours of high demand were noted. The histogram shows that, almost 25% of the time, the travel time is a near-free-flow 9 minutes. The travel time only falls below 9 minutes when there is no external source of congestion active. The “tail end” of the travel time distribution, however, is dominated by weather and incident events. In particular, travel times ranging between 15 and 20 minutes (or double the free-flow travel time) only occur when either an incident or a weather event is active. Travel times greater than 20 minutes only occur when there is an incident on the route.

Interestingly, it is apparent from this graph that sometimes, even when an incident is active, the travel time falls below 10 minutes. This is likely due to the fact that this analysis does not account for the severity of incidents in the travel time tagging process. The incident travel times shown in this figure that are near the median are likely minor incidents that were promptly moved to the shoulder and then cleared.

Another way of viewing the travel time reliability impacts of different sources is to plot the travel time probability density functions (PDFs) under each source condition. Travel time PDFs for the baseline, incident, and weather conditions are each shown in Figure 3-3. The PDFs shown in this use case were assembled using non-parametric kernel density estimation. As the baseline PDF plot shows, the distribution of travel times is very small when there is no external congestion source active on the corridor; there is only a 2 minute difference between the median travel time and the 95th percentile travel time in this case. When an incident is active on the corridor, the distribution of travel times is much wider. An incident increases the median travel time on the facility by 2 minutes over the baseline condition and, with a 95th percentile travel time of 18.7 minutes, requires travelers to add a buffer time of 9.8 minutes, almost doubling their typical commute, to arrive on time during an incident. A weather event increases the median travel time even higher, to 15 minutes, resulting in a buffer time comparable to that caused by an incident.

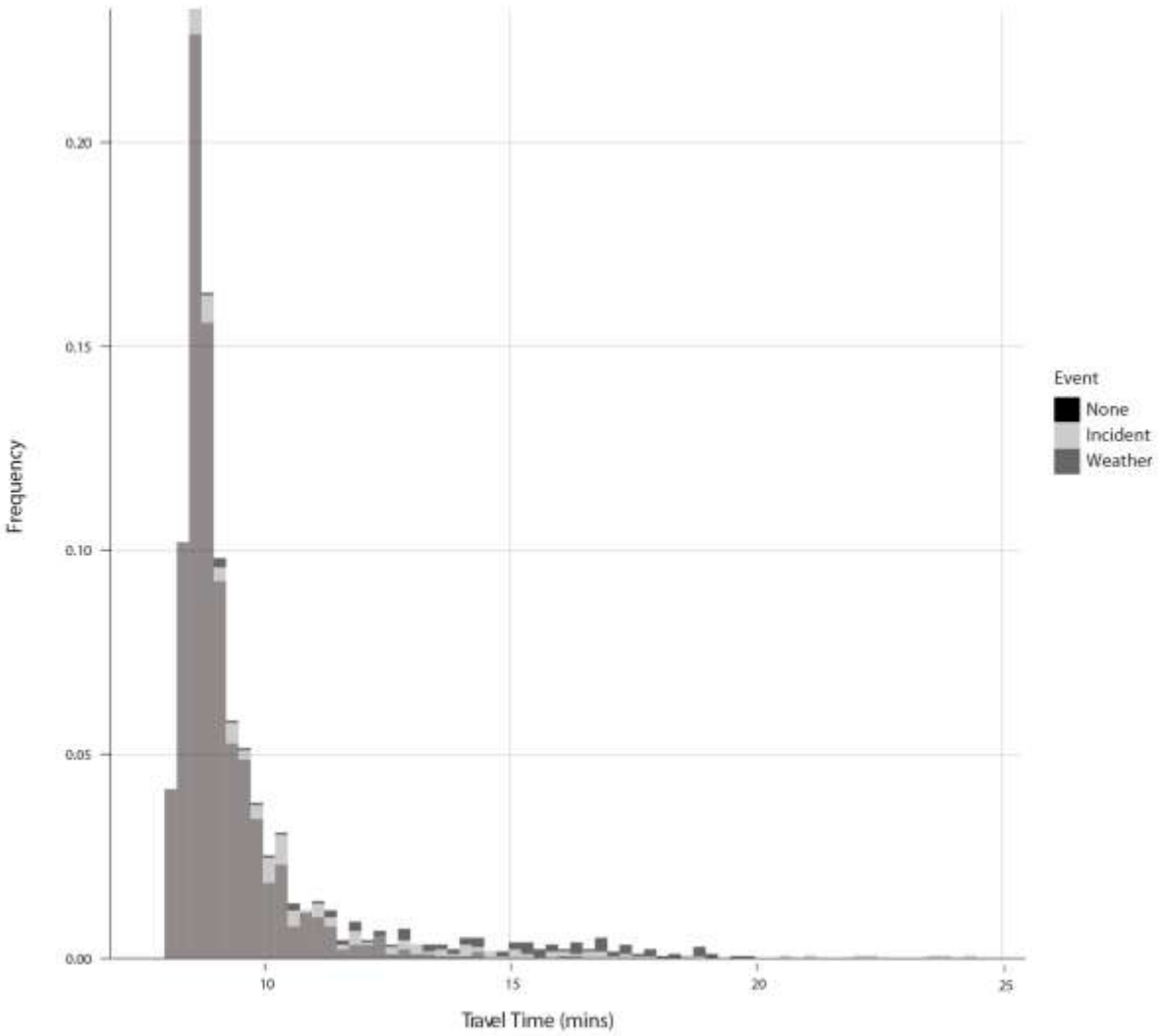


Figure 3-2: AM weekday distribution of travel times, WB I-8

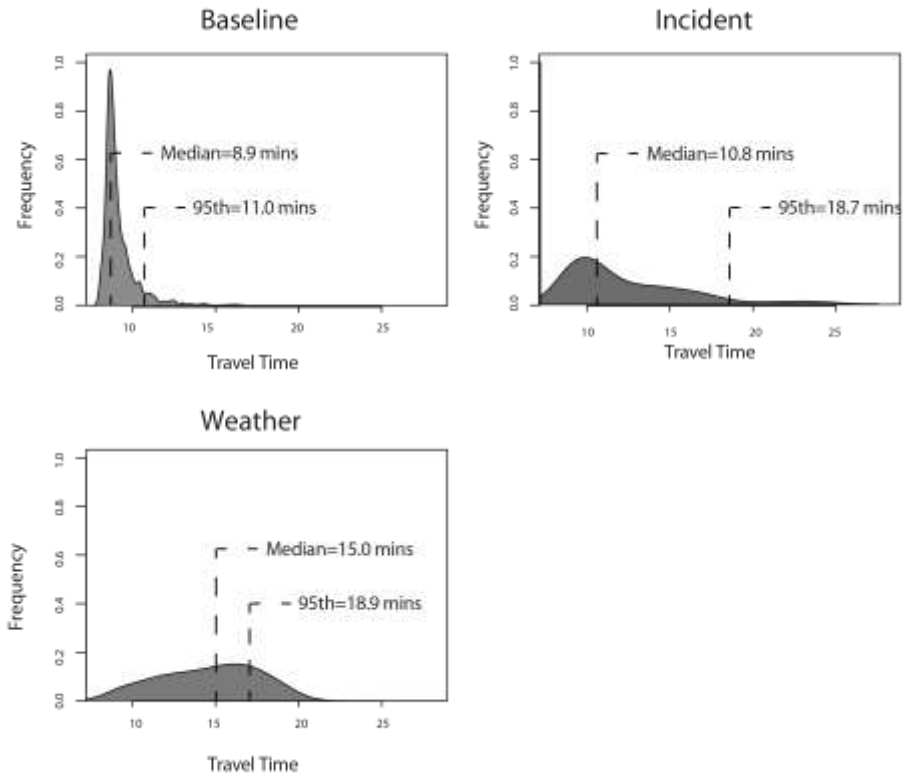


Figure 3-3: AM weekday travel time PDFs, WB I-8

A final way of summarizing this analysis is shown in Table 3-2, which lists the percentage of time that each source condition was active when travel times exceeded the 85th percentile travel time (10.6 minutes) and the 95th percentile travel time (15.0 minutes). As shown in the table, each of the three source conditions (none, incidents, and weather) occurred approximately 1/3 of the time that travel times exceeded the 85th percentile. For travel times that exceed the 95th percentile, weather is responsible for the largest share, followed closely by incidents. When the travel time exceeds the 95th percentile during the AM period on this facility, there is almost always some type of causal condition active on the roadway.

Table 3-2: AM weekday travel time variability causality, WB I-8

Source	Active when travel time exceeded 85th percentile	Active when travel time exceeded 95th percentile
Baseline	37.7%	3.3%
Incident	31.2%	41.1%
Weather	30.6%	55.6%

The conclusions that can be made from the AM time period analysis are that weather almost always slows down travel times significantly. Travelers need to plan to more than double their travel time over the typical condition when it is raining on this route. Incidents have a wider range of impacts on the corridor, depending on the severity. At their 95th percentile level, incidents increase travel times by almost 10 minutes over the median condition. Given no incidents or weather on this route, travelers can expect to see a travel time less than the 14.5

minute 95th percentile. Thus, when no non-recurrent sources of congestion are active, travelers need only add a buffer time of 5.5 minutes to arrive at their destination on-time.

PM Peak. The same analysis was also conducted for the PM peak period. The travel time variability source analysis for the PM period includes two factors that were not active during the morning: special events and high demand. There were three special events active on this corridor over the study period: one San Diego Chargers Monday Night Football game and two college football games. All three events took place at Qualcomm Stadium. Additionally, there were three time periods over the study date range that experienced greater than 1.1 times the normal demand level that were unrelated to special events. The breakdown of travel times by source is shown in Figure 3-4. Since the majority of traffic on this route commutes during the AM time period, the distribution of travel times during the PM period is small: there is a difference of only 0.7 minutes between the median travel time and the 95th percentile travel time. Travel times exceeding the 95th percentile have contributions from multiple factors. Travel times between 10 minutes and 12 minutes appear to be predominately caused by precipitation. Travel times exceeding 12 minutes appear to be caused by incidents or special events. The travel times measured during high demand time periods do not vary significantly from the median travel time.

Figure 3-5 shows the different PDFs for the five source conditions active during the PM period over the four months. At a glance, it is clear that the baseline and high demand event conditions have very tight, similarly shaped distributions, with less than a minute difference between the median and 95th percentile travel times. The lack of variability impacts of high demand is likely because the baseline volume is low enough during this time period that increasing it by 10% has minimal traffic impacts. While special events are rare on weekdays on this route, they can have a significant travel time impact when they do occur. The large difference between the median special event travel time and the 95th percentile special event travel time is likely due to the uncertainty of determining when the special event's travel time impacts would occur during the data tagging process. The 16.2 minute 95th percentile travel time likely represents the short time period when the majority of people are trying to access the special event venue, and the faster special event travel times are likely from the periods further before the event start when attendees are just beginning to trickle in. The impacts of incidents during the PM period are similar to those in the AM period, though the travel time variability impact of incidents is larger during the heavier morning commute. The PDF for the weather condition is of a different shape and a smaller distribution than it is in the other two time periods. This is possibly due to smaller amounts of precipitation in the PM period that were noted during the data collection process.

Table 3-3 summarizes the contribution of each source condition to travel times exceeding the 85th percentile (8.9 minutes) and the 95th percentile (9.2 minutes). The 85th percentile travel time is very close to the median travel time, so there are many cases when the travel time exceeds the 85th percentile but no causal source is occurring. However, when travel times exceed the 95th percentile, there is a weather event 50% of the time and an incident 30% of the time. The contribution of the other factors to high travel times is low, due to the fact that they are infrequent.

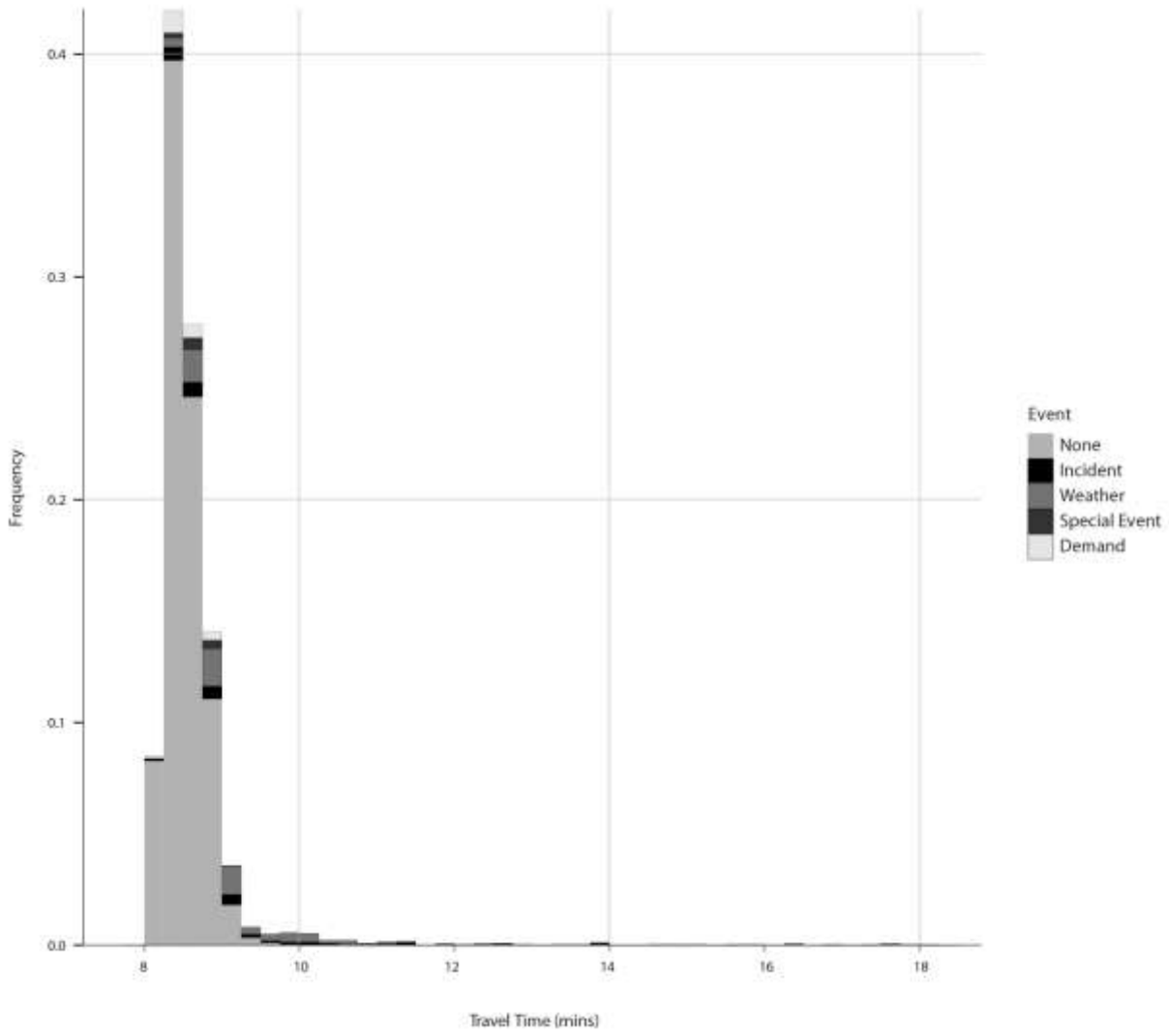


Figure 3-4: PM weekday distribution of travel times, WB I-8

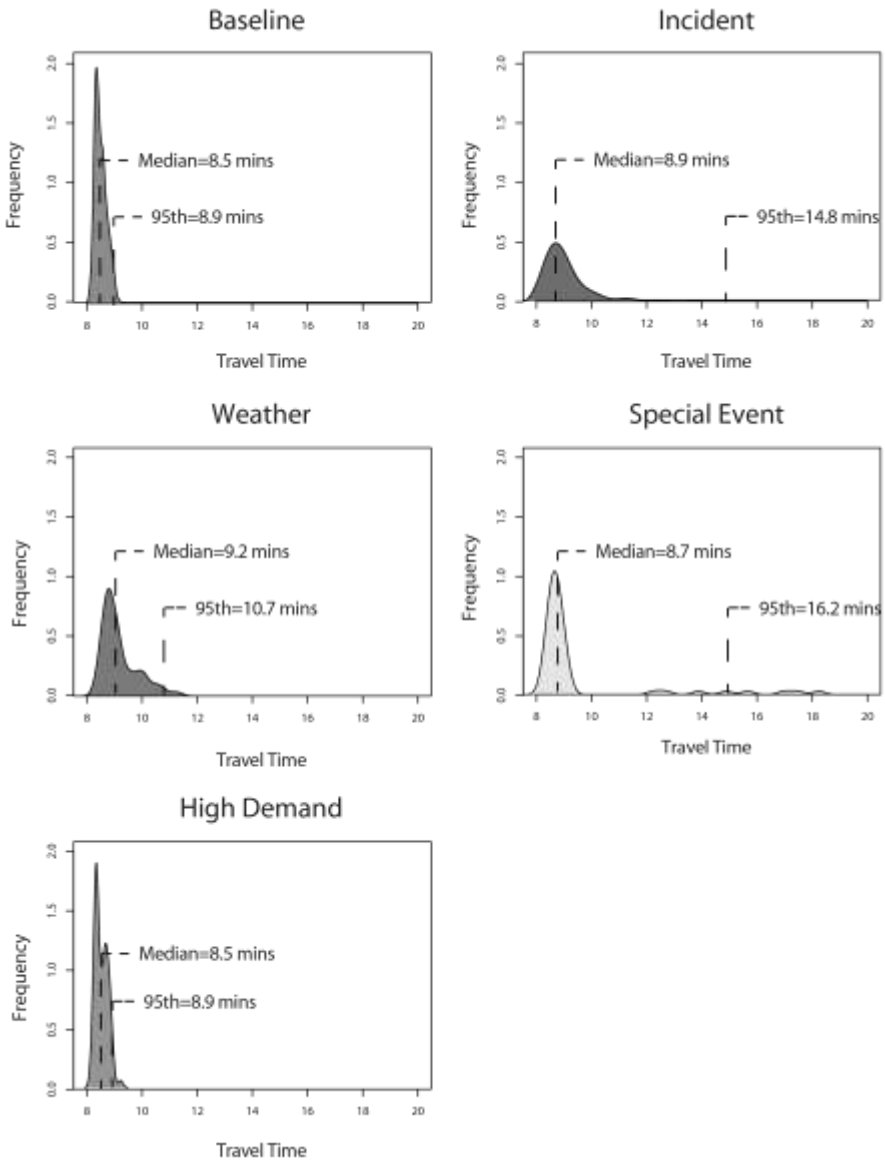


Figure 3-5: PM weekday travel time PDFs, WB I-8

Table 3-3: PM travel time variability causality, WB I-8

Source	**Active when travel time exceeded 85th percentile**	**Active when travel time exceeded 95th percentile**
Baseline	59.7%	15.2%
Incident	13.4%	29.8%
Weather	22.4%	50%
Special Event	3.6%	4.5%
High Demand	1.0%	0.6%

Synthesis. From a planning and operational standpoint, the only room for reliability improvement on this route exists during the AM period, as this is the only time period where substantial travel time variability exists. While little can likely be done to reduce the variability caused by weather, focusing on better incident response or incident reduction methods could reduce the overall variability on the facility, which currently requires travelers to add a buffer time of 5.6 minutes (63%) to their AM commute to consistently arrive on time. In the other two time periods, travel time variability is minimal and the travel time impact of incidents is less severe than in the AM.

From a traveler perspective, this analysis provides insight into the range of conditions that can be expected given certain events. For instance, weather appears to slow down travel times across all time periods. It may prove useful to provide information to travelers on the travel times that they can expect to experience during rainy conditions, so that they can appropriately plan for an on-time arrival or defer a trip until conditions improve. Additionally, special events, when they occur, cause travel times to more than double on this route. In these instances, operators may want to consider providing information for alternate routes so that through-travelers can avoid the event-based congestion.

Route 2 Results

For the northbound I-5 route, travel time variability and its contributing factors were investigated for weekends during the entire year of 2009. Data on incidents, weather, lane closures, special events, and demand fluctuations were collected from PeMS and external sources as described in the Methods section. Due to the preference of scheduling freeway lane closures during overnight, weekend hours, no lane closures were active on the route during the selected hours and date range. As a result, the contribution of lane closures to travel time variability on this route is zero. The contributions of the factors to travel time variability were investigated for two different time periods, which corresponded to observed traffic patterns on the facility: (1) Morning, 8:00 AM-12:00 PM; and (2) Afternoon, 12:00 PM-9:00 PM.

Morning. Figure 3-6 shows the distribution of travel times during the weekend morning hours on northbound I-5. There is very little spread in the travel times measured on this corridor during the AM period; there is only a difference of one minute between the median and 95th percentile travel times. The travel times exceeding the 95th percentile predominantly occurred under incident and weather conditions. There were a number of high demand time periods on this corridor, when VMT exceeded 1.1 times the average VMT for weekend mornings, especially during the summer months due to increased beach traffic. However, travel times during high demand time periods never exceeded the 95th percentile, so the demand increases in the morning are typically not significant enough to cause severe congestion. There were no special events recorded during the morning hours of the study period.

