SUPPLEMENT D

USE CASE ANALYSES

INTRODUCTION

This document shows how the Travel Time Reliability Monitoring System (TTRMS) can be used to address questions about network reliability. Early on, the study team recognized that these "use cases" provided a perspective on how the monitoring system should be designed. They helped shape the system's functional specifications.

The narrative for each use case includes a description of the question being asked, the reason it would be posed, the steps involved in obtaining the answer, the inputs needed including external data to answer the question, and the results that would be developed.

Travel time and travel rate probability density functions (TT-PDFs and TR-PDFs) are always at the heart of addressing the questions. Other metrics are popular today like the travel time index, planning time index, and buffer time; but these are not employed here. However, the values of those metrics can be derived from the PDFs. Effectively, the PDFs are interpreted in the context of the question asked. SHRP 2 Project L14, scheduled to be completed in mid-2012, is tasked with determining which of these measures, or others, would be most effective in conveying reliability information. The intent here is to create the right PDF. This having been said, there are places in the report where it seems helpful to mention one or more of these common measures, but no endorsement of any one of these specific measures is intended. In a couple instances, the ideas of disutility and risk are used to portray the results.

OVERVIEW OF THE USE CASES

The use cases fit the template shown in Table D-1. The template calls for a definition of the type of person asking the question (user), the question being posed, the inputs needed to answer the question, the steps involved in answering the question, and the results expected.

Table D-1: Use Case Template

User	The type of TTRMS user posing the question
Question	A description of the inquiry and why it would be posed.
Inputs	The data and information needed to answer the question. This description helps users understand the inputs required; and programmers understand the data inputs that must be assembled.
Steps	A list of the actions that have to be performed to answer the question.
Result	The TTRMS output at the completion of the use case.

Three additional comments about the use cases are helpful. First, the term "on-time" is an easy concept to grasp but one which is difficult to define in technical terms. Even though people think about "on-time" as meaning "not missed", there is no guarantee about being on time. Here "on-time" means arriving with a certain probability of not being late – or possibly early as is

often the case for freight shipments. Second, anywhere the acronym TT-PDF is used (or TT-CDF, the cumulative density function), it refers to the PDF for individual vehicle travel times unless the text says otherwise. Third, fairly technical information is presented for the results – for example TT-PDFs for the routes that might be selected. This does not mean that such information is the only way to convey the results. Rather, it implies that such information is the basis for the answer; but the communication paradigm might be simpler, as in a single number (e.g., from SHRP2 Project L14).

The use cases are clustered around types of TTRMS users most likely to make the inquiry. They are also broken down into providers and consumers, i.e., the supply and demand sides of system use. The stakeholders, shown in Table D-2, come from four categories:

- *Policy and Planning Support*: Agency administrators and planners that have responsibility for and make capital investment and operational decisions about the system.
- *Overall Highway System*: Operators of the roadway system (supply), including its freeways, arterials, collectors, and local streets and drivers of private autos, trucks, and transit vehicles (demand).
- *Transit Sub-system*: Operators of transit systems that operate on the highway network, primarily buses and light rail (supply) and riders (demand).
- *Freight Sub-system*: Freight service suppliers (supply) and shippers and receivers that make use of those services (demand).

Table D-2: User Types and their Classification

System User Type	Service Provider (Supply)	Users (Demand)
Policy and Planning Support	Administrators and planners	
Overall Highway System	Highway system operators (public or private)	Privately owned vehicle (POV) drivers, taxi drivers, limousine drivers, etc.
Transit Sub-System	Transit operators, transit vehicle operators	Transit passengers
Freight Sub-System	Carriers, freight movers, truck drivers	Freight customers (including both shippers and receivers)

Agency administrators and planners typically want summary information about system performance. They want to know how various factors affect reliability, like growing demand, or inclement weather, so they can make investment decisions or formulate policies that help to ensure system reliability will be acceptable.

System operators, transit operators, and freight service providers think in terms of service provided: whether trips take longer or shorter than they ought to or they promised they would. These inquirers want technical, quantitative information, both (near) real-time data for operations management and archived historical trend data for strategic and investment planning.