Figure 3-7 illustrates the travel time PDFs that were assembled for each source condition. The baseline and weather PDFs have a very small distribution. The lack of travel time variability during weather conditions is likely related to the fact that there were only a few weekend days of precipitation over the study year, and the precipitation was relatively light during those days. The high demand PDF has a longer tail, showing that enough demand can cause slower travel times on this facility. Incidents appear to have the biggest impact on travel time variability during the AM hours, requiring motorists to add a buffer time of 8.5 minutes to the typical travel time

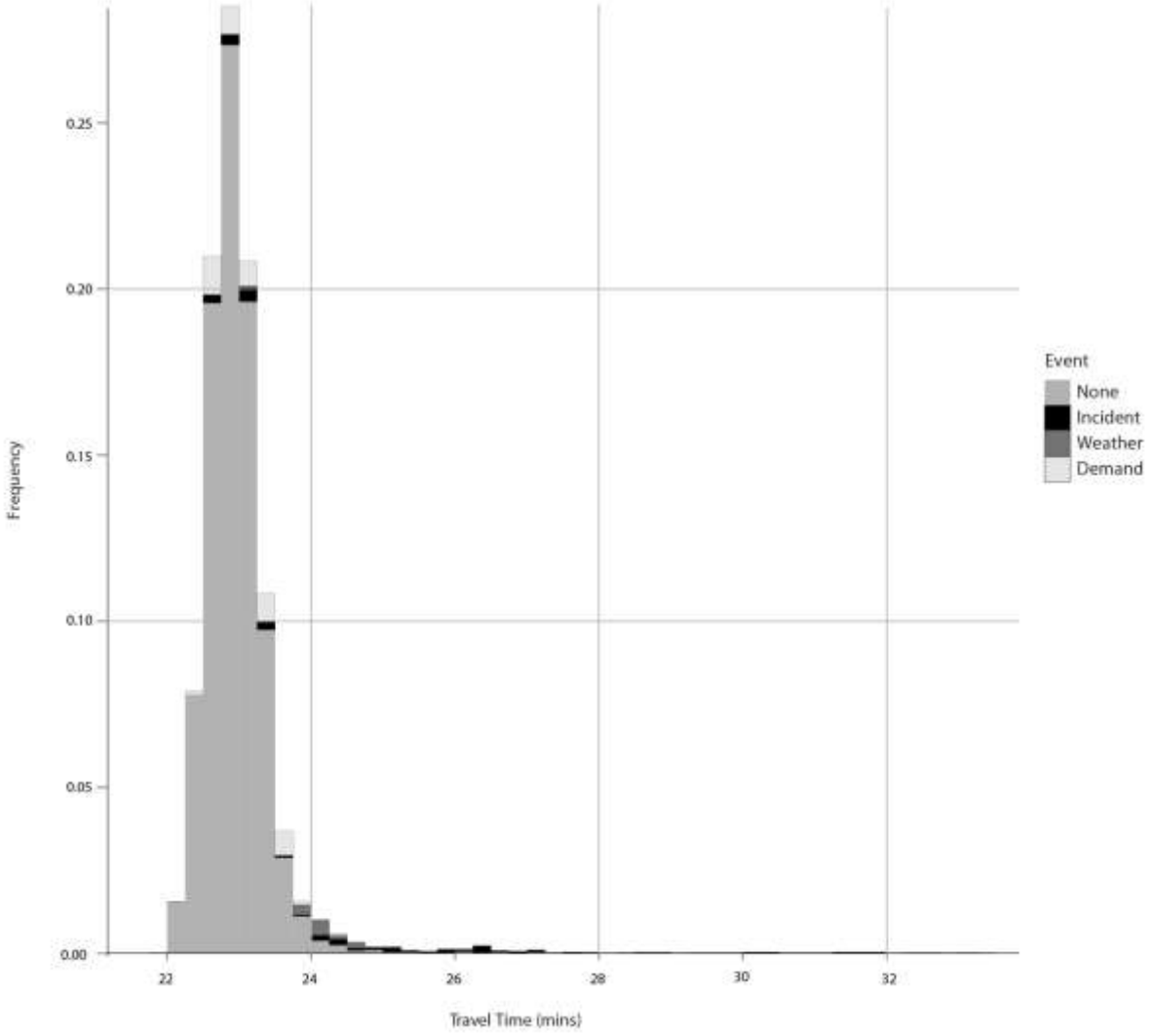


Figure 3-6: Weekend morning distribution of travel times, NB I-5

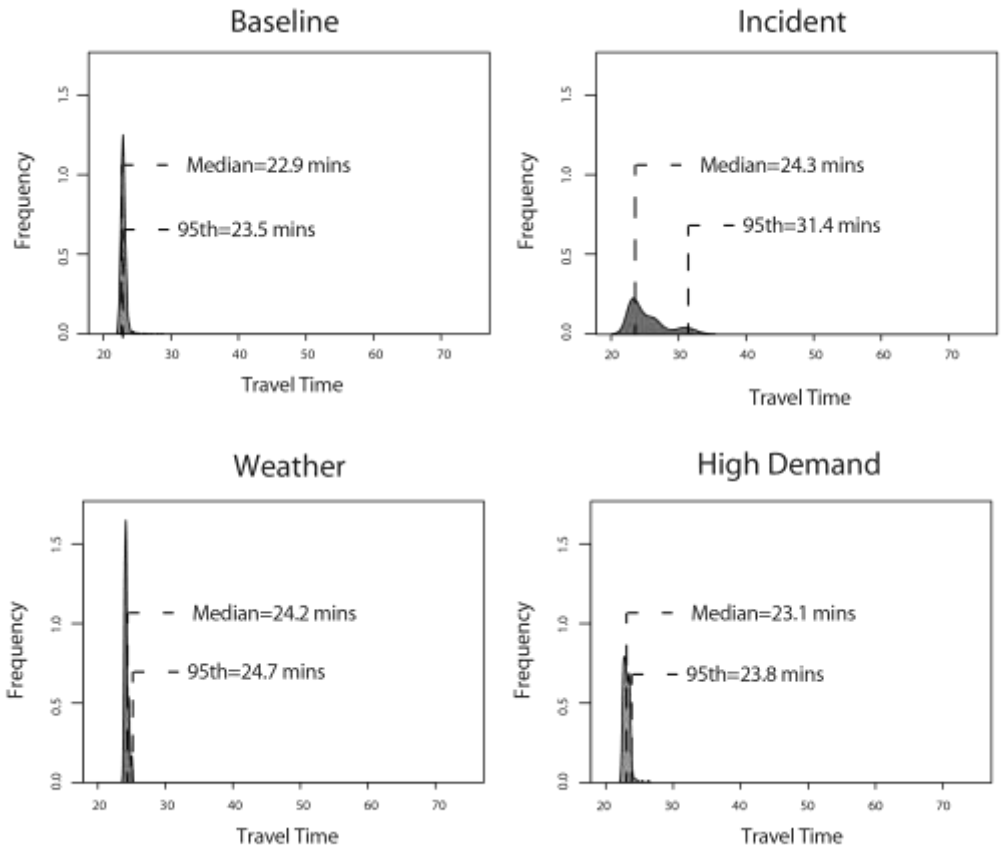


Figure 3-7: Weekend morning travel time PDFs, NB I-5

Finally, Table 3-4 summarizes which source conditions were active when travel times exceeded the 85th and 95th percentile travel times on this route. While the high percentages for the baseline condition indicate that the sources of congestion cannot explain much of the variability, the variability on this route is very low. As such, it is conceivable that a number of travel times that would be considered typical for the corridor are falling outside of the 95th percentile threshold.

The results of the weekend morning analysis show that travel conditions remain relatively uniform throughout the year, though some variability is caused by incidents and rare levels of high demand.

Table 3-4: Weekend morning travel time variability causality, NB I-5

Source	**Active when travel time exceeded 85th percentile**	**Active when travel time exceeded 95th percentile**
Baseline	79.5%	64.2%
Incident	11.3%	20.9%
Weather	0.4%	0.1%
High Demand	6.5%	8.8%

Afternoon. Figure 3-8 shows the distribution of travel times by source condition during weekend afternoons and evenings on northbound I-5. As compared with the morning, the PM

travel time distribution has a significantly longer tail, with travel times ranging from 23.5 minutes free-flow to over 70 minutes, which occurred during a special event. Travel times exceed the 95th percentile travel time under various source conditions: in particular, incidents and special events. The special events considered in this analysis were the San Diego County Fair and the Del Mar horse races. Both events are active on multiple days during the summertime and are known to have major impacts on corridor traffic.

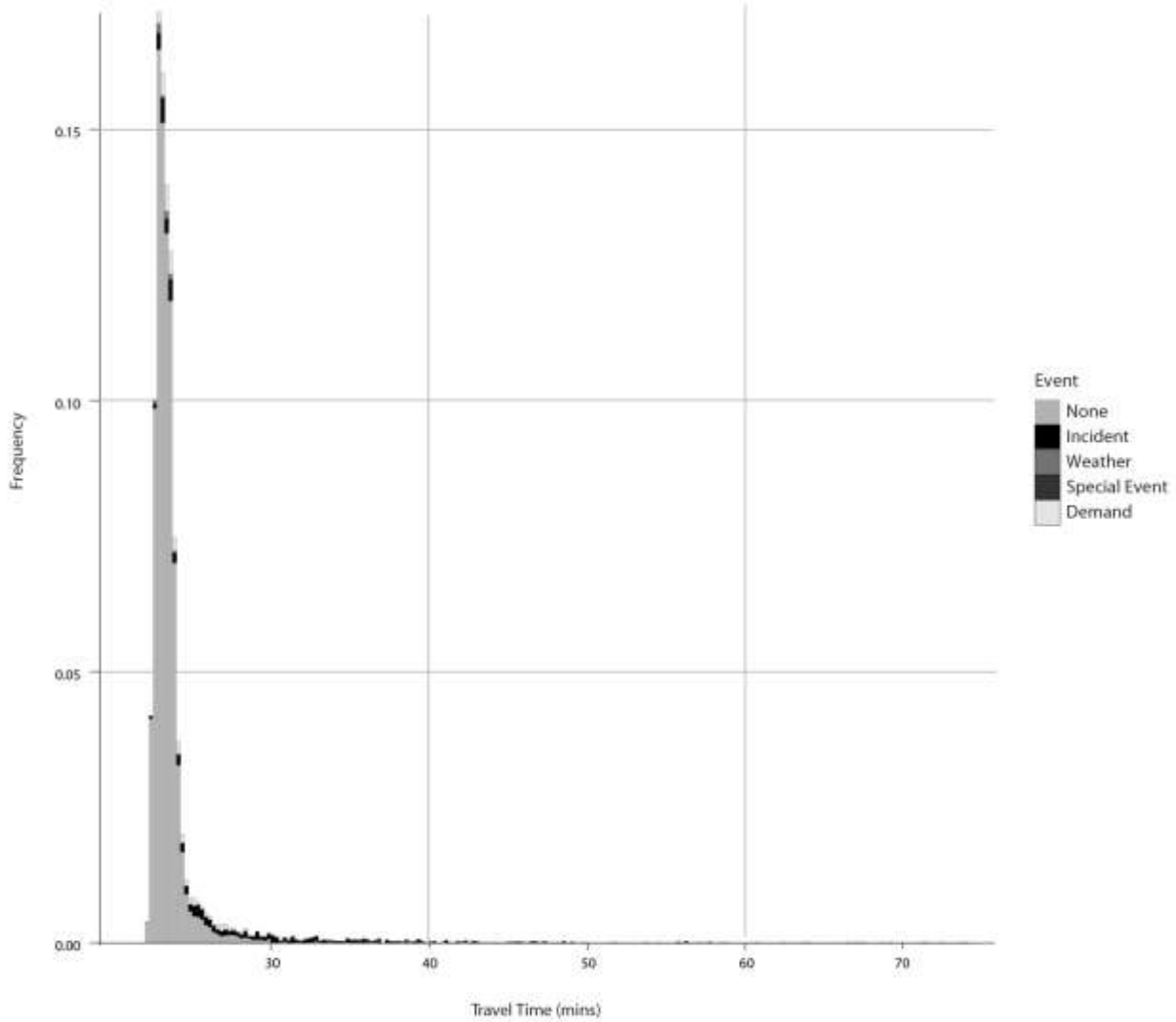


Figure 3-8: Weekend afternoon distribution of travel times, NB I-5

Figure 3-9 illustrates the different travel time PDFs assembled for the various source conditions that occurred on weekend afternoons on this study corridor. Similar to the morning time period, the PDFs for the baseline condition and the weather condition show little travel time variability. The weather events recorded over the study period were very minor, which might explain the difference in weather variability impacts between this corridor and the westbound I-8 corridor analyzed previously in this use case validation. High demand unrelated to any specific special event has the potential to increase travel times, but only in extreme circumstances; the typical demand fluctuations on the corridor incur only minor variability impacts. The sources that cause the most travel time variability are incidents and special events. The median travel time

during an incident is three minutes higher than the normal median travel time, and can be almost double the free-flow travel time at the 95th percentile level. On this corridor, special events are the source that has the potential to cause the highest travel time variability. Though they are relatively infrequent in that they are concentrated in the summer months, the median travel time during a special event requires an additional travel time of 15 minutes, a 64% increase over the ordinary median travel time. The 95th percentile travel time during a special event requires a buffer time of 45 minutes over the normal median travel time, requiring travelers to almost triple their typical travel time during this time period.

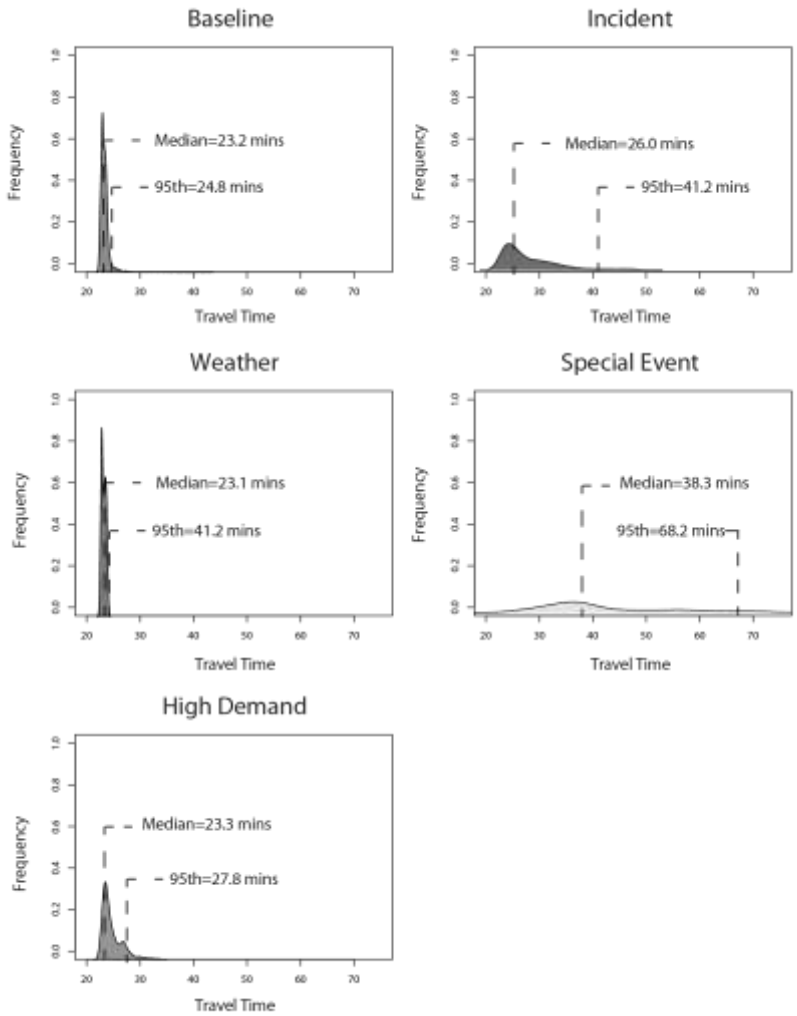


Figure 3-9: Weekend afternoon travel time PDFs, NB I-5

Finally, Table 3-5 summarizes which source conditions were active when travel times exceeded the 85th percentile and 95th percentile travel times on the route. Incidents and special events appear to be responsible for the majority of travel times that exceed the 95th percentile.

Table 3-5: Weekend afternoon travel time variability causality, NB I-5

Source	**Active when travel time exceeded 85th percentile**	**Active when travel time exceeded 95th percentile**
Baseline	51.4%	20.2%
Incident	29.1%	48.2%
Weather	0.0%	0.0%
Special Event	8.8%	25.3%
High Demand	10.8%	6.3%

Synthesis. The morning weekend travel time variability on the corridor is very minor, leaving little room for improvement from planning or operational interventions. The afternoon period, however, has significant travel time variability. This variability is predominantly caused by incidents throughout the year and by high demand and special events during the summer months. Because special events can cause such extraordinary travel time variability (causing travel times to double or triple the typical travel time on the route), traveler information during these event time periods is key. Diverting through traffic whose destination is not the event to alternate routes, or encouraging them to travel when the event is not active, could help mitigate the variability caused by these events.

Conclusion

This use case analysis illustrates one potential method for linking travel time variability with the sources of congestion. The methods used are relatively simple to perform with data that is generally available, either from the travel time reliability monitoring system or from external sources. The application of the methodology to the two study corridors in San Diego reveals key insights into how this type of analysis should be performed. Firstly, to ensure that sufficient travel time samples within each source category are being captured, this analysis should be performed on no less than three month's worth of data. It also should be performed separately for different days of the week, depending on the local traffic patterns. For example, the magnitude of the contributions of the sources to travel time variability on the northbound I-5 study corridor would likely be very different on weekday afternoons, when the corridor is serving commuters, than on weekend afternoons, when the corridor is serving recreational and event traffic. Additionally, it is important to consider the seasonal dependence of the congestion factors when selecting the time period for analysis, and when reviewing the analyses. For example, weather was shown to be a large contributing factor to travel time variability on the westbound I-8 corridor because the study period was November through February. If the analysis period was over the summer, the contribution of weather to travel time variability on this corridor would be nearly zero, as San Diego receives virtually no precipitation outside of winter. Finally, the contributions of the sources should be analyzed separately by time of the day, in a manner consistent with local traffic patterns. For example, while incidents had a major impact on the median travel time and the planning time during the AM commute period on the westbound I-8 study corridor, they had little variability impact during other parts of the day. Elucidating the time-dependence of the factors is critical to providing outputs that can be used by planners and engineers to improve the reliability of their facilities.

Use Case 2: Using planning-based reliability tools to determine departure time and travel time for a trip.

Summary

The purpose of this use case is to demonstrate how a reliability monitoring system can help travelers better plan for trips of varying levels of time-sensitivity. Currently, most traveler information systems that report travel times to end users focus solely on the average travel time, and give users little insight into the variability of their travel route. While this may be fine for trips with a flexible arrival time, it is less useful for trips for which the traveler must arrive at the destination at or before a specified time (such as a typical morning commute to work). This use case demonstrates how a reliability monitoring system can provide information both on the average expected travel time and the worst-case planning travel time so that the user can choose a departure time commensurate with their need for an on-time arrival. It also helps users choose between alternate routes; whereas one route may offer a faster average travel, it may have more travel time variability than a parallel route that is slower on average but has more consistent travel times.

Users

This use case is of most value to travelers, who are the end consumers of information that informs on the average and planning travel times for alternate routes between selected origins and destinations. The analysis behind this use case is also of value to operators, who can post estimated average and planning travel times throughout the day on variable message signs, to help travelers on the road choose between different routes based on their need for an on-time arrival.

Scope

The use case validated in this section is broad and could provide a wide range of travel time reliability metrics to end users in a number of different formats. To narrow down the scope of this use case for validation purposes, this section will explore the specific use case defined below:

> *The user wants to view, for alternate routes, the latest departure times needed to arrive to a destination at 5:30 PM on a Friday: (1) on average and (2) to guarantee on-time arrival 95% of the time.*

This definition means that the system needs to provide, for each alternate route, the median travel time and planning time for trips traveling between 5:00 PM and 5:30 PM on Fridays. It is envisioned that this use case involves the traveler utilizing the monitoring system for information in advance of a trip, likely from a computer, although other applications and dissemination methods are possible.

Site

Three alternate routes, which travel from just south of the I-5/I-805 diverge near La Jolla and Del Mar to the US Naval Base in National City, south of downtown San Diego, are studied in this use case. The three routes are shown in Figure 3-10. Route 1 is approximately 17 miles long and travels only along southbound I-5. Route 2 is approximately 16 miles long and travels along southbound I-805, southbound I-15, and southbound I-5. Route 3 is also 16 miles long and travels along southbound I-805, southbound SR-163, and southbound I-5.

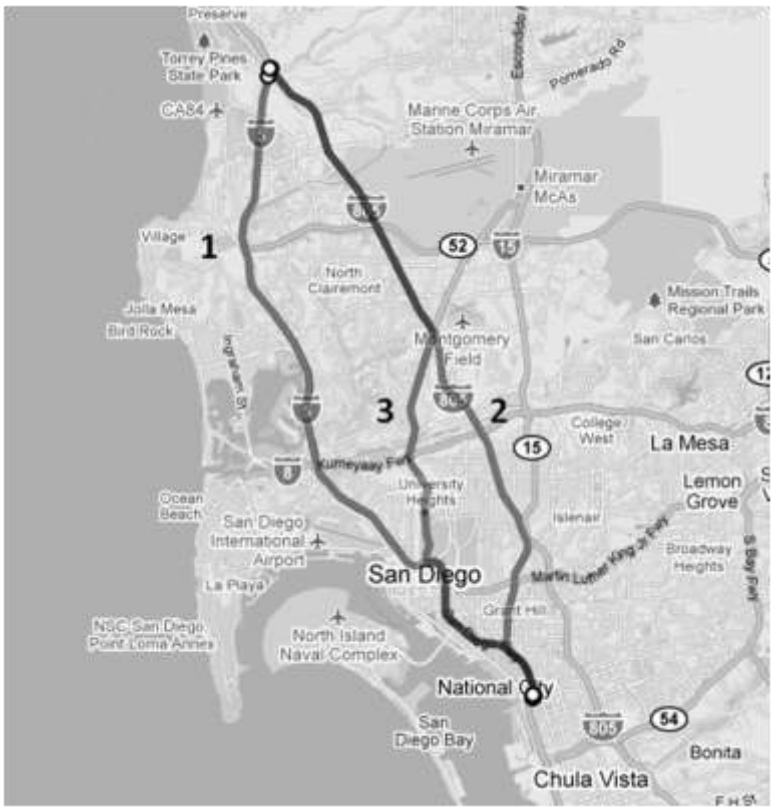


Figure 3-10: Freeway Use Case 2 Alternate Routes

Methods

The state of the practice for the few agencies who currently report travel time reliability metrics through their traveler information systems is to compute them from travel time probability density functions (PDFs) assembled based on the time of day and day of the week of the trip for which information is being requested. For example, to give a user the average and 95th percentile travel time for a Wednesday afternoon trip departing at 5:30 PM, the system might obtain all of the travel times for trips that departed between 5:15 PM and 5:45 PM for the past 10 weekdays.

The time-of-day and day-of-week approach to travel time reliability is valid and is used to validate multiple use cases at the San Diego site. However, this use case evaluation incorporates the work that the research team has conducted into categorizing a route's historical and current performance into "regimes", and assembling travel time PDFs based on similar regime designations. Regimes are a way of categorizing travel times based on the prevailing operating condition when the travel time was measured. Regimes can be considered an extension of the time-of-day approach to reliability; on most corridors, regimes typically have a strong relationship with the time of day of travel. For example, a route that travels from a suburb to a downtown area may have four different operating regimes on weekdays: (1) a severely congested regime during the AM peak; (2) a mildly congested regime during the midday period; (3) a moderately congested regime during the PM peak; and (4) a free-flow regime that occurs during the middle of the night. There may also be "transitional" regimes that are observed when a route switches from congested to uncongested. Weekends may only have a free-flow regime and a slightly congested regime. An example regime assignment for a route that has five weekday regimes and two weekend regimes is shown in Figure 3-11. As is evident from this

figure, regimes are closely related to the time-of-day, but help capture the variability in operating conditions that occur across different days of the week, as well as to show the similarity in operating conditions across certain hours of the day.

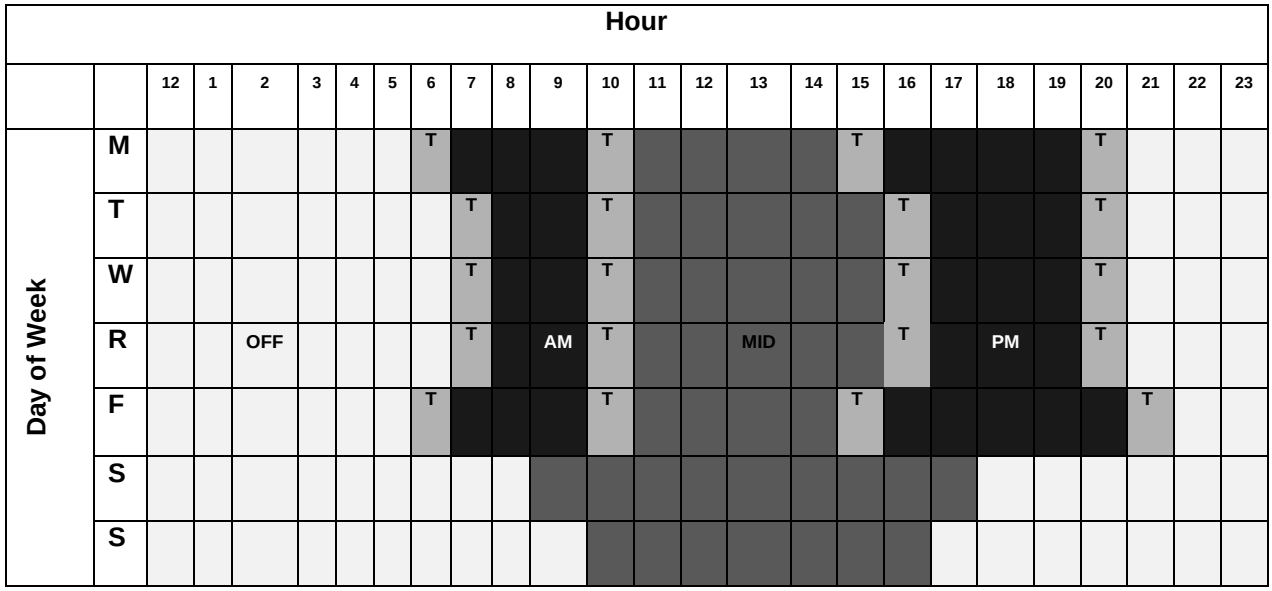


Figure 3-11: Example regime assignment for a route

Regime assignment is addressed in the Methodological Advances chapter of this case study, and the team is further refining its regime assignment methodologies. In this use case validation, each route is assigned a regime for each 5-minute time period of each day of the week. Routes are categorized into one of four regimes (free-flow, slightly congested, moderately congested, and severely congested) based on the ratio of the average travel time during the time period to the free-flow travel time, otherwise known as the travel time index (TTI). This metric was selected for regime identification because it is travel time-based and groups sets of travel times based on similar baseline operating conditions and levels of congestion, rather than a strictly time-of-day based categorization.

Following the regime identification process, travel times are assembled into regime-based PDFs based on the time of day and day of week of the traveler's request for trip information. From these PDFs, average travel times and planning times are computed and used to generate required departure times for each route based on the time-sensitivity of the trip.

Validation

The validation consists of three steps: (1) regime identification; (2) PDF generation; and (3) user output.

Regime Identification. In this use case, the travel time PDFs used to calculate reliability metrics for alternate routes are assembled based on regime conditions. In a travel time reliability monitoring system, this regime assignment step would be done prior to the user making the request for travel time information for alternate routes. For the three alternate routes, regime assignments were made for each day of the week type, based on local traffic patterns. The five day of week types selected for separate regime classifications were: (1) Monday; (2) Mid-week days (Tuesday, Wednesday, Thursday); (3) Friday; (4) Saturday; and (5) Sunday. Each 5-minute period of each day of the week type was assigned to a regime based on average TTI during that time-period. Average TTIs for each time period were calculated using 6 months of 5-

minute travel time data (excluding holidays). The breakdown of regimes by TTI is shown in Table 3-6. These TTIs were selected by assuming a free-flow speed of 65 mph, then assuming that average speeds less than 40 mph represent severely congested conditions, speeds between 40 and 50 mph represent moderately congested conditions, and speeds greater than 60 mph represent slightly congested conditions. Other routes in other regions may need different thresholds or numbers of regimes to accurately capture the varying levels of congestion along an individual corridor.

Table 3-6: Regimes by travel time index

Regime	TTI	Color	Route 1 Travel Time	Route 2 Travel Time	Route 3 Travel Time
Free-flow	<1.1		<15.6 mins	<13.4 mins	<15.4 mins
Slightly congested	1.1-1.3		15.6-18.5 mins	13.4-15.8 mins	15.4-18.2 mins
Moderately congested	1.3-1.6		18.5-22.7 mins	15.8-19.5 mins	18.2-22.4 mins
Severely congested	>1.6		>22.7 mins	>19.5 mins	>22.4 mins

The connection between regimes and travel times for each of the three study routes is shown in Table 3-6. The colors in the table correspond with the regime assignments by day of week type for each of the routes, shown in Figure 3-12, Figure 3-13, and Figure 3-14. While the regime assignments in these tables are shown for each 20-minute time period, regimes were actually assigned to each 5-minute time period.

The regime assignment allows for a comparison of the average performance by day of week and time of day on each of the three different routes. The free-flow travel times on each route are fairly comparable. Route 2 is the shortest route and has the fastest free-flow travel time (12.2 minutes). Route 1 and Route 3 are of comparable length; Route 1 has a slightly faster free-flow travel time (14 minutes) than Route 3 (14.2 minutes). Analysis of the regime tables shows that the duration of congestion on Route 1 is much narrower than it is on the other route, and there is only severe congestion right around the 5:00 pm hour during the midweek days. The duration of congestion on Route 2 is very wide; it lasts throughout the midday, is severe during the 5:00 PM hour on the midweek days, and is severe beginning at 4:00 PM on Friday. Route 3 is the only one of the routes to have AM congestion throughout the work week. It is also the only one of the routes to have weekend congestion, possibly because it traverses through San Diego's Balboa Park, a popular tourist destination. Congestion is severe on Route 3 Tuesday-Friday during the 5:00 PM hour.

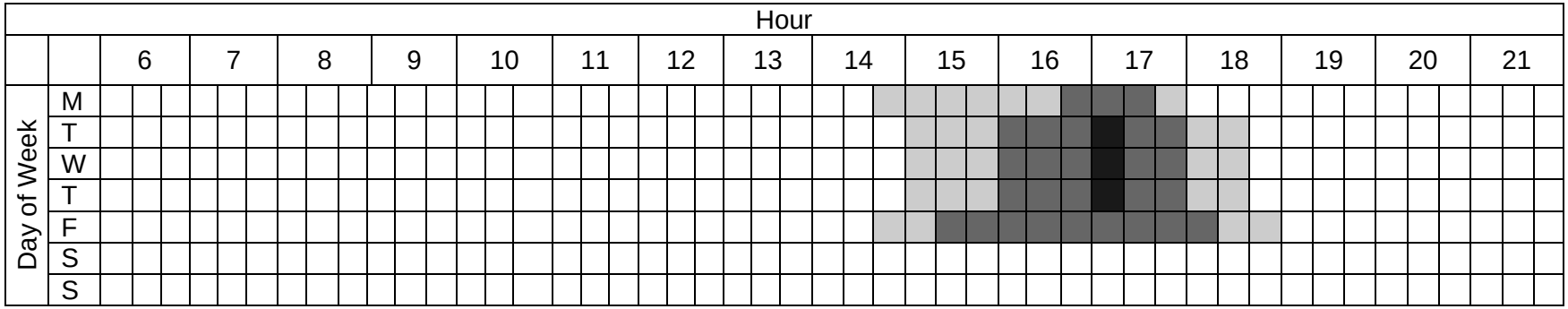


Figure 3-12: Route 1 (southbound I-5) regimes

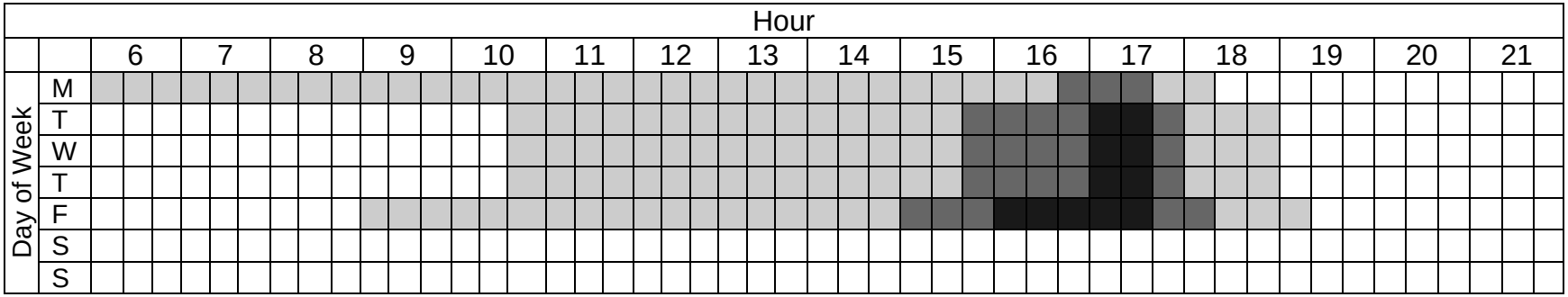


Figure 3-13: Route 2 (southbound I-15) regimes

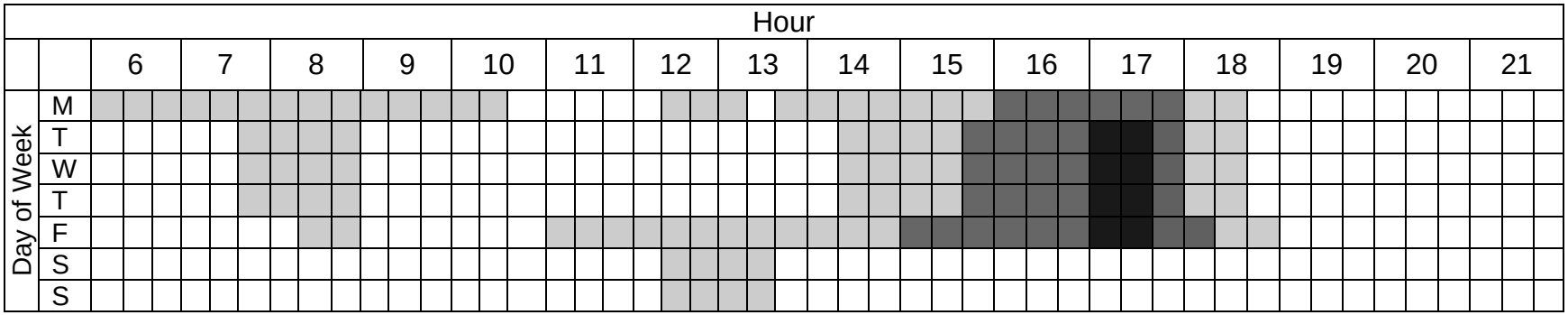


Figure 3-14: Route 3 (southbound SR-163) regimes

PDF Generation. While regime assignments are made off-line, this validation assumes that the regime-based PDFs are assembled in real-time, in response to a user's request for information. Future work by the research team will develop methods for creating PDFs off-line and storing them in advance of a user query, to reduce the need for real-time computation.

This validation assumes that the user wants to know the average and planning departure times for three different routes that allow for arrival at 5:30 PM on a Friday to the destination. As such, PDFs are generated for each of the three routes' operating regimes during the Friday 5:00 PM hour. The regime matrices show that Route 1 is in the moderately congested regime and Routes 2 and 3 are in the severely congested regime during this time period. As such, this validation effort generates travel time PDFs for each route using all of the travel times within the same regime category measured on Fridays over the past six months. An alternate method is to generate PDFs based on travel times within the same regime category measured on *any* day. In this case, since 6 months of data were used to form the PDFs, it was determined that Friday data alone would generate sufficient travel time data points to form an accurate PDF.

The plots of each PDF are shown in Figure 3-15. Route 1 appears to have the smallest distribution of travel times during this time period; the most frequently occurring travel time is around 20 minutes. Route 2 has significantly more travel time variability during this time period; while the most frequently occurring travel times on Friday during severe congestion are around 18 minutes, the travel time PDF has a long tail end, and travel times upward of 30 minutes can occur. The most frequently occurring travel time on Route 3 is approximately 24 minutes, and the route has significant travel time variability on Fridays.

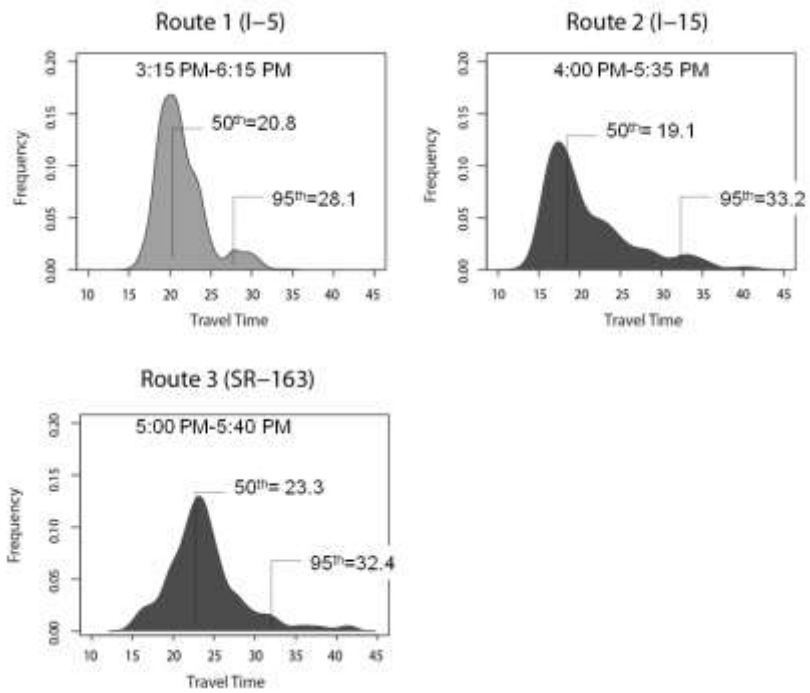


Figure 3-15: Alternate route travel time PDFs, 5:30 PM trip

User Outputs. In this step, the travel time PDFs are generated into useful summary metrics to assist the user in itinerary planning. In this case, the goal is to provide the user the departure times needed to arrive on-time on average and with a buffer time along each route. The median and planning travel times on each route during the user's desired time of travel are summarized in Table 3-7. Route 2 has the fastest median travel time, but this route also has significant travel time variability, requiring a traveler with a non-flexible arrival time to add a buffer time of 14 minutes to the median travel time to ensure on-time arrival 95% of the time. Route 1 is almost 2 minutes slower than Route 2 on average, but offers significant (5 minutes) time savings when variability is included. Even Route 3, which has a much slower median travel time than the other two routes, has a faster planning time than Route 2.

Table 3-7: Median and planning travel times along alternate routes

Route	Median Travel Time (mins)	Planning Travel Time (mins)
Route 1 (I-5)	20.8	28.1
Route 2 (I-15)	19.1	33.2
Route 3 (SR-163)	23.3	32.4

Table 3-8 synthesizes these travel time estimates into information that is of most use to the end user- recommended departure times. These departure time estimates are termed "departure time for 50% on-time arrival" and "departure time for 95% on-time arrival" to help the user plan the trip with consideration of the need for an on-time arrival. Other applications of this use case could provide departure times calculated from other reliability metrics, such as the 85th percentile travel time rather than the 95th, or the 99th percentile travel time for trips where on-time arrival is imperative.

Table 3-8: Alternate route departure time estimates

Route	Departure time for 50% on-time arrival	Departure time for 95% on-time arrival
Route 1 (I-5)	5:09 PM	**5:01 PM**
Route 2 (I-15)	**5:10 PM**	4:56 PM
Route 2(SR-163)	5:06 PM	4:57 PM

Conclusion

This use case validation illustrates the value of incorporating reliability-based travel time estimates into traveler information systems for use in advance of trips, so that travelers can plan itineraries based on their need for on-time arrival. As proven by the San Diego validation, the route that is the fastest on average is not always the route that consistently gets travelers to their destination on-time. Providing buffer time measures for alternate routes conveys this message to the end user, ultimately giving them more confidence in the ability of the transportation system to get them to their destination on-time.

Use Case 3: Combining real-time and historical data to predict travel times in real-time

Summary

The purpose of this use case is to extend the system capabilities described in the freeway planning time use case in order to support the prediction of travel times along a route in real-time, using both historical and real-time data. While a number of methods for performing this data fusion to predict travel times have been implemented in practice, most only generate a single expected travel time estimate. This use case validation extends the methodology to generate, in addition to a single expected travel time, a range of predictive travel times that incorporate the measured historical variability along a route.

Users

This use case if of the most value to travelers, who currently lack quality real-time information on expected travel times while en route to a destination. The analysis behind this use case is also of value to operators, who can use these methodologies to provide better predictive travel times to post on variable message signs or via other dissemination technologies.

Scope

This use case validation describes methodologies for predicting near-term travel time ranges along a route. Specifically, it predicts travel time ranges for a 5:35 PM Thursday trip for two alternate routes.

Site

Two of the same alternate routes used to validate freeway use case 2 (alternate route planning times) were used to validate this predictive travel time use case. Both routes begin just south of the I-5/I-805 diverge and end near the United States Naval Base in National City. The first route, called the I-15 route, travels along southbound I-805, southbound I-15, and southbound I-5. The second route, called the I-5 route, travels solely along I-5. Maps of these two routes are shown in Figure 3-16.

Southbound I-15 Route

Southbound I-5 Route

Figure 3-16: Freeway Use Case 3 alternate routes

Methods

Per the use case requirements, the validation needs to use both data from the historical archive as well as real-time data to generate travel time predictions for trips that are already occurring or are to begin immediately. To meet these requirements, a "nearest neighbors" approach was adopted, which uses the measured real-time conditions along a route to search for similar conditions in the past, then predicts a travel time based on historical travel times measured under similar conditions. Similar approaches have been well-documented in literature, and a nearest neighbors approach is currently used in PeMS to predict travel times along a route for the rest of the day *(1, 2)*. The method used in this validation extends upon traditional techniques to incorporate reliability information; instead of providing one predictive travel time, this use case validation outputs a range of predictive travel times that incorporate the potential variability in travel times that may occur, as gathered from similar historical conditions. The employed methodology is only valid for near-term travel time prediction. As such, this use case assumes that predictions are only made for the next three upcoming five-minute time periods.

To estimate a real-time predictive travel time range for a route, the methodology compares travel time data collected over the past six five-minute time periods with travel time data collected over the same six time periods over the most recent 15 days of the same day of the week. In this use case, which aims to predict travel times for a 5:35 PM Thursday trip, this means that travel times measured between 5:00 PM and 5:30 PM on the current day are compared with travel times measured between 5:00 PM and 5:30 PM over the 15 most recent Thursdays.

The "nearest neighbors" to the current day are selected by comparing the "distance" between the measured five-minute travel time on the historical day with the measured travel time for the same five-minute period on the current day. The distances between travel times for different five-minute periods are weighted differently, such that similarity for the five-minute trip that immediately precedes a trip is weighted more than similarity for the five-minute trip that occurred 30-minutes before the current trip. The weighting factors used for each 5-minute period are shown in Table 3-9.

The following variables are used to explain the methodology:

T_C = current day travel time

T_h = historical day travel time

d_h=distance between current day five-minute travel time and historical day five-minute travel time

D_h=total distance between current day travel time and historical day travel times for all five-minute periods prior to a trip

x= time period prior to trip start (ranges from 1 for 5-minutes prior to 6 for 30-minutes prior)

w= weight factor

The distance d_h between the current day travel time and the historical day travel time is calculated using the following equation:

$$d_h(x) = w(x) * (T_h\ x\ - T_c\ x\ )^2$$

The total distance D_h between a current day and a historical day is calculated by summing up all the distances d_h using the following equation:

$$D_h = \overline{\sum_{x=1}^{6} d_h(x)}$$

Table 3-9: Weighting factors (w) for minutes prior to trip

Minutes Prior to Trip	Weight factor
5 (x=1)	1
10 (x=2)	½
15 (x=3)	¼
20 (x=4)	$^1/_8$
25 (x=5)	$^1/_{16}$
30 (x=6)	$^1/_{32}$

The result of the distance calculation step is a measure of travel time closeness between each historical day and the current day. From here, the method of k-nearest neighbors is followed; rather than selecting the travel time profile of the nearest day as the predicted travel time, the method considers the travel time profiles from the three nearest days in order to make a prediction. The goal of this use case is to predict a travel time range for the next three five-minute time periods. In this validation, the expected travel time for the next three time periods is computed as the median of the travel times from the three nearest neighbor days. The lower bound of the predictive range is computed as the expected travel time minus the variance of the three neighbor travel times. The upper bound of the predictive range is computed as the expected travel time plus the variance of the three neighbor travel times.

Results

The travel time prediction methodology was used to compute predictive travel time ranges for the two example alternate routes between 5:35 PM and 5:45 PM on Thursday, August 12, 2010. Because there is data on what the travel times actually were on this day, this validation has a “ground-truth” data source with which to compare the estimates generated by the selected methodology.

I-15 Route. To predict 5:35 PM to 5:45 PM travel times on Thursday, August 12, 2010, five-minute travel times between 5:05 PM and 5:45 PM were obtained for 15 Thursdays, between April 29, 2010 and August 12, 2010.

The distance calculation method was used to determine the nearest neighbors. Table 3-10 shows the travel times measured for each five-minute time period over the 15 selected days. The first row shows the travel times measured on the “current” day of August 12, and all other rows show the travel times measured on each previous Thursday. The last column shows the total distance measured between the travel times on each day and the travel times on the current day. The three shaded rows indicate the days on which the distance was lowest, which were concluded to be the most similar to the current day.

Figure 3-17 compares the travel times measured on the predicted day with those measured on the closest three Thursdays, and extends the x-axis to show the travel times on these three days for the periods of 5:35 PM, 5:40 PM, and 5:45 PM. These are the travel times from which the predictive range for the current day is to be calculated. The thick black line indicates the travel times for the current day up until 5:30 PM.

Figure 3-18 shows the results of using the median of the nearest neighbor travel times approach to make a prediction of the expected travel times for the upcoming 15 minutes, and compares these predictions to the travel times that were actually measured on this day. Table 3-11 shows this information in tabular form, and also gives the predictive travel time ranges, which account for travel time variability in the evolving traffic conditions. As shown in the table, each actual measured travel time fell within the predictive range. The expected travel times only varied from the measured travel times by 5%.