Drivers, transit riders, and shippers want qualitative, anecdotal and objective, quantitative information about reliability. They think in terms of: 1) deviations in trip time relative to the total trip time, or 2) how often they are able to arrive within a particular time window (or their

shipments). What they experience affects departure times, mode choice, route choice, and even destination and location choices. Moreover, they make location decisions based on expected network reliability.

Factors that affect reliability are clearly of interest to all system users. Some factors are internal to the system such as its operational control (e.g., signal timing), base capacity, and maintenance (e.g., work zones); others relate to the users, like incidents, unusually high demand, and special events; and still others are related to exogenous factors like weather and the performance of complementary and competing modes.

The use cases are listed in Table D-3. They are categorized consistent with Table D-2 into those that pertain to agency administrators and planners, system operators and users, transit passengers, schedulers or operators, freight customers or operators.

Table D-3: Use Cases for the Travel Time Reliability Monitoring System

Category	Subgroup	Use Cases
System Administrators and Planners	Administrators	AE1: See What Factors Affect Reliability AE2: Assess the Contributions of the Factors AE3: View the Travel Time Reliability for a Subarea AE4: Assist Planning and Programming Decisions AE5: Document Agency Accomplishments AE6: Assess Progress Toward Long-Term Reliability Goals AE7: Assess the Reliability Impact of a Specific Investment
	Planners	AP1: Find the Facilities with Highest Variability AP2: Assess the Reliability Trends over Time for a Route AP3: Assess Changes in the Hours of Unreliability for a Route AP4: Assess the Sources of Unreliability for a Route AP5: Determine When a Route is Unreliable AP6: Assist Rural Freight Operations Decisions
Roadway Network Managers and Users	Managers	MM1: View Historical Reliability Impacts of Adverse Conditions MM2: Be Alerted When the System is Struggling with Reliability MM3: Compare a Recent Adverse Condition with Prior Ones MM4: Gauge the Impacts of New Arterial Management Strategies MM5: Gauge the Impacts of New Freeway Management Strategies MM6: Determine Pricing Levels Using Reliability Data
	Drivers – Constrained Trips	MC1: Understand Departure Times and Routes for a Trip MC2: Determine a Departure Time and Route Just Before a Trip MC3: Understand the Extra Time Needed for a Trip MC4: Decide How to Compensate for an Adverse Condition MC5: Decide En-Route Whether to Change Routes
	Drivers – Unconstrained Trips	MU1: Determine the Best Time of Day to Make Trip MU2: Determine How Much Extra Time is Needed

Table D-3: Use Cases for the Travel Time Reliability Monitoring System (continued)

Category	Subgroup	Use Cases
Transit System	Transit Planners	TP1: Determine Routes with the Least Travel Time Variability TP2: Compare Exclusive Bus Lanes with Mixed Traffic Operations
	Transit Schedulers	TS1: Acquire Reliability Data for Building Schedules TS2: Choose Departure Times to Minimize Arrival Uncertainty
	Transit Operators	TO1: Identify Routes with the Poorest Reliability TO2: Review Reliability for a Route TO3: Examine the Potential Impacts of Bus Priority on a Route TO4: Assess a Mitigating Action for an Adverse Condition
	Transit Passengers	TC1:Determine the On-Time Performance of a Trip TC2: Determine an Arrival Time Just Before a Trip TC3: Determine a Friend's Arrival Time TC4: Understand a Trip with a Transfer
Freight System	Freight Service Providers	FP1: Identify the Most Reliable Delivery Time FP2: Estimate a Delivery Window FP3: Identify how to Maximize the Probability of an On-Time Delivery FP4: Assess the On-Time Probability for a Scheduled Shipment FP5: Assess the Impacts of Adverse Highway Conditions FP6: Determine the Start Time for a Delivery Route FP7: Find the Departure Time and Routing for a Set of Deliveries FP8: Solve the Multiple Vehicle Routing Problem under Uncertainty FP9: Alter Delivery Schedules in Real-Time
	Freight Customers	FC1: Minimize Shipping Costs due to Unreliability FC2: Determine Storage Space for Just-in-Time Deliveries FC3: Find the Lowest Cost Reliable Origin FC4: Find the Warehouse Site with the Best Distribution Reliability

Note: TTR = Travel Time Reliability

AGENCY ADMINISTRATORS AND PLANNERS

This section describes the use cases that agency administrators and planners might employ to learn about system reliability, determine what factors cause the system to be unreliable, and track reliability performance over time.