Table 3-10: Neighboring Thursday travel times on I-15

Date	5:05 PM	5:10 PM	5:15 PM	5:20 PM	5:25 PM	5:30 PM	Distance
8/12/10	28.3	28.1	27.9	26.1	25.9	24.6	--
5/06/10	17.1	18.1	18.7	18.8	18.5	17.7	10.4
5/13/10	18.6	18.0	18.4	18.6	18.1	18.3	10.2
5/20/10	18.8	19.7	19.8	19.7	18.8	18.4	9.4
5/27/10	15.6	16.5	16.9	17.0	16.9	16.4	12.5
6/03/10	28.0	27.9	28.1	27.9	27.6	26.8	2.7
6/10/10	17.5	19.1	20.1	21.0	21.0	21.0	6.9
6/17/10	18.2	19.2	19.0	19.2	18.5	17.1	10.6
6/24/10	34.8	35.0	36.0	37.4	37.0	37.4	16.5
7/01/10	24.6	25.2	25.9	24.9	24.8	24.3	1.6
7/08/10	17.5	18.2	18.4	17.1	16.1	15.7	13.0
7/15/10	15.8	16.1	16.4	16.5	16.9	16.5	12.6
7/22/10	20.7	22.0	22.4	22.5	22.6	22.9	4.4
7/29/10	20.8	20.4	20.3	20.0	20.2	19.5	8.0
8/05/10	22.9	24.5	26.2	26.4	25.7	25.1	1.6

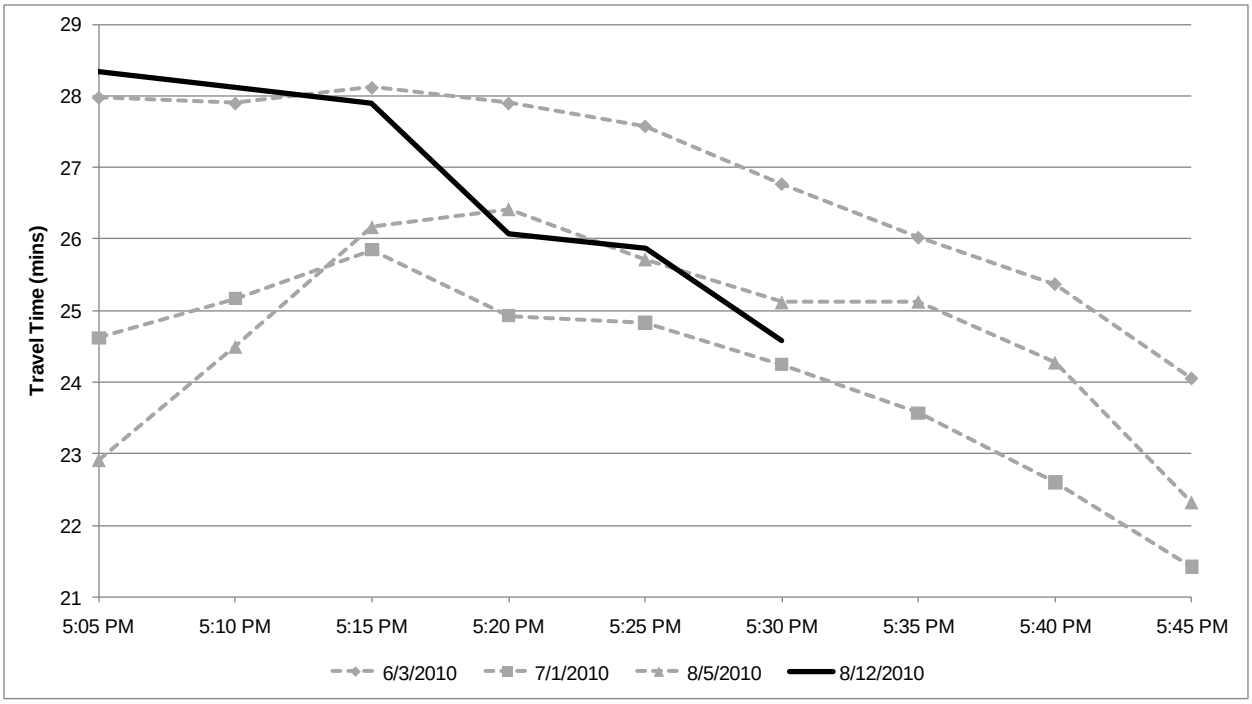


Figure 3-17: Travel time profiles of three closest Thursdays, I-15

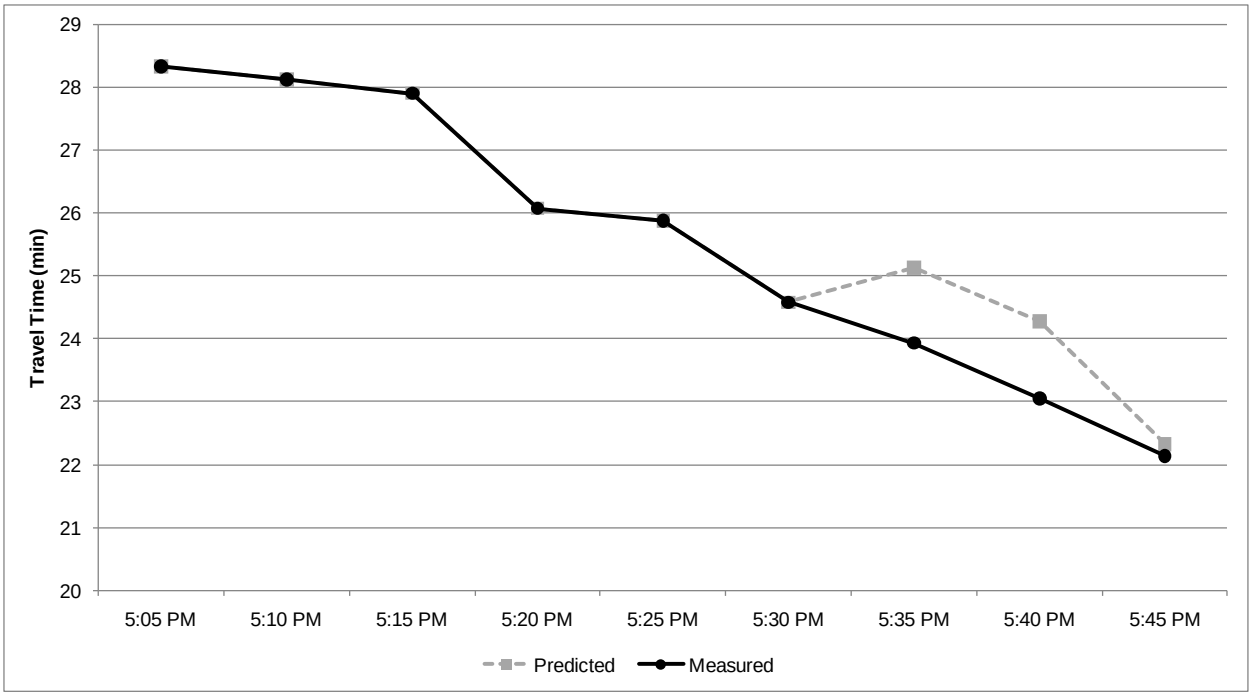


Figure 3-18: Measured and Predicted Travel Times, 8/12/2010, I-15

Table 3-11: Predicted vs. actual travel times, 8/12/2010, I-15

	5:35 PM	**5:40 PM**	**5:45 PM**
Predicted Lower Range	23.6 mins	22.3 mins	20.6 mins
Predicted Upper Range	26.7 mins	26.2 mins	24.1 mins
Predicted	25.1 mins	24.3 mins	22.3 mins
Measured	23.9 mins	23.1 mins	22.1 mins
Measured in range of predicted?	Yes	Yes	Yes
% difference between predicted and measured	5.0%	-5.2%	-1.0%

I-5 Route. The same approach was taken to estimate a predictive travel time range for the alternate southbound I-5 route for the same 15 minute time period. Figure 3-19 plots the travel times for the three closest Thursdays identified by the distance calculation method. The heavy black line indicates the travel times for the current day up until 5:30 PM.

Figure 3-20 compares the median travel time prediction for the upcoming 15 minute period with the actual travel times that were measured on this route and day. Table 3-12 expands this information to show the lower and upper bounds of the predicted travel time ranges, and compares the estimates with the travel times actually measured on this day. Each measured travel time fell within the predictive range, and expected travel times varied from the measured travel times by less than 5%.

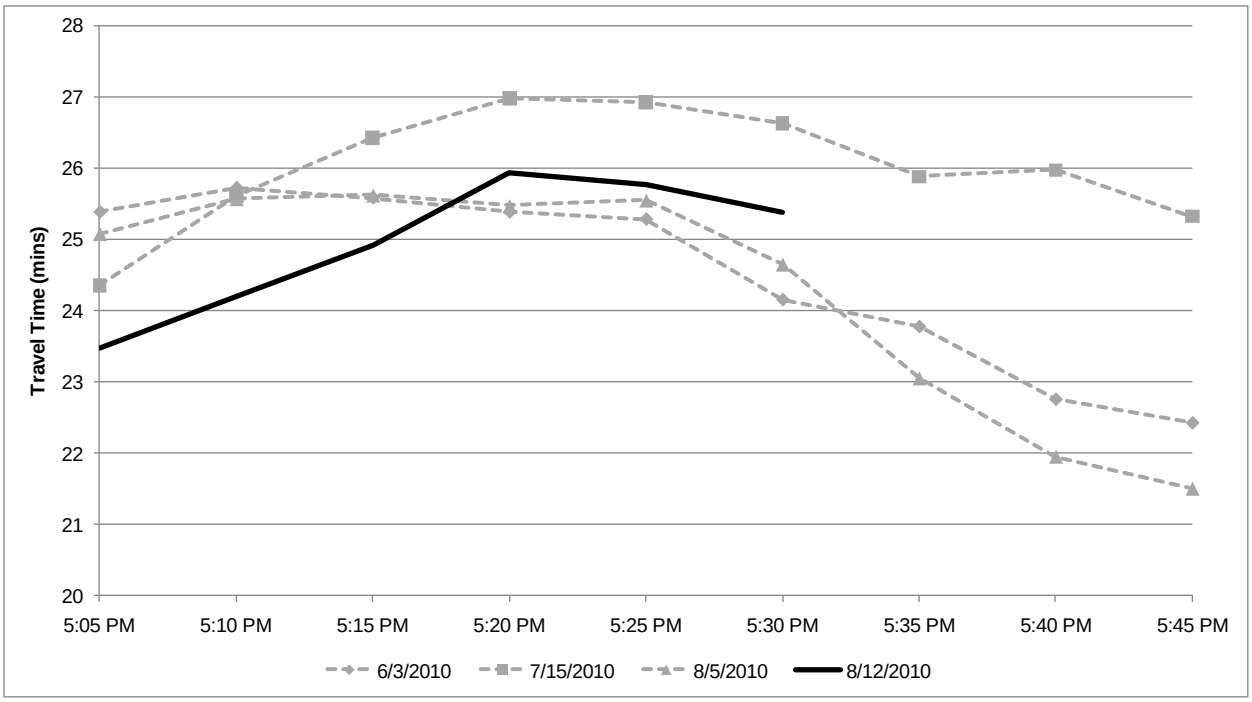


Figure 3-19: Travel time profiles from three closest Thursdays, I-5

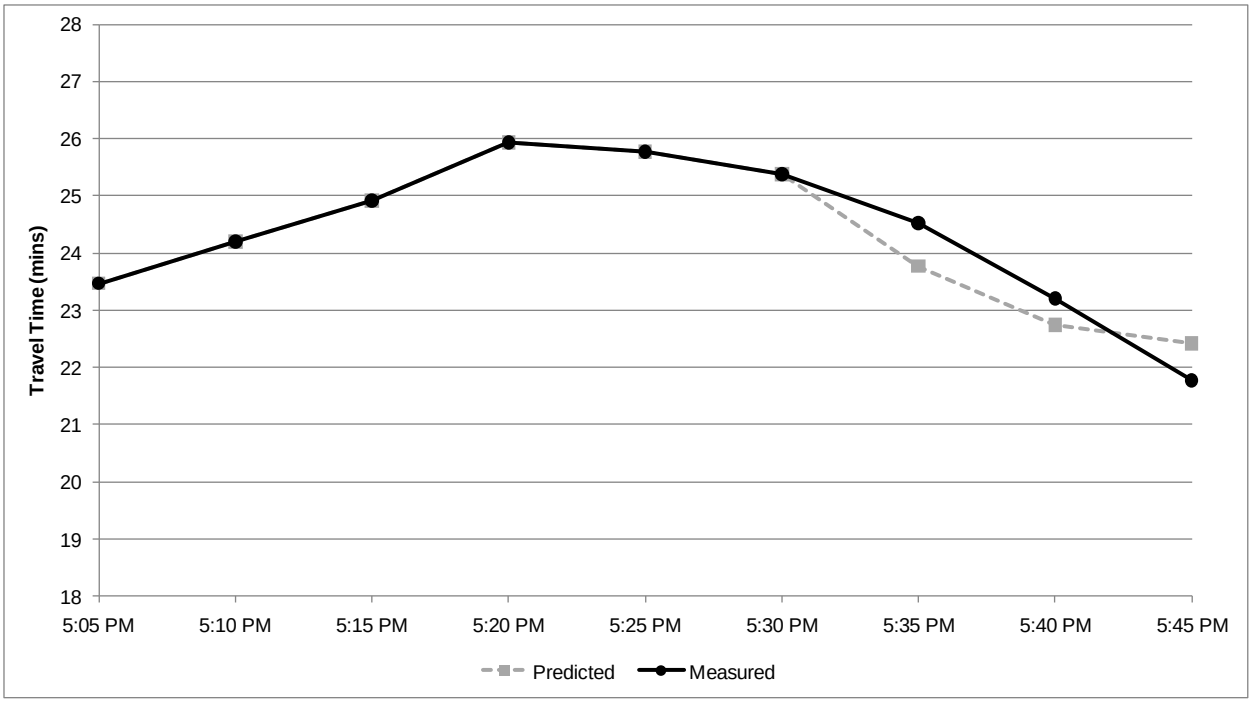


Figure 3-20: Measured and predicted travel times, 8/12/2010, I-5

Table 3-12: Predicted vs. actual travel times, 8/12/2010, I-5

	5:35 PM	**5:40 PM**	**5:45 PM**
Predicted Lower Range	21.6 mins	18.2 mins	18.4 mins
Predicted Upper Range	25.9 mins	27.3 mins	26.4 mins
Predicted	23.8 mins	22.8 mins	22.4 mins
Measured	24.5 mins	23.2 mins	21.8 mins
Measured in range of predicted?	Yes	Yes	Yes
% difference between predicted and measured	-2.9%	-1.7%	3.8%

Synthesis. It is envisioned that the results of the travel time prediction methodologies can be used to provide updated travel time information in real-time, to help users select alternate routes based on current traffic conditions as well as historical travel time patterns and reliability. For the example case, the following information could be posted on a variable message sign to provide travelers with current information.

TRAVEL TIMES TO NATIONAL CITY

I-5: 21-26 MIN

I-805/I-15: 23-27 MINS

Conclusion

This use case validation shows that it is possible to provide predictive travel time ranges and expected near-term travel times by combining real-time and archived travel time data. The

validation uses a k-nearest neighbors approach to compare recent travel times from the current day with travel times measured on previous days. It then approximates near-term travel times based on the measurements from the most similar days. The travel time predictions for both study routes proved very similar to the actual travel times measured on the sample day. The travel time ranges output by the prediction method provide a way to report travel time reliability information in real-time to give travelers a more realistic idea of the range of conditions they can expect to see during a trip.

TRANSIT

Use Case 1: Using planning-based reliability tools to determine departure times and travel times for a trip.

Overview

Perhaps the most commonly occurring use case related to transit data is the case of the transit user seeking information about the system for trip planning purposes. This happens thousands of times each day in cities across the country, and with good reason. The dissemination of traveler information such as real-time arrivals, in-trip guidance, and routing can lead to a more satisfactory transit experience for the user and potentially increase ridership.

Conversely, uncertainty can also have a significant effect on the traveler experience. The agony associated with waiting for transit service has been well documented; research suggests that passengers overestimate the time they spend waiting by a factor of 2 to 3 compared to in-vehicle time *(3)*. Meanwhile, driving is often perceived as offering travelers a greater sense of control when compared to other modes. Offering transit users accurate and easily accessible information on the transit system, while certainly stopping short of providing direct control over the trip, can give peace of mind to transit riders, reducing uncertainty along with the discomfort of waiting for service. As the reliability of this information improves, so will the experience of transit users.

The use of planning-based reliability tools to determine departure times and/or travel times for a trip therefore has the potential to improve passenger understanding of the state of the transit network, leading to less uncertainty and greater ease of use of the transit system.

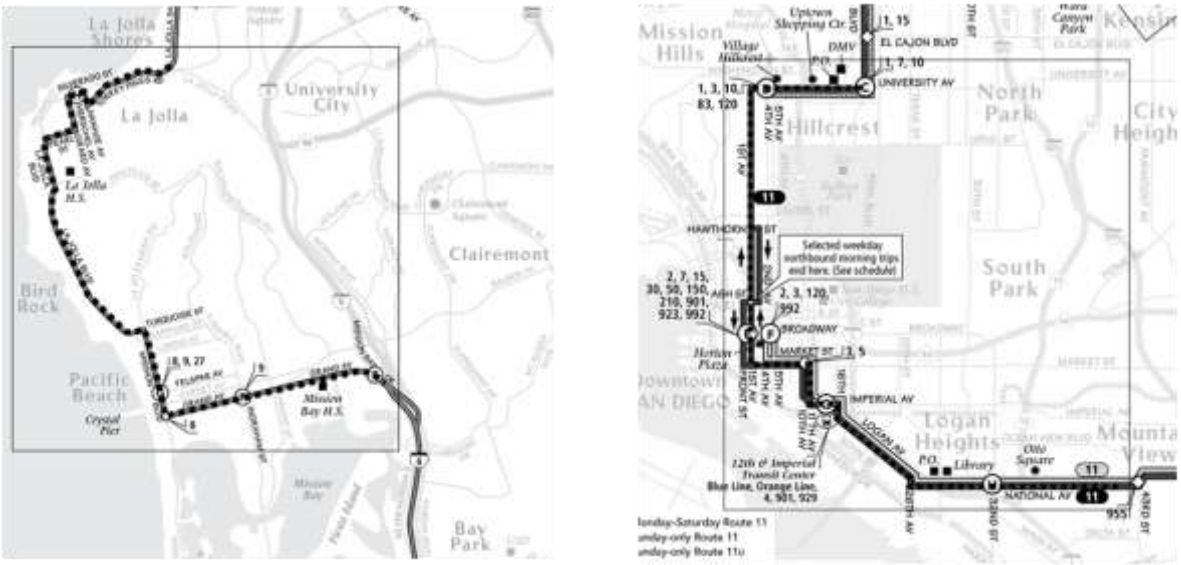
Site Characteristics

Transit agencies are rarely able to equip their entire fleets with Automated Passenger Count (APC) or Automated Vehicle Location (AVL) sensors, making it difficult to conduct a thorough analysis of the entire network. For San Diego's bus network, approximately 40% of buses have APC/AVL sensors installed, though not all of these sensors are fully operational. Due to malfunctioning sensors and limitations in the distribution of APC/AVL equipped vehicles, in reality only 30% of San Diego routes are covered by transit vehicles equipped with functioning APC/AVL sensors.

The San Diego #30 North bus route was chosen for this study primarily because it is the route for which the largest quantity of APC data was available for the period of study (August 2010). A subset of the route spanning from the Grand Avenue exit on Highway 5 along the coast to the intersection of Torrey Pines Road and La Jolla Shores Drive (8.13 miles) was chosen for this study.

For comparative purposes, the San Diego #11 North bus route was also examined. This route also contains a comparatively large amount of APC data for August 2010. It travels

through the Southcrest neighborhood at 40th Street and National Avenue West on National Avenue, through downtown and north on 1st Avenue to University Avenue and Park Boulevard. The total length for the portion of the route analyzed here is 11.68 miles. Both routes are shown in Figure 3-21.



Route #30 Route #11

Figure 3-21: Analyzed portions of #30 and #11 bus routes

Data

The data used in this analysis was obtained from SANDAG. It is APC data collected from August 1 to August 31, 2010, and it consists of measurements taken every time the vehicle opens its doors. Each data point contains the following variables, among others:

- Operator ID
- Vehicle ID
- Trip ID
- Route ID
- Door open time
- Door close time
- Number of passengers boarding
- Number of passengers alighting
- Passenger load

Notably absent from this data is any kind of service pattern designation, which is necessary to group similar trips together for comparison purposes. Route ID is not a sufficient level at which to group trips, since a single route often consists of multiple service patterns (e.g., express patterns and alternate termination patterns). This means that the APC data must be preprocessed in order to identify which trip measurements can be grouped into the same service pattern.

The APC passenger count data is collected by detecting disturbances of dual light beams positioned at the doors of the transit vehicle. Boardings and alightings are detected based on the order in which the beams are broken by a passenger entering or exiting the vehicle. This data can be unreliable as some preprocessing of the data occurs on the sensor itself; specifically, the passenger load is never allowed to drop below zero.

For the subset of the #30 route considered here, scheduled trip times range from 32 minutes to 38 minutes, and scheduled headways range between 13 and 46 minutes (the mean scheduled headway is 21.6 minutes). Approximately 700 vehicle trips over 20 weekdays in August 2010 were analyzed. Of the APC data for this entire route, 50% is imputed. It is necessary to impute data for points where the measured data is missing or does not make physical sense. For example, if a given transit stop has no passengers waiting at it, and no riding passengers have requested a stop there, it is common for the transit vehicle to skip this stop. This results in a missing APC data point for that stop that must be imputed. This practice is particularly common at the beginnings and ends of runs, thus for this subset of the route it is expected that the percent of data imputed is lower than 50%.

For the subset of the #11 route considered here, scheduled trip times range from 40 minutes to 56 minutes, and scheduled headways range between 15 and 76 minutes (the mean scheduled headway is 30 minutes). Approximately 850 vehicle trips over 20 weekdays in August 2010 were analyzed. Of the APC data for this route, 53.20% is imputed.

Approach

Most other analyses of AVL and APC data consider transit trip components (e.g., run time, dwell time, and headways) separately *(4, 5, 6, 7)*. This can be considered an agency-centric approach as it attempts to answer questions that a transit system operator may be interested in such as “How are dwell times affecting on-time performance?” and “What is an appropriate layover time?”.

In this analysis, we combine headways and in-vehicle travel times in order to view transit performance measurement from a more passenger-centric perspective. The service experienced by the passenger is studied by focusing the analysis on answering the fundamental passenger question “If I were to go to the bus stop at a certain time, when would I arrive at my destination?”.

This study assumes that passengers do not plan their transit trips according to real-time or scheduled data, but rather follow a uniform arrival pattern throughout the day, beginning their transit trips independently of the state of the system.

Methods

To begin this validation, the literature was surveyed to determine the recommended planning-based means for calculating the best departure time for a trip in a general way. An appropriate departure time will take into account the variability within the transit system, while being calculated in a way that is intuitive and useful to users.

The SHRP2 L02 Task 2-3 report presents the results of focus group interviews conducted with passenger travelers which attempted to uncover the most meaningful travel time metrics for different trip scenarios. The results show that for daily, unconstrained trips, planning time is the most appropriate metric for passengers. Planning time is a travel time metric that accounts for variability within the system, representing a percentile (often the 85th or 95th) travel time for a trip. That is to say, the planning time for a trip is the travel time that should be

accounted for in order for the traveler to be on time a certain percentage of the time. “Trip” here is taken to mean a pattern of movement between two points at a certain time of day, thus planning time is always computed based on travel times for a single trip over a range of dates.

In order to satisfy this use case and determine the planning time for a transit trip, we must find the travel times for a single trip over a range of days. It is possible to calculate such a table based on APC data alone. To do this:

1. We choose 8.13 miles of the #30 North route (from the Grand Avenue exit on Highway 5 along the coast to the intersection of Torrey Pines Road and La Jolla Shores Drive) to analyze for this use case.
2. We use the APC data to measure actual travel times for trips along this route beginning every two minutes throughout the day. These trips begin independently of the bus schedule.
3. We repeat the previous step for each of the dates in the study range.
4. We now have a table whose columns are dates, rows are times of day, and values are travel times along this transit route. We compute the PDF distribution of travel time for each of the trips in this table.

The notion of computing such a table of travel times is common in highway performance measurement, but less common for transit performance measurement, which tends to focus on travel time in relation to a schedule (schedule adherence) rather than absolute travel time.

The results of this analysis for August 31, 2010 can be seen in Figure 3-22. The troughs correspond to trips that begin immediately before the departure of a bus. The peaks represent trips that began just after the departure of a bus. The steadily downward sloping lines following peaks indicate trips that begin between bus departures; the trips within a single downward sloping section are related in that they all go on to travel on the same bus, whose arrival is indicated by the following trough. The travel times are complemented by a Marey graph of the trips for this day. It can be seen that the troughs correspond to bus departures.

A similar Marey graph and travel time plot, also for August 31, 2010, are shown below in Figure 3-23 for Route #11, North.

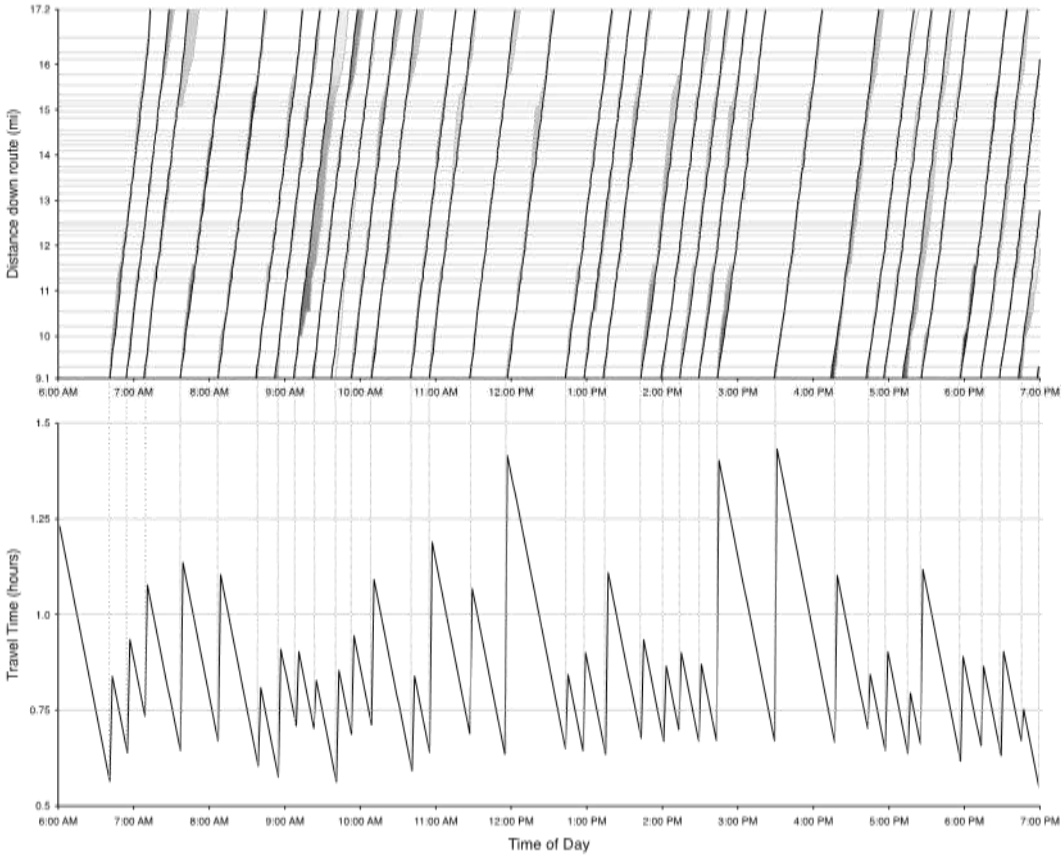


Figure 3-22: Marey graph (top) and passenger travel times (bottom) by time of day for Route #30 on 8/31/2010

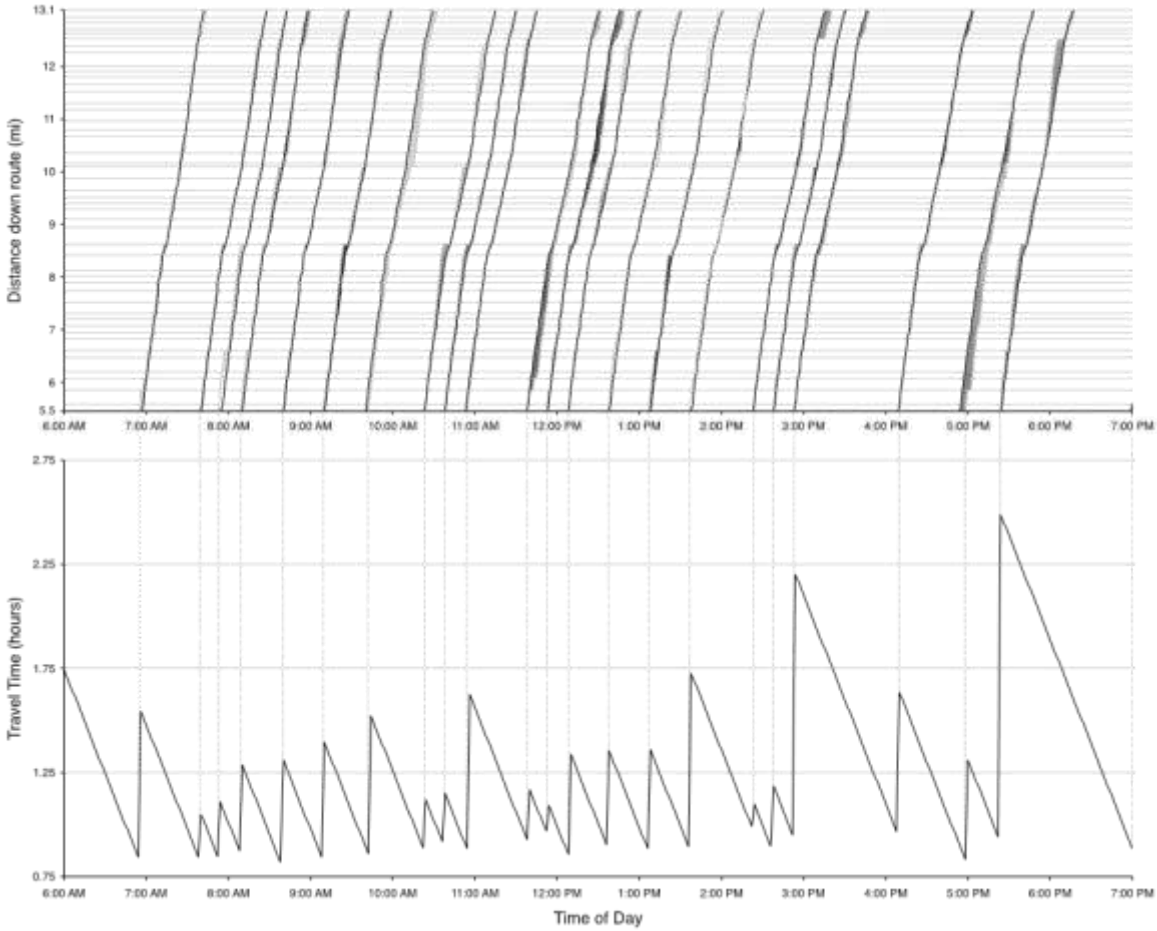


Figure 3-23: Marey graph (top) and passenger travel times (bottom) by time of day for Route #11 on 8/31/2010

Results

Analyzing multiple days yields statistical measures of travel time variability. Here, 22 weekdays in August 2010 are analyzed following the preceding methodology to obtain Figure 3-24, which depicts average travel time as well as the distribution of travel times along the vertical axis, with darker shading corresponding to higher frequency.

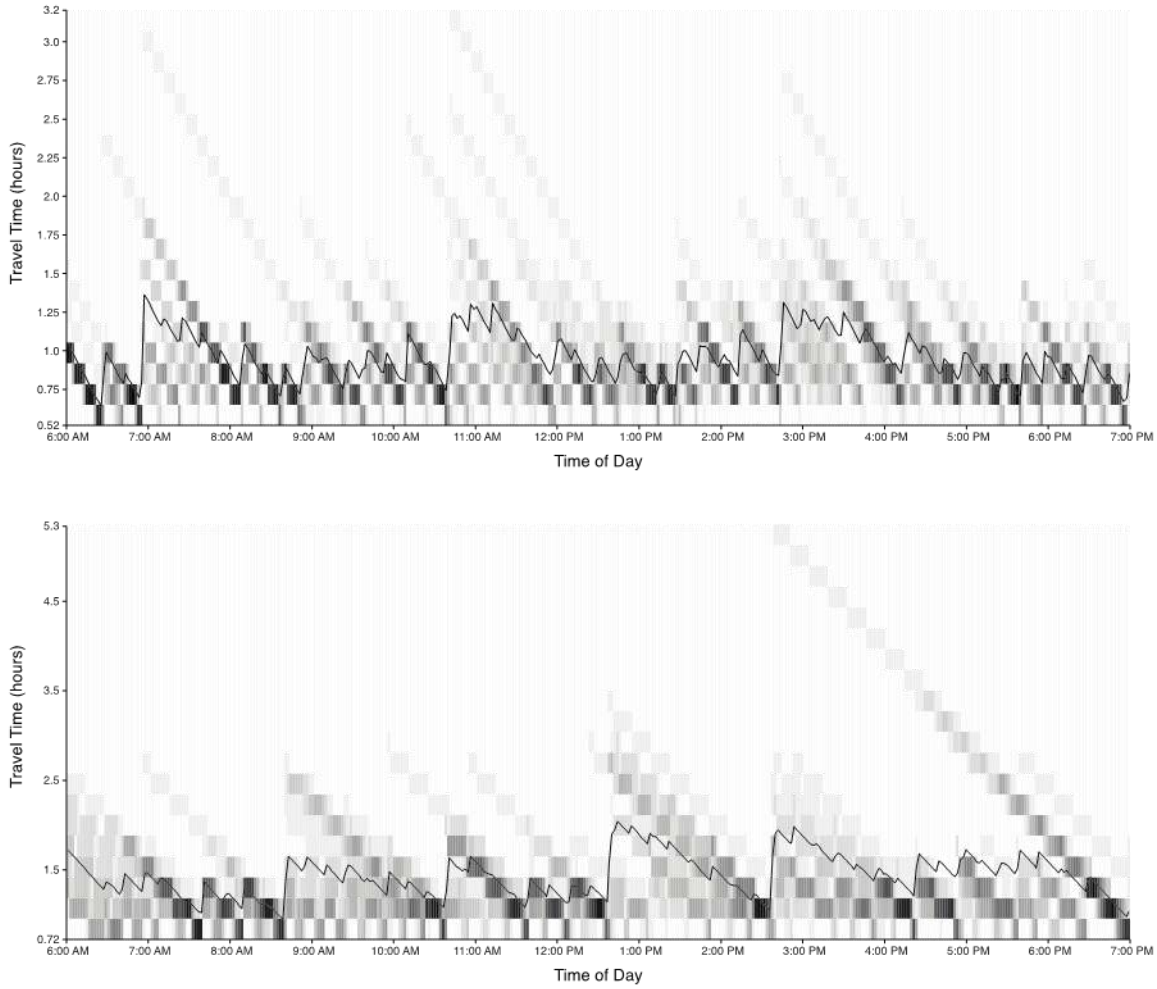


Figure 3-24: Planning time for trips on Route #30 North (top) and Route #11 North (bottom)

All that remains to complete the validation of this use case is to select a desired arrival time and subtract the expected travel time from it. The expected travel time can be extracted from the distributions presented in Figure 3-24, and a range of expected travel times are given. Interpolation may be necessary to obtain precise arrival times depending on the sample size. Table 3-13 and Table 3-14 present departure times and travel times resulting from this analysis. Because bus departures are discrete and not continuous events, it is possible that a range of departure times can correspond to a single arrival time. This effect goes away with larger sample sizes.

Table 3-13: Departure times and planning times on Route #30 North

75th Percentile departure time	**75th Percentile travel time**	**85th Percentile departure time**	**85th Percentile travel time**	**95th Percentile departure time**	**95th Percentile travel time**	**Arrival time**
6:54 AM	1h 6m	6:53 AM	1h 7m	6:52 AM	1h 8m	8:00 AM
10:06 AM	54m	9:53 AM	1h 7m	9:45 AM	1h 15m	11:00 AM

2:02 PM	58m	2:00 PM	1h	1:58 PM	1h 2m	3:00 PM
4:03 PM	57m	4:00 PM	1h	3:27 PM	1h 33m	5:00 PM

Table 3-14: Departure times and planning times on Route #11 North

75th Percentile departure time	**75th Percentile travel time**	**85th Percentile departure time**	**85th Percentile travel time**	**95th Percentile departure time**	**95th Percentile travel time**	**Arrival time**
6:26 AM	1h 34m	--	--	--	--	8:00 AM
8:55 AM	2h 5m	8:41 AM	2h 19m	8:40 AM	2h 20m	11:00 AM
12:40 PM	2h 20m	12:38 PM	2h 22m	12:38 PM	2h 22m	3:00 PM
2:54 PM	2h 6m	2:52 PM	2h 8m	2:37 PM	2h 23m	5:00 PM

Conclusion

The most direct analysis would be achieved by restricting the date range to dates with identical schedules, however, in practice it can be rare to find days with the exact same schedule. Regardless, for routes with headways smaller than 10 minutes it is common for passengers to arrive at bus stops independently of the schedule, thus the constant arrival pattern used in this simulation may be more meaningful.

Agencies should strive to either reduce transit travel times across the day, or establish reliable times of day when the transit travel time can be expected to be low. As seen in the transition between Figure 3-22 and Figure 3-23, as more days are added to the analysis, the strong peaks correlating to regular bus departures can become obscured if the transit schedule is not regular day to day. This results in the slightly blurry look of the distributions in Figure 3-24. However, if a period of study is selected in which the transit schedule is fixed, the troughs will always appear in the same locations indicating good reliability across days from the transit user's perspective.

Use Case 2: Conducting offline analysis on the relationship between travel time variability and the seven sources of congestion

Summary

This use case aims to quantify the impacts of the seven sources of congestion: (1) incidents; (2) weather; (3) lane closures; (4) special events; (5) traffic control; (6) fluctuations in demand; and (7) inadequate base capacity, on travel time variability for transit trips. To perform this analysis, methods were developed to extract travel times from Automated Passenger Count (APC) bus data. These travel times were then flagged with the type of event they occurred under (if any) and aggregated into travel time probability density functions (PDFs). From these PDFs, summary metrics such as the median travel time and planning travel time were computed to show the extent of the variability impacts of each event condition.

Users

This use case has broad applications to a number of different user groups. For transit planners, knowing the relative contributions of the different sources of congestion toward travel time reliability would help them to better prioritize travel time variability mitigation measures on a route-specific basis. The outputs of this use case would also be of value to operators, providing them with information that informs on the range of operating conditions that can be expected on a route given certain event conditions. Finally, the outputs of this use case would have value to travelers, by providing better predictive travel times under certain event conditions that could be posted in real-time on variable message signs at stops or on vehicles, or on traveler information websites. This information would help users better know what to expect during their trip, both during normal operating conditions and when a congestion-inducing event is occurring.

Site

Three routes were selected for the evaluation of this use case, in order to highlight the varying contributions of congestion factors to travel time reliability across different routes, service patterns, and times of day. The first route analyzed is Route #20, Southbound, which travels from the Kearny Mesa area down SR-163 into downtown San Diego. For this analysis, we select a subset of the route spanning 16.4 miles. This study section of Route #20 begins near the intersection of Miramar Road and Kearny Villa Road on the northern edge of the Marine Corps Air Station Miramar and continues South along SR-163 to downtown San Diego. At Balboa Ave. and SR-163, after traveling along SR-163 for 6.6 miles, Route #20 takes a detour to Fashion Valley Transit Center at Friar's Road and SR-163 before reentering SR-163 at I-8. Finally, the route terminates in downtown San Diego at 10th Avenue and Broadway.

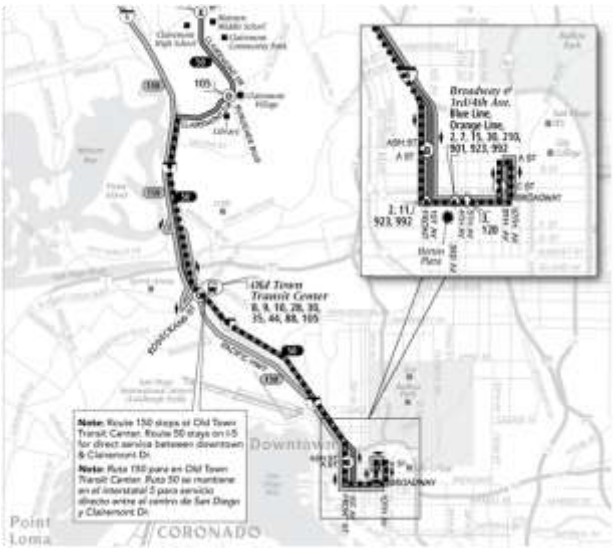
The second route analyzed here is Route #20 X, which is identical to Route #20 except that it does not stop at the Fashion Valley Transit Center. Here, we study a 14.7-mile long stretch of Route #20 X beginning near the intersection of Miramar Road and Kearny Villa Road on the northern edge of the Marine Corps Air Station Miramar and continuing South along SR-163 for 12.6 miles to downtown San Diego, terminating at 10th Avenue and Broadway.

The third route analyzed is Route #50, Southbound, which travels along I-5 into downtown San Diego. This route begins near the Clairemont Drive on-ramp to I-5, continues south along I-5 for 6.4 miles, and ends 0.8 miles later at 10th Avenue and Broadway. The route is 7.2 miles long.

Both Routes #20 and #50 were chosen because they travel for significant distances along freeways, meaning that roadway incident data can be obtained for them through PeMS. Secondly, these routes were chosen because they travel towards downtown, which hosts several special events during the period of study, so their travel times can be analyzed for the effect of special events. Finally, these are routes for which a comparatively large amount of APC data is readily available.

A map of all routes is shown in Figure 3-25.

Route #20 and 20x (dashed)



Route 50 (dashed

Figure 3-25: Transit Use Case 2 routes

Methods

These routes were analyzed to determine the travel time variability impacts caused by three sources of congestion: (1) incidents; (2) special events; and (3) fluctuations in transit demand. Traffic control contributions were not investigated as ramp metering location and timing data could not be obtained. Weather contributions were not considered due to the lack of inclement weather in San Diego for the August 2010 study period (the only month for which the APC data could be obtained). Lane closures were also not considered as they are expected to have little impact on transit service, even when the transit route runs along a freeway. The impacts of inadequate base capacity were not considered for the same reason.

For every weekday run for which data was available on each of the three routes described above, APC data was analyzed to determine the in-vehicle travel time from delivered service records. Passenger loadings were also extracted from the APC data.

To link travel times with the event condition that was active during their measurement, each transit run for which a travel time was obtained was tagged with one of the following events: (1) baseline (none); (2) special event; (3) incident; or (4) high demand. A travel time was tagged with “baseline” if none of the factors were active during that run. A travel time was tagged with “incident” if an incident was active anywhere on the route during that run. Incident start times and durations reported through PeMS were used to determine when incidents were active along the route. Incidents with durations shorter than 15 minutes were not considered. A travel time was tagged with “special event” if a special event was active at a venue along the route during that time period. Special event time periods were determined from the start time of the event and the expected duration of that event type. For example, if a football game at Qualcomm Stadium had a start time of 6:00 PM and was scheduled to end around 9:00 PM, the event was considered active between 4:00 PM and 6:00 PM and between 8:30 PM and 10:00 PM, as this is when the majority of traffic would be accessing the venue. Finally, a travel time was tagged with “high demand” if the number of passengers on board the transit vehicle reached or exceeded 50 at any point during the run. For cases in which more than one factor

was active, the travel time was tagged with the factor that was deemed to have the larger travel time impact (for example, when a long-lasting incident coincided with a trip that also ran during the edge of a low-attendance special event window, the travel time was tagged with “incident”).

Tagged travel times were then divided into different categories based on the time of the day, since the impacts of the congestion sources are time-dependent. For all three transit routes, three different time periods were evaluated: (1) AM Peak, 7:00 AM-9:00 AM; (2) Midday, 9:00 AM-4:00 PM; and (3) PM Peak, 4:00 PM-8:00 PM.

Finally, within each time period, travel time probability density functions (PDFs) were assembled for all measured travel times.

Results

Route #20, Southbound. For Route #20, Southbound, travel time variability and its contributing factors were investigated for the 22 weekdays in August 2010. The period of study was limited to a single month due to a shortage of data on other months. Data on incidents, special events, demand fluctuations and travel times were collected from PeMS, external sources, and the in-vehicle APC sensors, as described in the Site Description chapter.

Scheduled travel times for the subset of Route #20 considered here over the period of study range from 39 to 50 minutes, averaging 51.7 minutes. In August 2010, vehicles averaged 8.1 minutes longer to complete this portion of the route than the scheduled time.

The travel time distribution of trips on this route appears to be roughly unimodal with a high standard deviation, greater frequency on the smaller side of the mode, and several outlying trips with long travel times. The mode occurs at 54.2 minutes.

Over the period of study, this route saw 129 transit trips made. Among these 129 total trips, 7 special event, 2 incident, and 16 high demand trips were recorded. Figure 3-26 shows the travel time distribution for all trips over the study period, according to the event present (if any) during that trip.