Agency Administrators

Agency administrators are responsible for making decisions about how to expand the network and how to operate it. Hence, they want to ask questions about what factors affect reliability; to what extent they cause impacts; what trends can be observed across time; and what effects prior actions have had.

See What Factors Affect Reliability (AE1)

In this use case, the agency administrator wants to see what factors affect the reliability of the segments and routes in the system. That is, to what extent is system reliability affected by: incidents, weather, work zones, special events, traffic control devices, fluctuations in demand, and demand exceeding capacity. For example, the analysis might show that the system is experiencing unreliability largely due to incidents. If it did, the administrator might want to choose to increase spending on incident management systems or roadway safety improvements. The analysis might also help administrators set benchmarks against which they can test future improvements.

Table D-4: See What Factors Affect Unreliability (AE1)

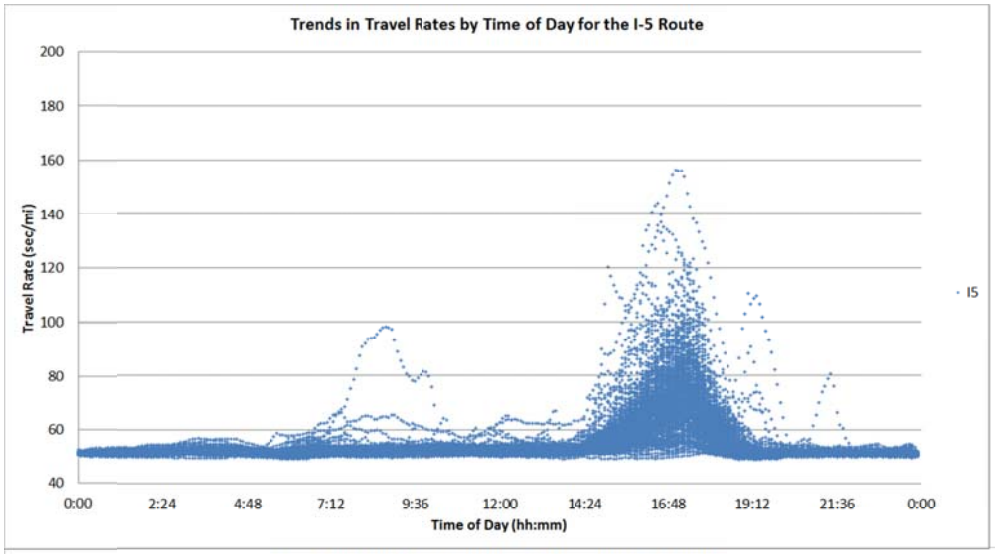
User	Agency Administrator
Question	What Factors Affect Reliability?
Steps	1. Select the system of interest (e.g., a region or set of facilities). 2. Select the timeframe for the analysis: the date range as well as the days of the week and times of day. 3. Assemble travel time (travel rate) observations for the system for the timeframe of interest. 4. Label each observation in terms of the regime that was operative at the time the observation was made, that is each combination of nominal congestion and non-recurring event (including none). 5. Prepare TR-PDFs for each regime identified. 6. Analyze the contributions of the various factors so that the differences in impacts can be assessed.
Inputs	Travel times and rates for the system and date range of interest plus information about the nominal system loading that would have been expected and any non-recurring events.
Result	A set of TR-PDFs that portray the impacts of various factors on travel time reliability.