Figure 3-27 shows the distribution of travel times during the weekday AM peak of August 2010. Relatively few trips occurred during the AM Peak on Route #20. Those that did appear to be clustered together around 44.2 minutes. This could be due to fluctuations in the transit schedule throughout the day, with trips occurring early in the morning scheduled with shorter travel times than trips occurring later in the day. No events were flagged for trips occurring in this time period.

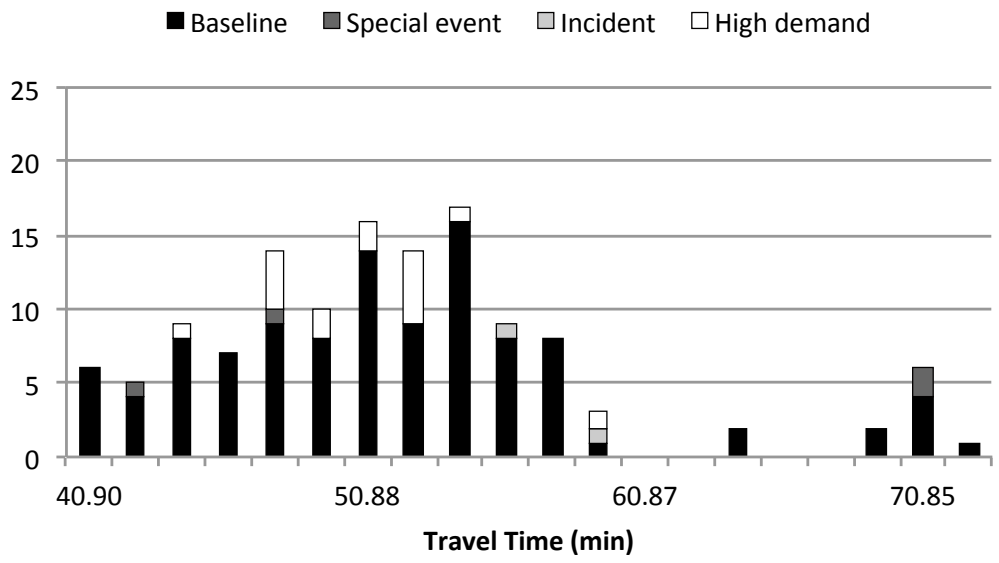


Figure 3-26: Total travel time distribution for Route #20, August 2010

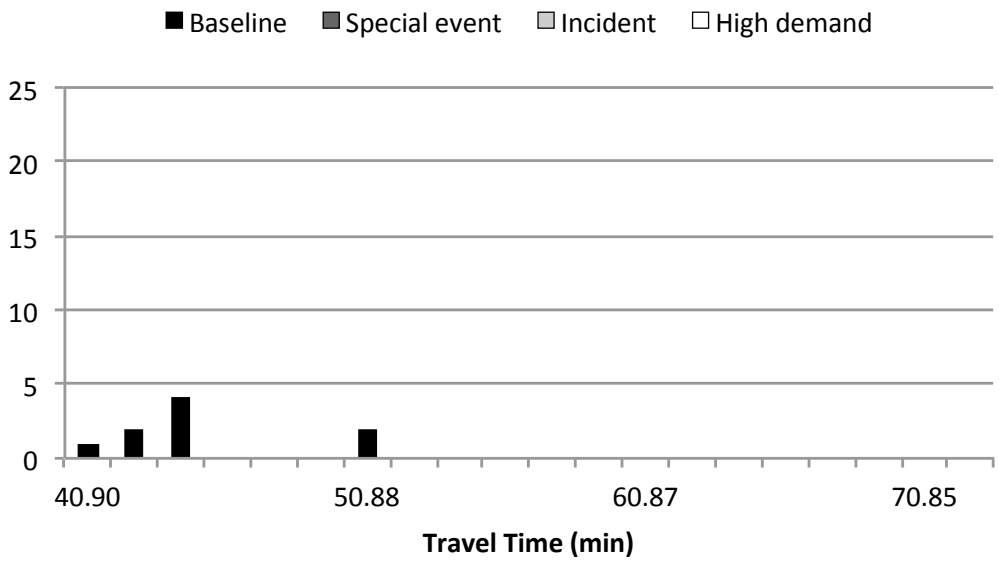


Figure 3-27: AM peak travel time distribution for Route #20, August 2010

Figure 3-28 shows the travel time distribution over the month for midday trips. Travel times for the midday period, in contrast to those seen in the AM peak, appear clustered around the primary mode seen in Figure 3-26 of 54.2 minutes. The distribution of variability-causing events is interesting, with the two recorded incident trips associated with longer-than-average trips, and two of the six longest trips associated with special events. However, all 11 high demand trips had shorter than average travel times, indicating that large passenger loadings do

not have much effect on travel times along this route during the middle of the day. This is good as 11 of the 14 high demand events on this route occurred during the middle of the day.

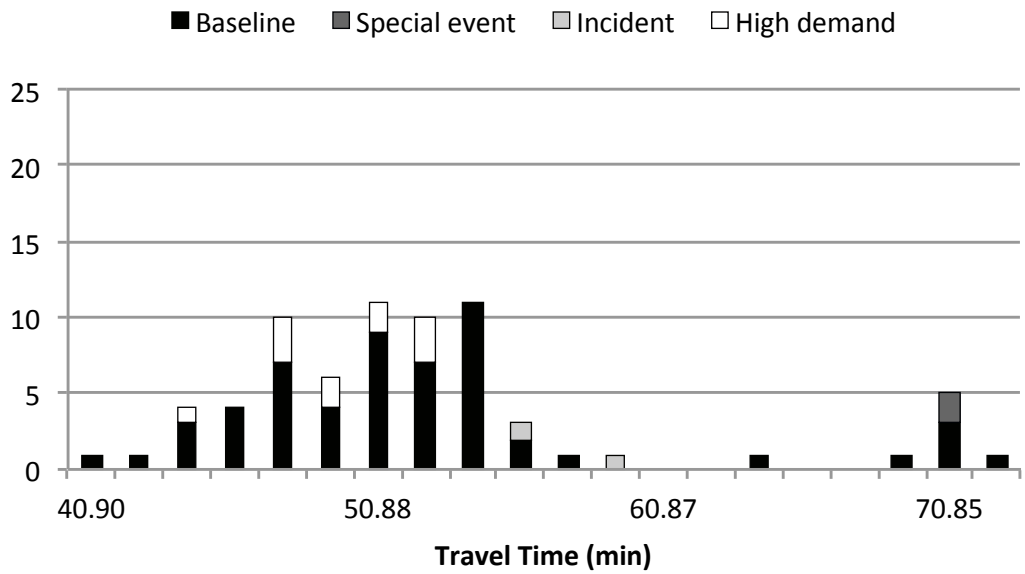


Figure 3-28: Midday travel time distribution for Route #20, August 2010

Figure 3-29 shows the travel time distribution of trips taken during the PM peak period. There is one special event associated with a relatively low travel time of 42.6 minutes. This event was a San Diego Padres baseball game and occurred late in the evening. High-demand events are also visible throughout the distribution, although they do not appear to be correlated with longer travel times. This is the most highly variable time period for which this route was analyzed.

Table 3-15 summarizes the contribution of each event condition to all travel times, to those exceeding the 85th percentile (57.2 minutes), and to those exceeding the 95th percentile (70.6 minutes). It can be seen that, although just 3.82% of all trips were associated with a special event, 10% of trips where travel times exceeded the 85th percentile were associated with a special event. When limiting the pool to trips that exceeded the 95th percentile travel time, a full 14.29% of that total can be associated with special events. From a planning and operational standpoint, this indicates that special events are associated with long travel times on this route. Thus, there could be some room for reliability improvements by improving signage, adding capacity, or advertising alternative routes during special events.

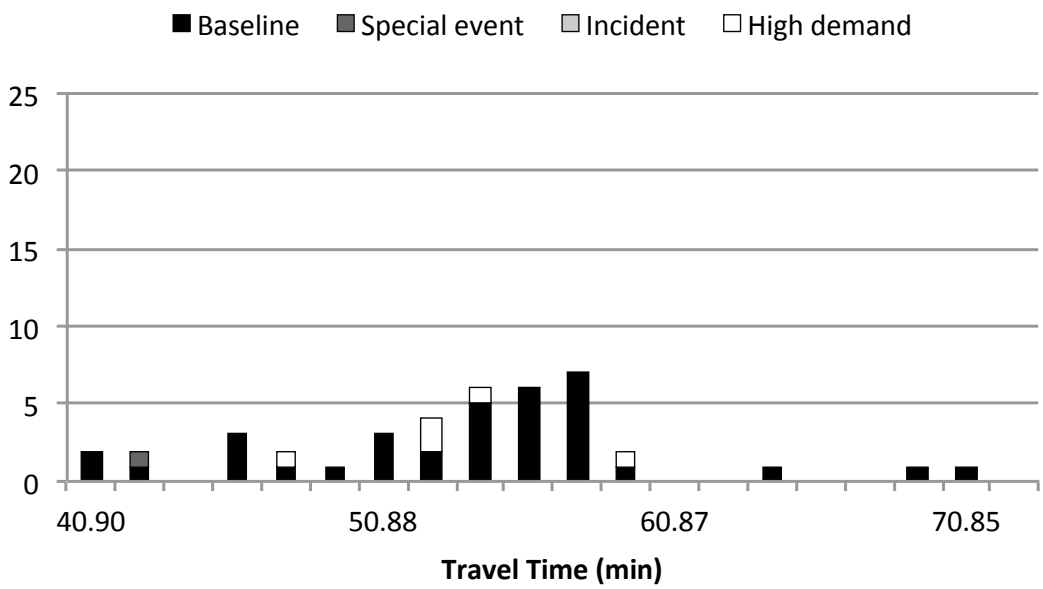


Figure 3-29: PM peak travel time distribution for Route #20, August 2010

Table 3-15: Travel time variability causality for Route #20

	Active	**Active when travel time exceeded 85th percentile**	**Active when travel time exceeded 95th percentile**
Baseline	82.4%	80.0%	85.7%
Special Event	3.8%	10.0%	14.3%
Incident	1.5%	5.0%	0.0%
Demand	12.2%	5.0%	0.0%

Route #20X, Southbound. Similarly to Route #20, for Route #20 X, Southbound, travel time variability and its contributing factors were investigated for the 22 weekdays in August 2010. The period of study was limited to a single month due to a shortage of data on other months. Data on incidents, special events, demand fluctuations and travel times were collected from PeMS, external sources, and the in-vehicle APC sensors, as described in the Methods section.

Scheduled travel times for the subset of Route #20 X considered here over the period of study range from 29 to 35 minutes, averaging 32.5 minutes, nearly a full 10 minutes less than Route #20. In August 2010, on average, buses took 10.1 more minutes than they were scheduled to complete this portion of the route.

A bimodal distribution can immediately be seen in Figure 3-30, which plots all trip travel times over the month, with most travel times clustered around the higher mode, 42 minutes, and a smaller grouping around 32 minutes. The source of the bimodal distribution is not immediately clear. There is virtually no correlation between the scheduled travel time and actual travel time (R^2 = 0.043) on this route; trips belonging to the lower mode do not necessarily have shorter

scheduled travel times. However, of the 11 trips with travel times less than 36 minutes, 10 correspond to the 7:13 AM run, and nine were made by the same driver. Of the 11 days when this smaller travel time was not seen, 10 had no 7:13 AM run scheduled. Thus, there seems to be an unknown factor associated with this particular run and driver which leads to a smaller travel time on this portion of the route.

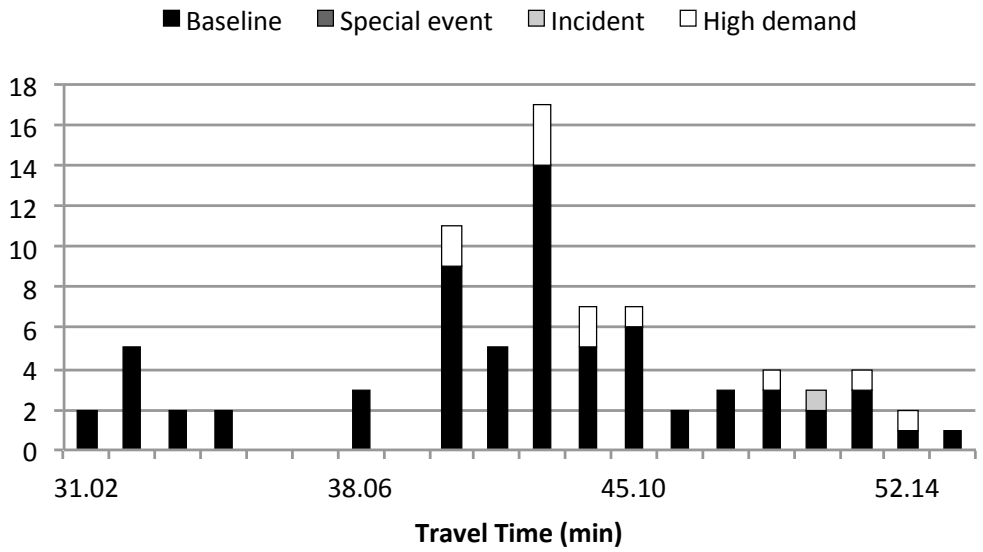


Figure 3-30: Complete travel time distribution for Route #20X, August 2010

Figure 3-31 depicts the distribution of travel times along Route #20 X during the AM Peak period (7:00 AM to 9:00 AM), labeled by event condition. The bimodal distribution described above can be seen most clearly here as all of the low-travel-time trips occur during the AM Peak, as discussed earlier. This is in stark contrast to the distribution of travel times for the AM Peak period on Route #20. Both modes appear to be tightly bunched. This bimodal distribution makes the AM Peak the period with the largest travel time variability for this route. There was only a single event condition measured during the AM Peak on this route: a high demand event which was associated with a travel time of 48.6 minutes.

Figure 3-32 depicts the distribution of travel times along Route #20 X during the midday period (9:00 AM to 4:00 PM), labeled by event condition. Here, a single mode is seen around 42.6 minutes. As with Route #20, the midday period saw the largest number of high passenger loadings on this route, with 8 high demand events. However, also similar to Route #20, these high loadings do not appear to be associated with longer travel times. There was a single incident event which was associated with the highest midday travel time seen on this route, 49.8 minutes.

Figure 3-33 depicts the distribution of travel times along Route #20 X during the PM Peak period (4:00 PM to 8:00 PM), labeled by event condition. There were few trips taken on this route during this time span, so no overwhelming travel time trend can be identified other than the high variability of travel times. The largest travel times seen on this route occurred during the PM period. Of the five largest travel times, two were associated with high demand events.

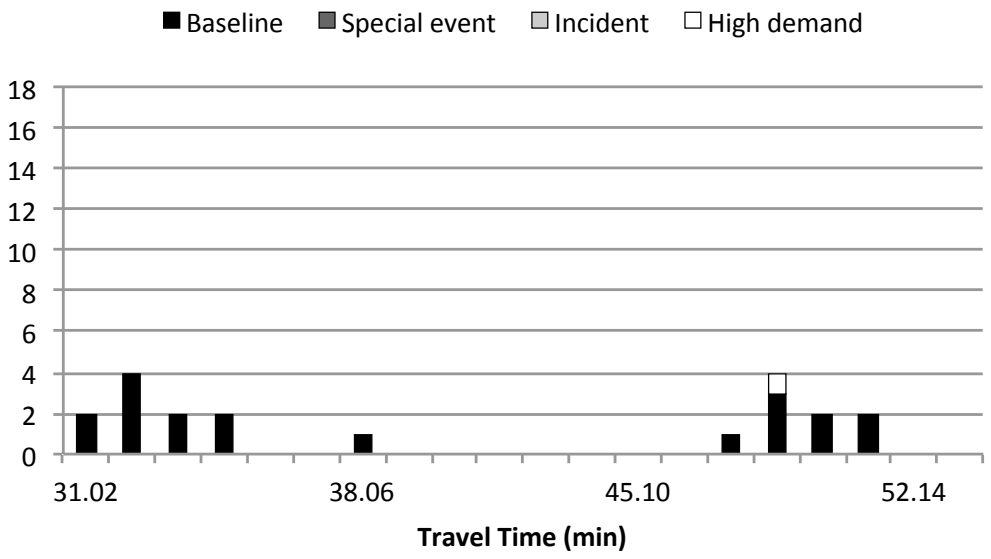


Figure 3-31: AM peak travel time distribution for Route #20X, August 2010

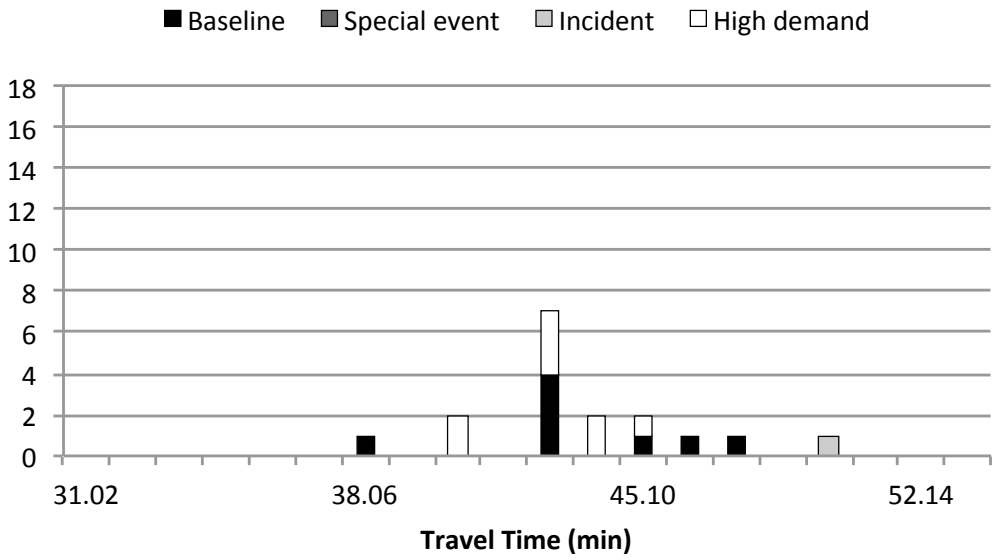


Figure 3-32: Midday travel time distribution for Route #20X, August 2010

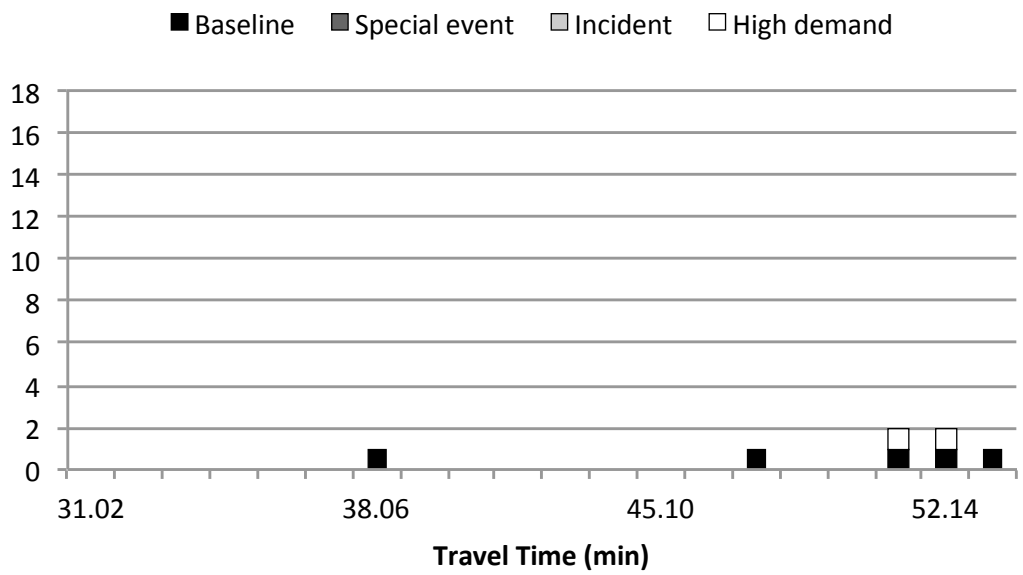


Figure 3-33: PM peak travel time distribution for Route #20X, August 2010

Table 3-16 summarizes the contribution of each event condition to all travel times, to those exceeding the 85th percentile (49.1 minutes), and to those exceeding the 95th percentile (51.4 minutes). It can be seen that, although 85.19% of all trips had no associated variability-inducing event, of those trips that exceeded the 85th percentile travel time, 25% were associated with either an incident or high demand, with high demand events occurring more often. Furthermore, all of these high demand trips which exceeded the 85th percentile travel time occurred during the PM Peak period. From a planning and operational standpoint, this indicates that there could be some room for reliability improvements by adding capacity to high-demand trips on this route during the PM peak.

Table 3-16: Travel time variability causality for Route #20X

	Active	**Active when travel time exceeded 85th percentile**	**Active when travel time exceeded 95th percentile**
Baseline	85.2%	75.0%	75.0%
Special Event	0.0%	0.0%	0.0%
Incident	1.2%	8.3%	8.3%
Demand	13.6%	16.7%	16.7%

Route #50, Southbound. For the subset of Route #50, Southbound considered here, travel time variability and its contributing factors were investigated for the 22 weekdays in August 2010. The period of study was limited to a single month due to a shortage of data on other months. Data on incidents, special events, demand fluctuations and travel times were collected from PeMS, external sources, and the in-vehicle APC sensors, as described in the

Methods section. Scheduled travel times for the 158 runs analyzed for this route range between 18 and 21 minutes, averaging 19.5 minutes. The average delivered travel time for this route was 28.75 minutes, a full 9.25 minutes more than the average scheduled travel time. Figure 3-34 shows the total distribution of trip travel times by event condition over the study period.

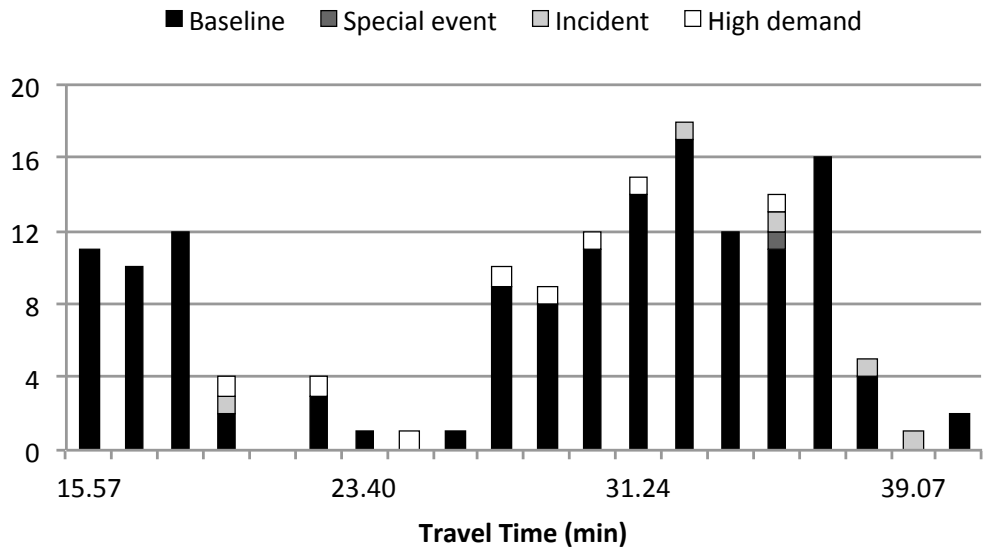


Figure 3-34: Complete travel time distribution for Route #50, August 2010

The AM peak distribution for this route, shown in Figure 3-35, appears similar to Route #20 X with two widely distributed modes appearing on either side of the distribution. However, unlike Route #20 X, this bimodal distribution was not exclusive to the AM peak period for this route. No events were flagged for trips occurring in this time period.

Similar to the other two routes analyzed here, the midday period, shown in Figure 3-36, carried the majority of high demand trips on this route, with four of the five high demand trips occurring here. However, continuing the trend of Routes #20 and #20 X, those high demand trips are not particularly strongly associated with longer travel times. A majority of the trips clustered around the low end of the travel time distribution occurred during the midday period.

Figure 3-37 depicts the travel time distribution of trips taken during the PM peak period on Route #50. Immediately visible is the apparent relationship between incident events and long travel times, as two of the three longest travel times seen during this month were associated with incidents (with the third associated with a special event).

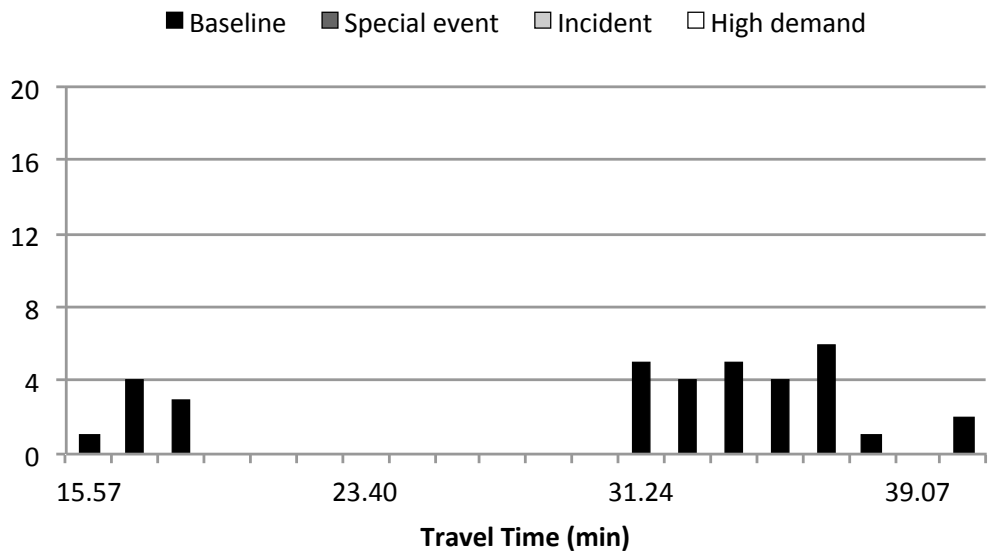


Figure 3-35: AM peak travel time distribution for Route #50, August 2010

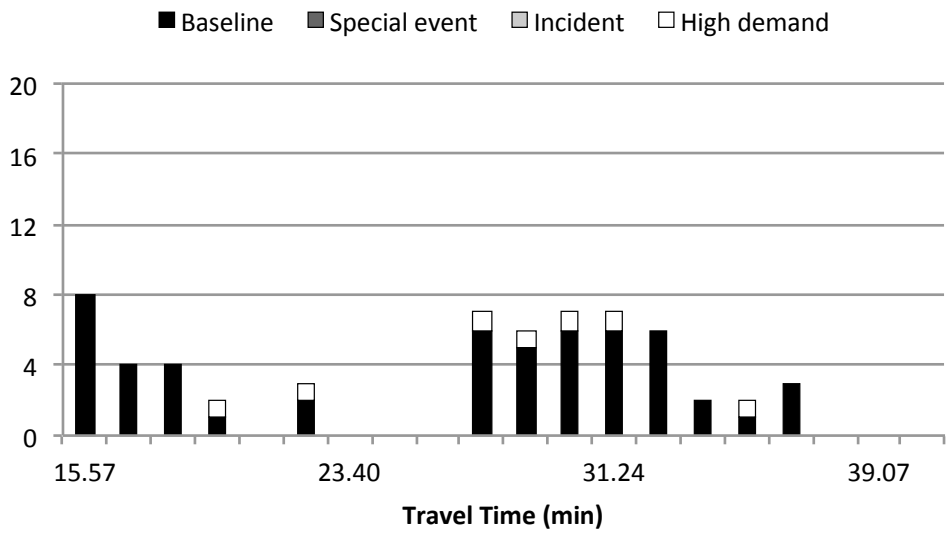


Figure 3-36: Midday travel time distribution for Route #50, August 2010

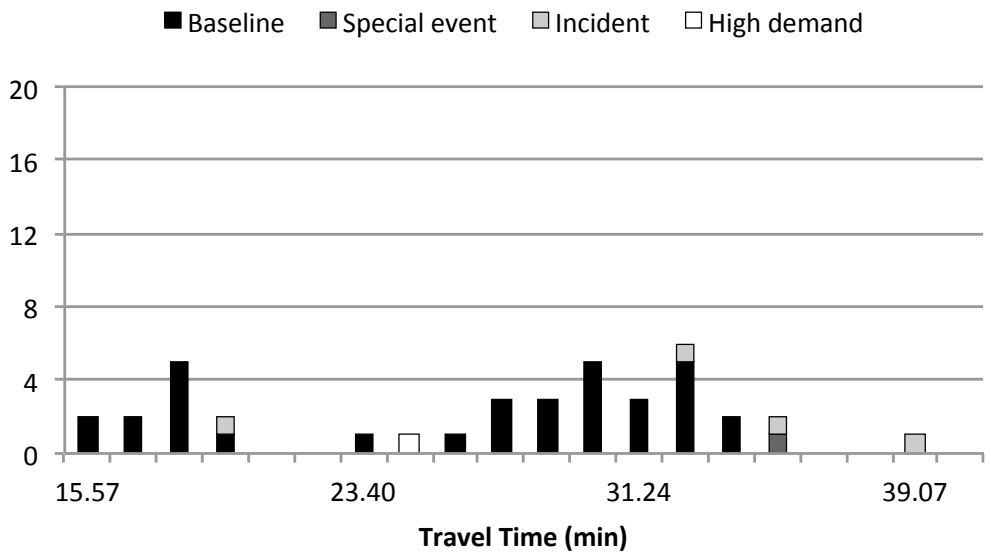


Figure 3-37: PM peak travel time distribution for Route #50, August 2010

Table 3-17 summarizes the contribution of each event condition to all travel times, to those exceeding the 85th percentile (35.9 minutes), and to those exceeding the 95th percentile (37.1 minutes). It can be seen that, although 92.36% of all trips had no associated variability-inducing event, of those trips that exceeded the 85th percentile travel time, the percent with no variability-inducing event dropped to 91.67%. When limiting the pool to trips that exceeded the 95th percentile travel time, a full 25% of that total can be associated with incidents (although special events were associated with just 3.18% of all trips). From a planning and operational standpoint, this indicates that there could be some room for reliability improvements by focusing more resources on clearing roadway incidents more quickly along this route to lessen the severity of their impact.

Table 3-17: Travel time variability causality for Route #50

	Active	**Active when travel time exceeded 85th percentile**	**Active when travel time exceeded 95th percentile**
Baseline	92.4%	91.7%	75.0%
Special Event	0.6%	0.0%	0.0%
Incident	3.2%	8.3%	25.0%
Demand	5.1%	0.0%	0.0%

Conclusion

This use case analysis illustrates one method for exploring the relationship between travel time variability and the sources of congestion. The methods used are relatively simple to perform provided that the transit APC data can be obtained and sufficiently cleaned. The application of the methodology to the three San Diego routes revealed key insights into how this type of analysis should be performed.

Of note is the limited sample size used in this analysis. To ensure statistical significance and meaningful analysis, ideally no less than three month's worth of data should be used to avoid invalid conclusions due to anomalies. Breaking the travel times down by time of day according to local traffic patterns is valuable as it isolates the effects of sources of congestion by time of day. For example, on Route #20 high passenger loadings are associated with longer trip times during the PM peak period, but not at other times of day.

FREIGHT

Use Case: Using freight-specific data to study travel times and travel time variability across an international border crossing.

Overview

Calculating travel time reliability for freight poses unique data challenges and begs the question: How does travel time reliability for freight transportation systems differ from the question of reliability in the overall surface transportation system? From the research performed in Tasks 2/3 of this project, the team determined that two primary factors differentiate freight systems and the overall surface transportation system: traveler context and trip characteristics.

Traveler context is a primary differentiator between freight trips and all other surface modes: rather than delivering travelers to a destination, a freight trip delivers goods. Because freight drivers are being paid to perform a freight trip, the commercial ecosystem surrounding this concept means that the entire program of scheduling and executing freight trips is much more organized than a typical passenger trip. Thus, freight drivers acquire and utilize travel time reliability information in a fundamentally different manner than other travelers. They also have different concerns. Freight movers were part of the stakeholder interview process conducted by the project team, and these differences have been previously outlined in Tasks 2/3 in this project.

In terms of trip characteristics, freight and overall travel have spatial differences, temporal differences, and facility differences. Spatial differences refer to the fact that origins and destinations with the heaviest freight traffic do not necessarily also have the highest overall traffic volumes. Numerous origin-destination surveys have been employed to identify high-priority freight corridors, and these can be used to focus freight reliability monitoring efforts. In terms of temporal differences, freight traffic generally does not follow the same temporal AM and PM peak pattern of passenger travel. In fact, many freight trips are made during off-peak hours to avoid recurrent congestion. Finally, facility differences refer to the existence in some locations of freight-only lanes or corridors, which would need to be monitored separately from general purpose travel lanes.

Given these differences, the project team decided to take a different approach than that taken for the freeway and transit data, and focus analysis on a very specific freight reliability concern: travel times and reliability across international border crossings.

Data Challenges

This freight use case validation presented a number of data challenges, mostly due to the fact that it is difficult to distinguish freight traffic within an overall traffic stream using conventional data sources. The project team considered estimating freight traffic volumes from single loop detectors, and then computing freight reliability statistics using the same methodologies employed in the freeway use case validations. However, these estimates, which rely on algorithms that compare lane-by-lane speeds in order to estimate truck traffic percentages, were deemed too unreliable to support accurate travel time variability computations. The team also considered using data from the handful of specialized weigh-in-motion sensors in the region that report vehicle classification data and truck weights, but these were too sparsely located to prove useful for travel time analysis. Because of the unsuitability of traditional traffic monitoring infrastructure for freight reliability calculations, the team's preference was to base analysis on freight-specific data.

There are troves of data on freight vehicle movements, including data on route reliability, available from one stakeholder group: freight movers themselves. Companies such as Qualcomm and Novacom have developed data systems for freight mover operations. They rely on global positioning systems (GPS) outfitted on individual trucks, tracking position and speed, generally on a sub-hour basis. While this data is frequently not fine grained enough to calculate some of the detailed urban reliability information that has been demonstrated elsewhere in this case study, it is adequate for freight movers to understand their travel time reliability environment and to schedule departures appropriately for the just-in-time-delivery windows demanded by their customers.

However, this data is not generally available for studies such as L02, because it is proprietary, competitive information that freight movers gather on their own operations. While these companies have begun to share this data with some partners (such as third party data providers), these deals are struck under terms of strict confidentiality and anonymity. There are some ongoing efforts to leverage this information for public sector agency analysis, such as the border crossing work at Otay Mesa currently underway by the Federal Highway Administration (FHWA) – described in the following section – but these efforts are still in the research phase and are not feasible for public sector agencies to put into operational practice.

In terms of the data required to understand reliability in freight systems, there is strong overlap with freeway and arterial data systems, as freight vehicles are generally part of the overall traffic stream. Because of this, they share the same overall reliability characteristics of the freeway and arterial systems as a whole. However, in many cases, the data required to understand freight movements is scarcer than data needed to understand the overall transportation system, simply because it is data that only pertains to a few percent of overall trips in a given region. The project team was fortunate enough to be given access by the FHWA to freight-specific GPS data collected at the Otay Mesa truck-only border crossing facility from Mexico into the United States. Because of this, this use case validation has a narrow geographic scope, but explores a major issue in freight travel.

Site

The Otay Mesa Crossing has a truck-only facility that, during peak season (which is from October to December), provides access to the US to approximately 2,000 trucks per day. The crossing is equipped to handle trucks that participate in the Free and Secure Trade (FAST) expedited customs processing program, as well as those required to undergo standard processing. US-bound trucks pass through Mexican Export processing prior to entering the US,

and are required to be screened at a California Highway Patrol (CHP) commercial vehicle weighing and inspection station before accessing US roadways.

For travel time analysis, the Otay Mesa crossing was broken up into 10 districts, as shown in Figure 3-38. These districts are:

1. Export Approach
2. Departure East
3. Departure West
4. Mexico Customs
5. USA Primary
6. USA Secondary Gate
7. USA Secondary
8. Secondary Departure
9. CHP Approach
10. CHP Inspection

Figure 3-38: Otay Mesa district map (8)

Data

As part of an FHWA project, data was collected at Otay Mesa from 175 trucks passing through the crossing repeatedly over December 2008 through March 2009. The total number of crossings for GPS-equipped trucks ranged from five percent to twelve percent of the total population of trucks passing through the Otay Mesa crossing. The resulting data set contained 900,000 individual points. A number of these data points were outside of the crossing analysis zone, and thus were discarded prior to analysis. Additionally, almost 30% of trip records contained no travel times, making them unusable for freight reliability analysis. As a result,

analysis was performed on the remaining 300,000 individual points, or a third of the total data set.

The Otay Mesa data was used to do two types of reliability analysis: (1) to evaluate the reliability within and across different districts; and (2) to evaluate the reliability associated with different types of inspections. For the district-level analysis, one data complication is that the quantity of reported travel times varies by district. Most individual districts have tens of thousands of travel time records, as shown in Figure 3-39. However, very few trip records (0.07%) contain travel times for all districts. The sparseness of this data makes it challenging to monitor travel times across groups of districts. For example, analyzing the travel time reliability between districts 4 and 7 requires a large set of trips with data points within both districts 4 and 7. Figure 3-40 shows the number of trips that spanned multiple districts. Those with zero districts indicate trips where data points were all outside of the geographical analysis range.

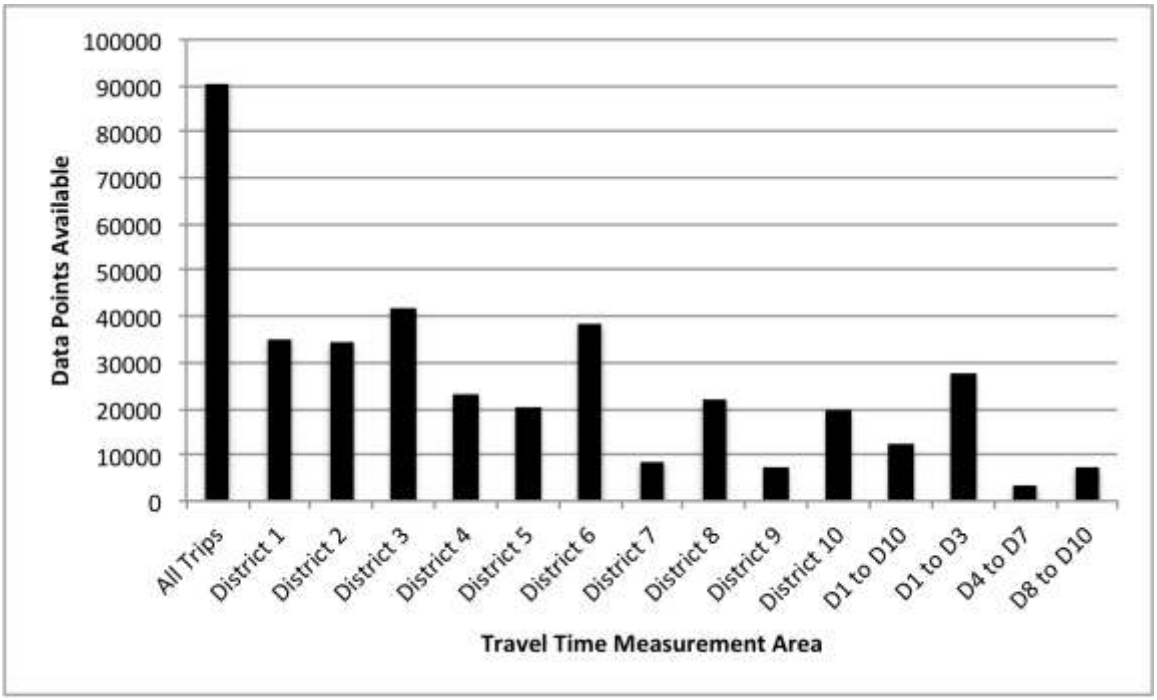


Figure 3-39: Otay Mesa GPS points by district

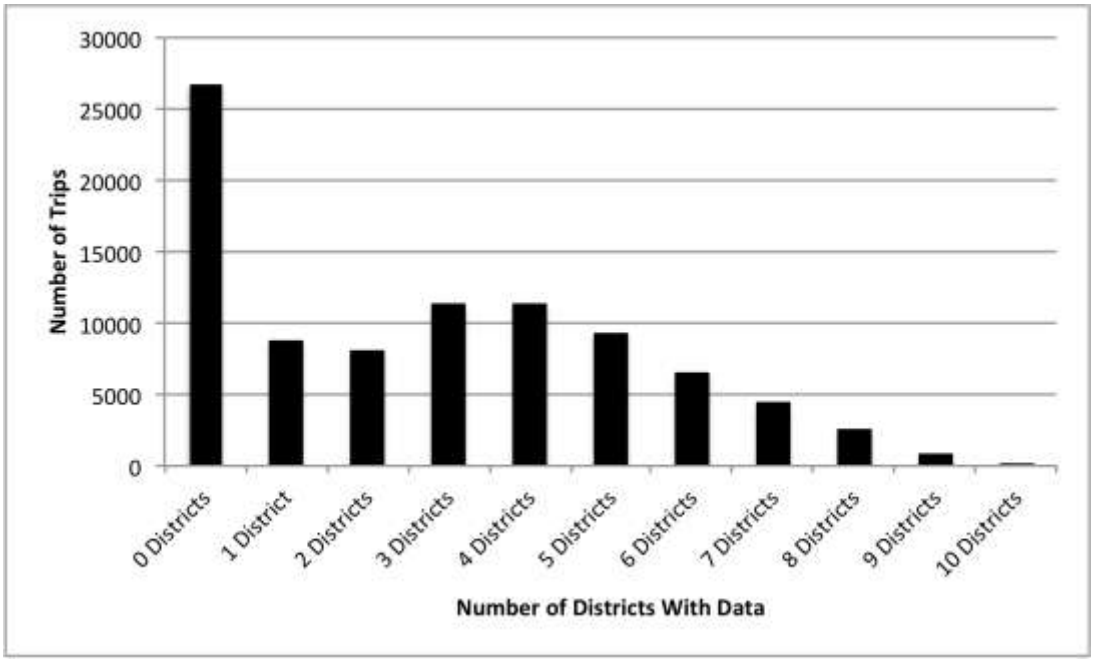


Figure 3-40: Otay Mesa trips spanning multiple districts

Results

As outlined in the data section, analysis focused on investigating reliability across OtayMesa districts and for vehicles subjected to different inspection types. The results of each type of analysis are detailed in the following subsections.

District Reliability. To understand which geographical segments of the border crossing have the most travel time variability, the research team assembled the travel time PDFs for trips within each of the 10 individual districts, and for two trips spanning multiple districts.

The PDFs for districts 1 through 6 are shown in Figure 3-41 and the PDFs for districts 7 through 10 are shown in Figure 3-42. All of the PDFs are plotted on the same x-axis scale, to facilitate comparison. This data is also summarized into median, standard deviation, and 95th percentile travel times by district in Table 3-18. From the plots, the district that notably stands out as having the most travel time variability is district 7 (USA Secondary Inspection). From the distribution, it appears that the most frequently occurring travel time through district 7 is about 15 minutes, but the trip regularly can take longer than an hour. The median travel time through this district is only 20 minutes, but the 95th percentile travel time is 90 minutes. Districts 1, 2, 3, 4, 8, and 10 also all have 95th percentile travel times at or greater than one hour, which are significantly higher than their median travel times of less than 10 minutes. The district with the most reliability is district 9 (CHP Inspection Approach). Here, the median travel time is only 12 seconds, with a 95th percentile travel time of 2 minutes.