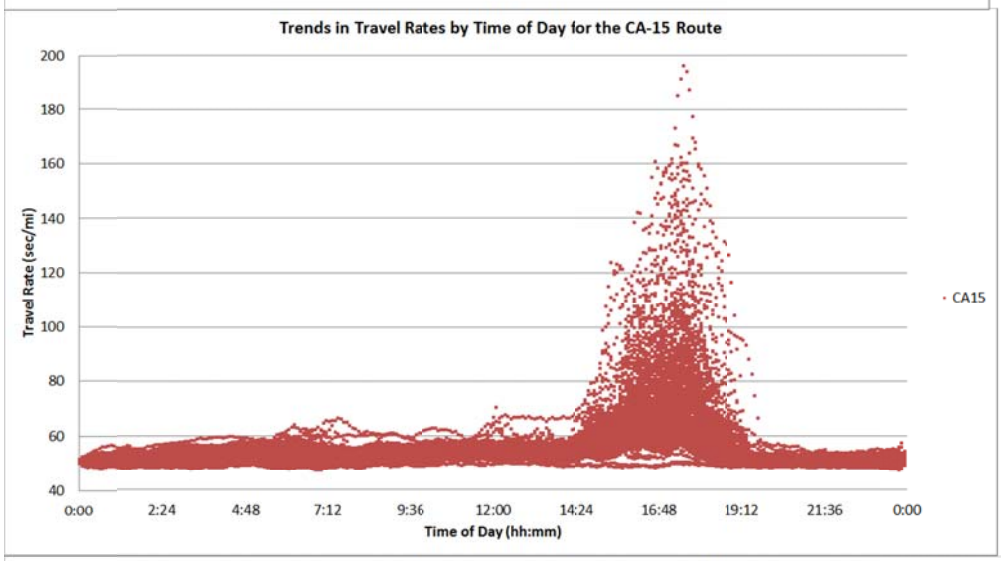
Step 1 is to select the "system" of interest – often, a region or set of facilities. In this instance the system selected is three freeway routes from A to B in San Diego, as shown in Exhibit D-1: I-5, I-805/ CA-15/I-5, and I-805/CA-163/I-5. In subsequent text, these three routes are identified more succinctly as I-5, CA-15, and CA-163.

Exhibit D-1: Sub-area being examined for use case AE1

Step 2 involves selecting the timeframe of interest. In this instance it is 2011, all weekdays, and all 24 hours during those days.

Step 3 focuses on assembling travel rate data. In this case the data are average travel rates from A to B for each route based on system detector data obtained by walking the time-space matrix for hypothetical trips that start every five minutes during the day on all three routes. The travel rates are displayed in





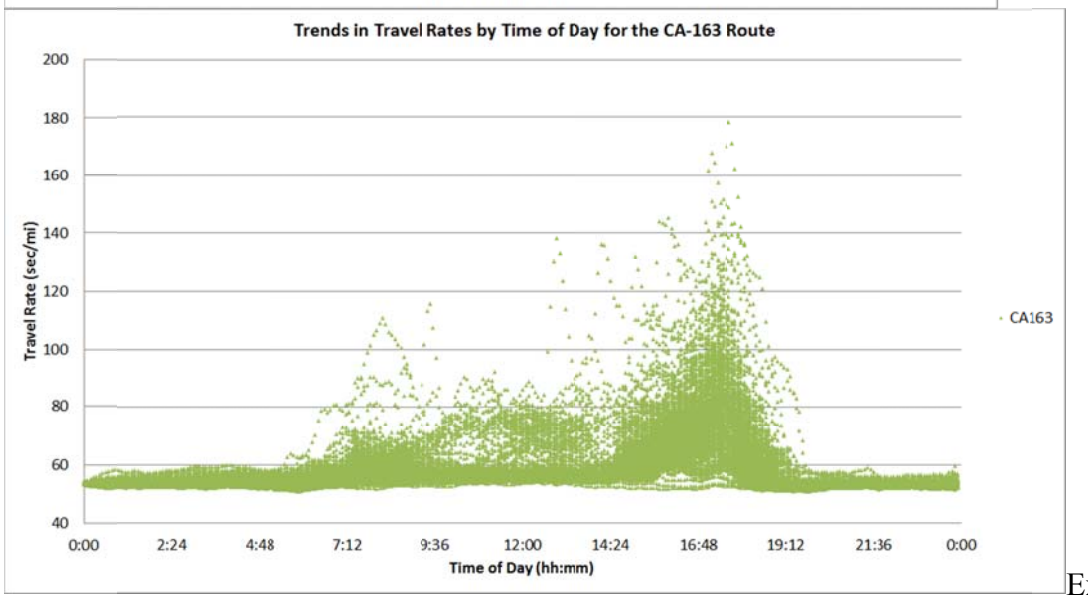


Exhibit D-2 plotted against time of day and **Error! Reference source not found.** plotted against VMT/hour.