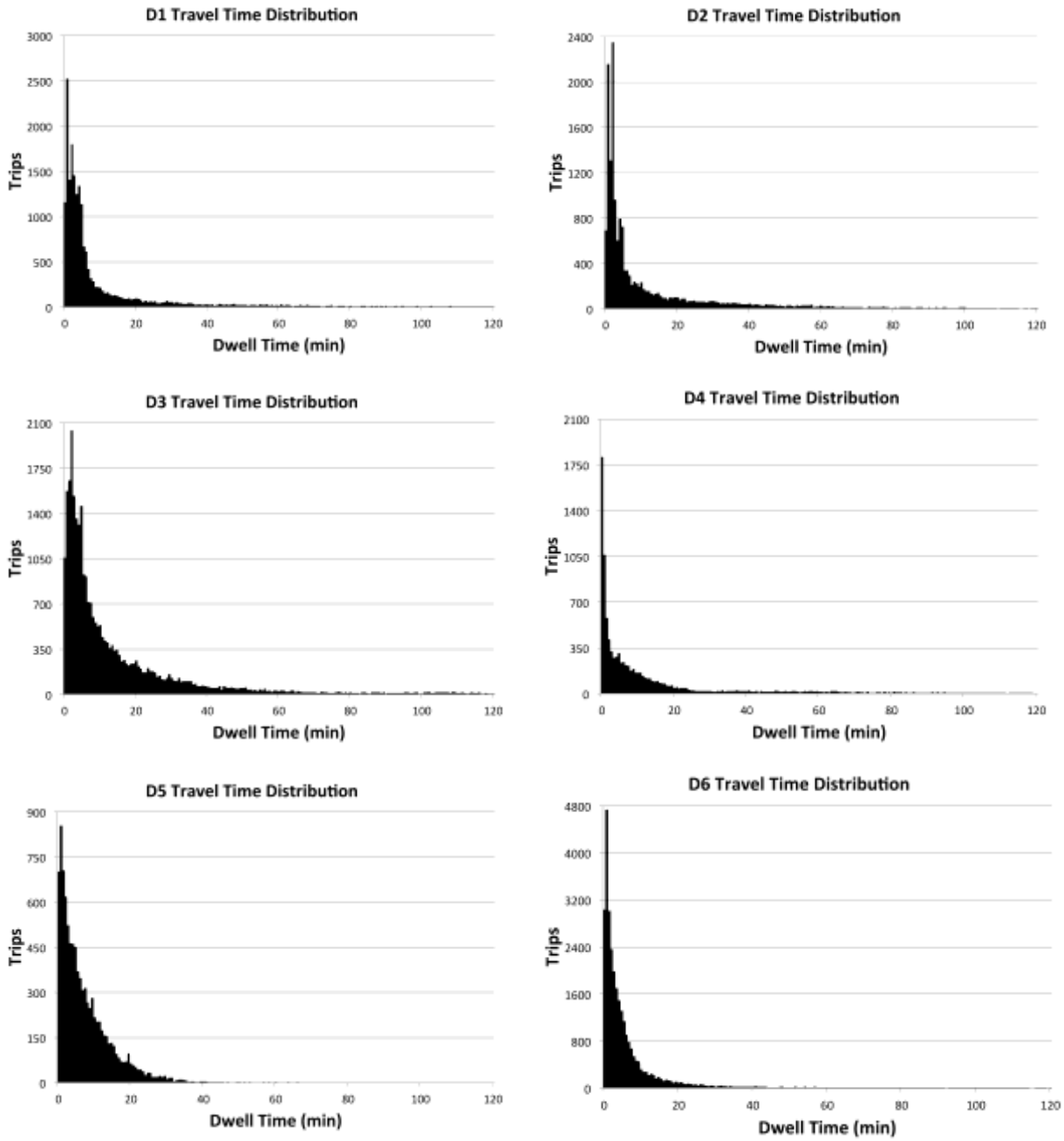


Figure 3-41: Districts 1 through 6 Travel Time PDFs

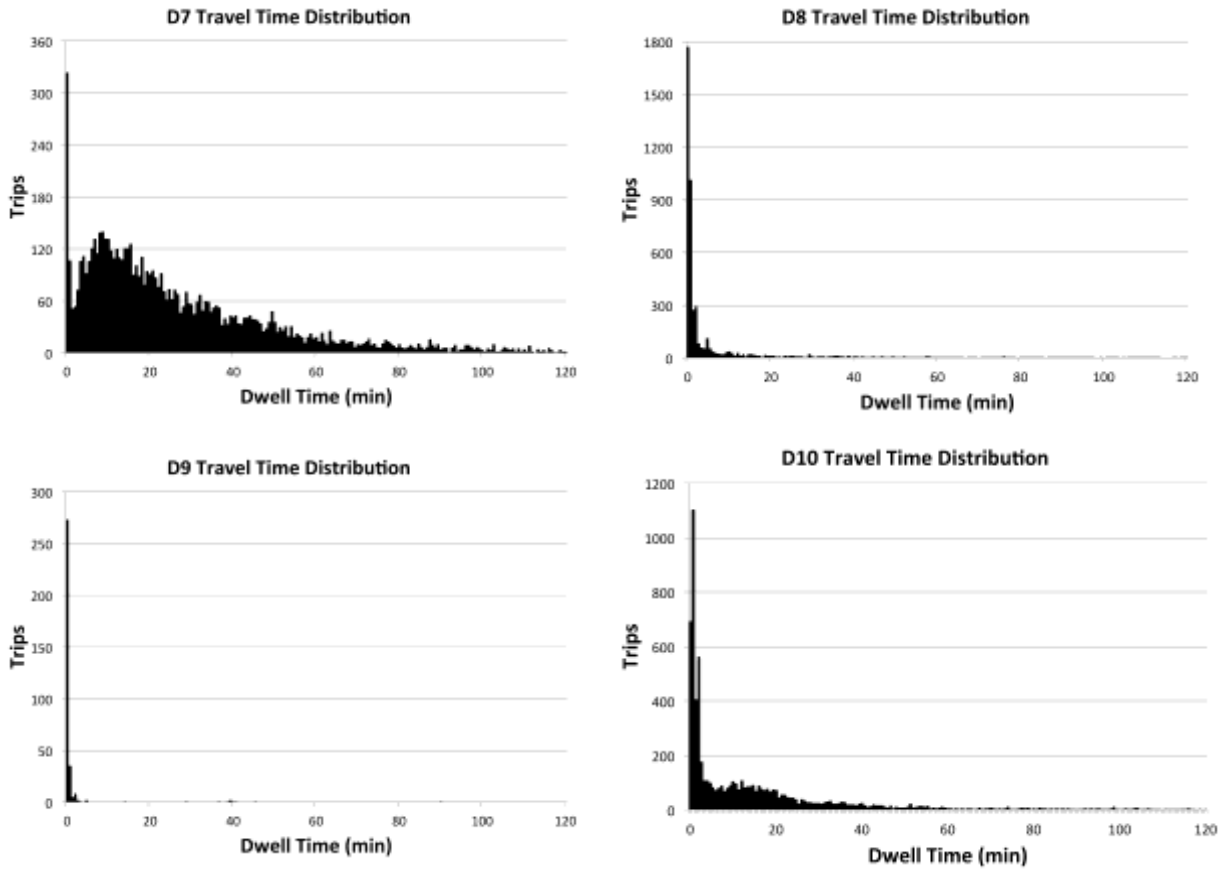
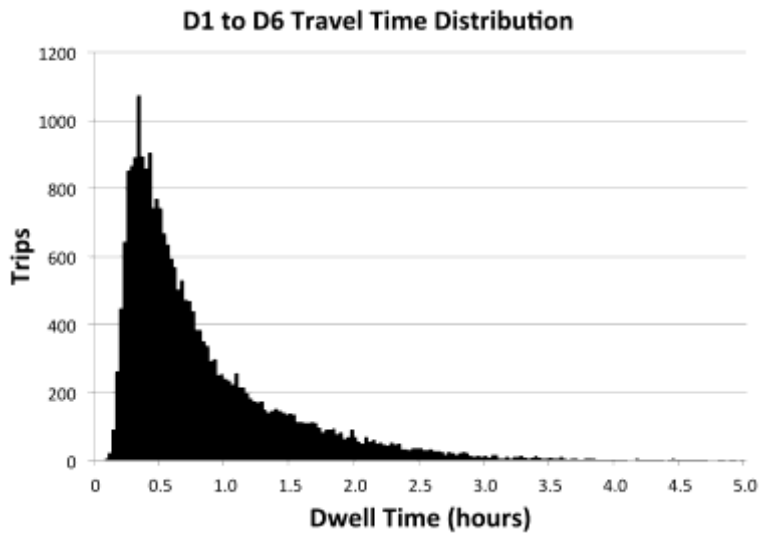


Figure 3-42: Districts 7 through 10 travel time PDFs

Table 3-18: District-by-district travel times and variability

District	Median Travel Time (mins)	Standard Deviation (mins)	95th Percentile Travel Time (mins)
D1	4	27	65
D2	4	21	59
D3	7	20	56
D4	5	24	68
D5	5	7	22
D6	3	16	29
D7	21	32	90
D8	1	83	65
D9	0.2	8	2
D10	7	36	87

The research team also looked at the travel times for trucks to get from district 1 to district 6 (the gate to the US Secondary Inspection) and to travel from district 1 to district 10. The PDFs for these two trips are shown in Figure 3-43, and the results are summarized into the median, standard deviation, and 95th percentile travel times in Table 3-19.



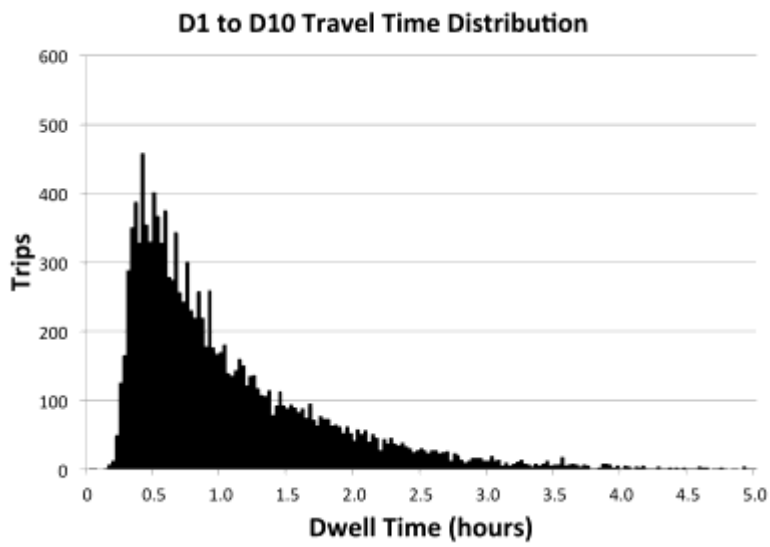


Figure 3-43: Cross-district travel times PDFs

Table 3-19: Cross-district travel times and variability

Trip	Median Travel Time (mins)	Standard Deviation (mins)	95th Percentile Travel Time (mins
D1 to D6	37	40	132
D1 to D10	50	48	157

The most commonly occurring travel time between district 1 and district 6 is slightly less than half an hour, though a significant number of trips can take upwards of one or two hours. The median travel time for this trip is 37 minutes, but the 95th percentile travel time is 2 hours and 12 minutes. The median travel time to pass through the Otay Mesa crossing (as

represented by the district 1 to 10 travel time samples) is only 50 minutes, but 5% of trips experience travel times exceeding 2.5 hours.

Checkpoint Reliability. The team also considered the average travel times and travel time variability of trucks passing through certain combinations of checkpoints at different times of the day. As described in the freight data section, many of the freight GPS data records included information on which checkpoints a truck had to pass through while making its trip. While all trucks have to go through certain checkpoints (Mexican Exports, US Inspection, and CHP inspection), some trucks are subjected to additional inspections (Mexico Secondary Inspection and/or US Secondary Inspection). These were used to calculate travel times and reliability for each hour of the day for different checkpoint combinations.

Approximately 15% of trucks that use the crossing qualify for FAST status, which means that, while they have to pass through all the required checkpoints, they can do so in designated FAST lanes *(1)*. Figure 3-44 below shows, for all days over which data was received, the total number of sampled FAST lane trucks that traveled during each hour and did not have to stop for any secondary inspections, the average travel time they experienced, and the standard deviation in the travel times they experienced. The data represents over 3,500 records of vehicles that made FAST lane trips. As is evident from the plot, the travel times and travel time variability are actually the highest in the early morning hours, when the fewest sampled trucks were traveling. This may be because drivers are resting or because there is less staff available to perform inspections. The peak number of trucks use the FAST lanes at around noon and between 4:00 PM and 6:00 PM. Average travel times are fairly steady throughout the day, hovering at or slightly above one hour. The standard deviation of the travel times also remains steady at 40 to 50 minutes, meaning that it is fairly frequent for FAST lane border crossings to take almost 2 hours.

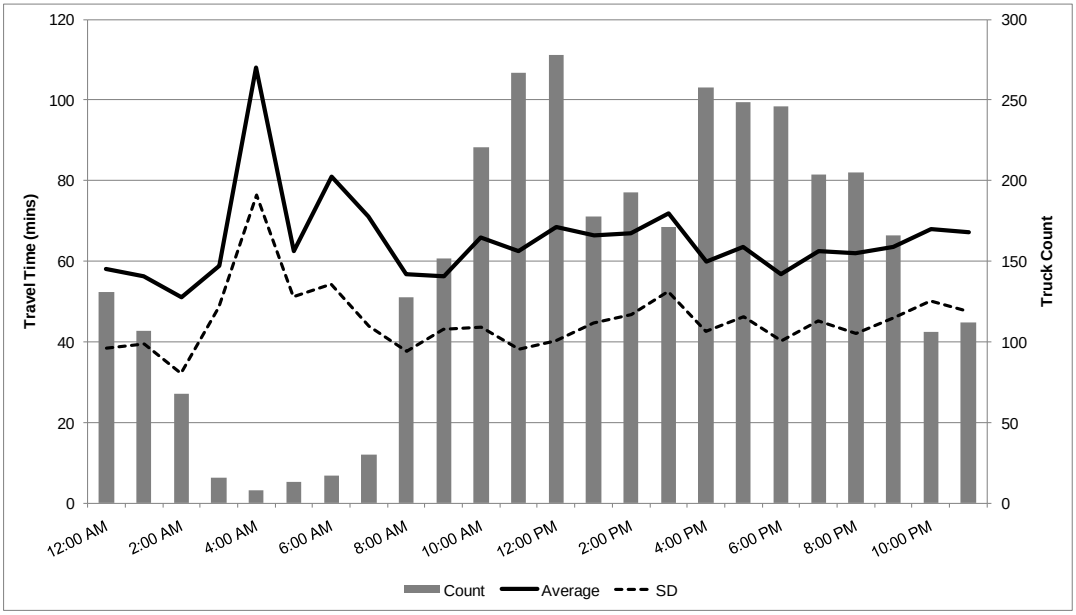


Figure 3-44: FAST truck counts, average travel times, and standard deviation travel times by hour

Figure 3-45 shows the same plot for 7,400 non-FAST trucks that were selected for US Secondary Inspections. As in the FAST lanes, travel times are the highest during the early

morning hours. Throughout the rest of the day, travel times are steady, but are 20 to 30 minutes higher on average than the FAST travel times.

Figure 3-46 shows the hourly vehicle counts and travel times for FAST trucks who were selected for a US Secondary Inspection. Interestingly, average travel times for FAST vehicles going through a US Secondary Inspection are actually slower (between 90 and 100 minutes) during most hours than they are for non-FAST vehicles (between 80 and 90 minutes) going through a US Secondary Inspection. The standard deviation of travel times for both types of trips are approximately the same.

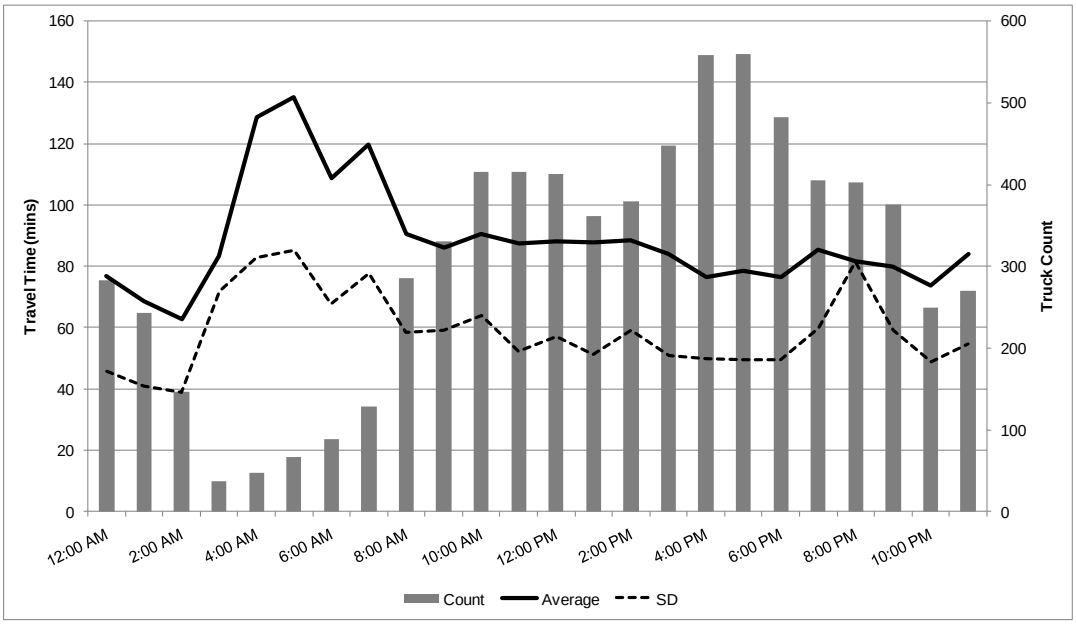


Figure 3-45: US Secondary truck counts, average travel times, and standard deviation travel times by hour

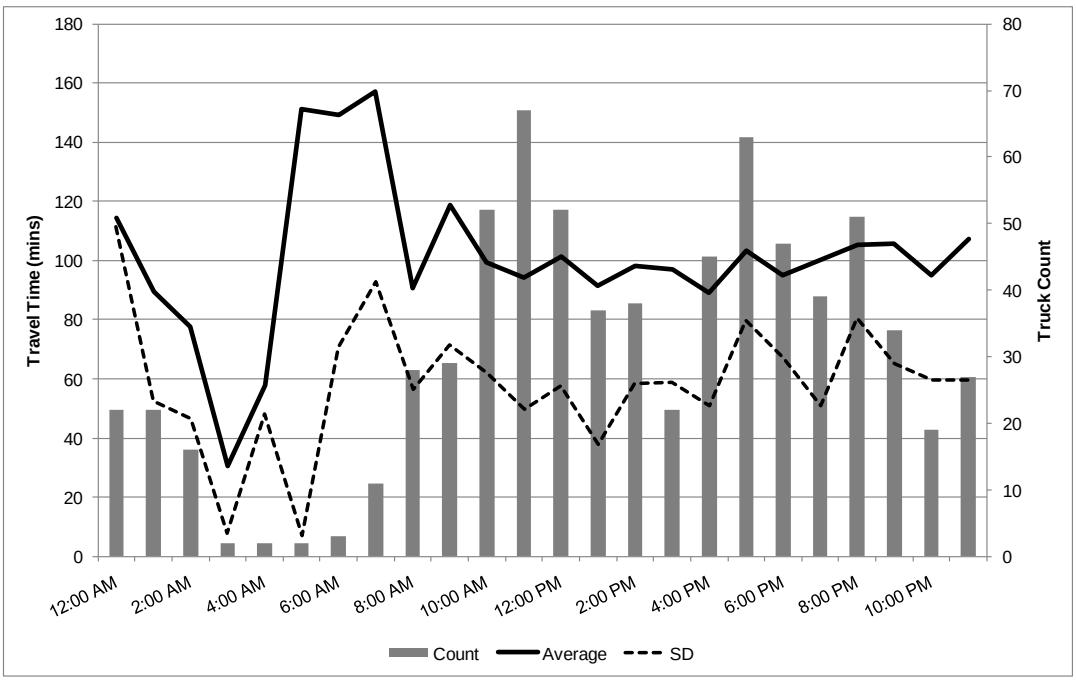


Figure 3-46: FAST US Secondary truck counts, average travel times, and standard deviation travel times by hour

Conclusions

This freight use case validation represents an initial use of the Otay Mesa truck travel time data to evaluate travel time reliability for different aspects of a border crossing. The research analyzed and compared travel time reliability across different physical sections of a freight-only border crossing, as well as for different combinations of inspection points passed through by individual trucks. By understanding where the bottlenecks are in the border crossing process and how they are impacting travel times and reliability, managers can begin to take steps to improve operations: for example, adding lanes to capacity-restricted locations or adding staff to checkpoints that are impacting reliability during peak hours of the day.

Extensions of the district-level analysis would group travel times by hour of the day to explain not just where travel time reliability is high, but when it is high as well. Extensions of the checkpoint-based analysis would look at travel time reliability for different days of the week, and for different seasons, because truck border crossings have strong temporal patterns that impact the underlying reliability analysis.

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4. LESSONS LEARNED

OVERVIEW

During this case study, we focused on fully utilizing a mature reliability monitoring system. We did this to illustrate the state of the art for existing practice. This was possible because of many years of coordinated efforts by transportation agencies in the region, led by the San Diego Association of Governments and Caltrans. These efforts put in a large sensor network, developed the software to process the data from these sensors, and created the institutional processes to utilize this information. Because this technical and institutional infrastructure was already in place, the team focused on generating sophisticated reliability use case analysis. The rich, multi-modal nature of the San Diego data presented numerous opportunities for state of the art reliability monitoring, as well as challenges in implementing guidebook methodologies on real data.

METHODOLOGICAL ADVANCEMENT

In terms of methodological advancement, the team used data from the Berkeley Highway Laboratory section of Interstate 80. This section is valuable because it has co-located dual loop detectors and Bluetooth sensors. This dataset provided an opportunity for the team to begin to assemble regimes and travel time probability density functions from *individual vehicle travel times.* These travel time PDFs are needed to support motorist and traveler information use cases. Since the majority of the upcoming case study sites will not provide data on individual traveler variability, it was important for the research team to study the connection between individual travel time variability and aggregated travel times, and whether the former can be estimated from the latter. In general, the team found that it was possible to divide the system into specific travel regimes, but has not yet harmonized these two different types of data. Work on answering these questions is ongoing, and will be used to refine the methodologies used at the next four case study sites.

TRANSIT DATA

The biggest data challenge in this case study validation was processing the transit data, which is stored in a newly developed performance measurement system. This case study represents the first research effort to use this data and this system. The team found that data quality is a major issue when processing transit data to compute travel times. Many of the records reported by equipped buses had errors, which had to be programmatically filtered out. Errors were due to a variety of reasons. Some buses reported that they were one route, but were serving a completely different set of stops. GPS malfunctions resulted in erroneous locations. Passenger count sensors failed and left holes in the data.

Following the identification and the removal of these data points, assembling route-based reliability statistics using a drastically reduced subset of good data presented the next challenge. This limited the number of routes that the research team could consider, since not all trips on all routes are made by equipped buses, and trips made by equipped buses contain a number of holes due to erroneous data records. From this experience, the research team concluded that transit travel time reliability monitoring requires a robust data processing engine that can programmatically filter data to ensure that archived travel times are accurate. Additionally, transit reliability analysis requires a long timeline of historical data, due to the fact that, typically, a subset of buses are monitored and a large percentage of obtained data points will prove invalid.

SEVEN SOURCES ANALYSIS

From a use case standpoint, the team was challenged to find the best ways to leverage the unique data available in San Diego to validate use cases that might not be possible to explore at other sites. On the freeway side, the team focused on relating travel time variability with the seven sources, since this dataset was unique to San Diego and the results have high value to planners and operators. In the past, the research team developed a sophisticated statistical model that can estimate the percentage of a route's buffer time attributable to each source of congestion. This model is documented in Chapter 11 of the guidebook. In this case study, the team opted to pursue a less sophisticated but more accessible approach that develops travel time PDFs for each source using a simple data tagging process. This approach was selected because it provides meaningful and actionable results without requiring agency staff to have advanced statistical knowledge.

CONCLUSIONS

The San Diego case study validation provided the first opportunity for the team to test guidebook recommendations, implement advanced methodologies, and formally respond to use cases. The research team plans to take the lessons learned during this process to modify the guidebook and better inform the future validation efforts.