Since the data for the entire year are shown, there are 72,000 values for each route. Hence, the total number of data points in the combined graphs is 216,000. Travel rates are needed because normalizing by the distance makes it possible to compare the performance of one route with the others without having the differences in length confound the analysis.

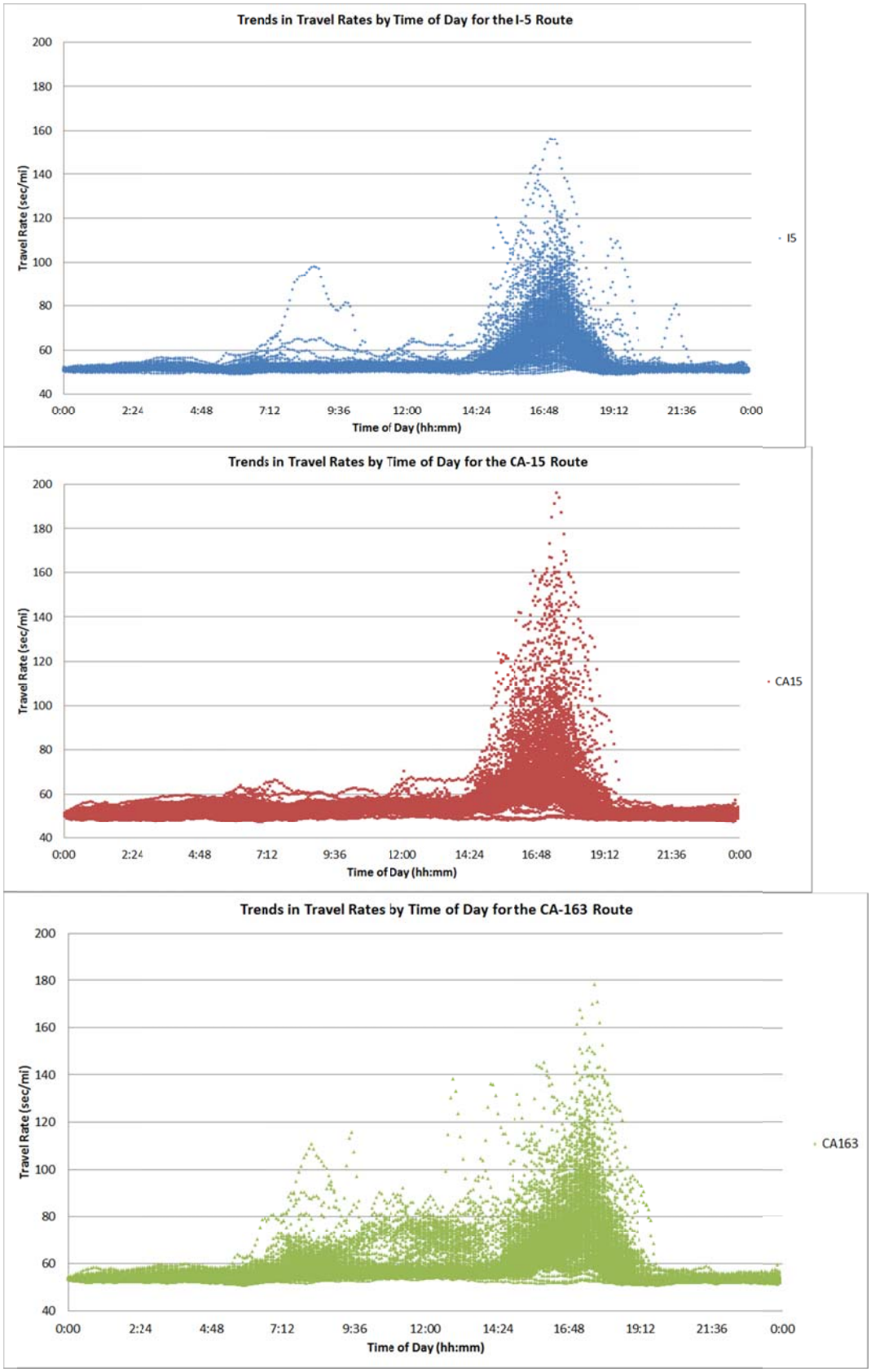


Exhibit D-2: Five-Minute Average Weekday Travel Rates for Three Routes in San Diego

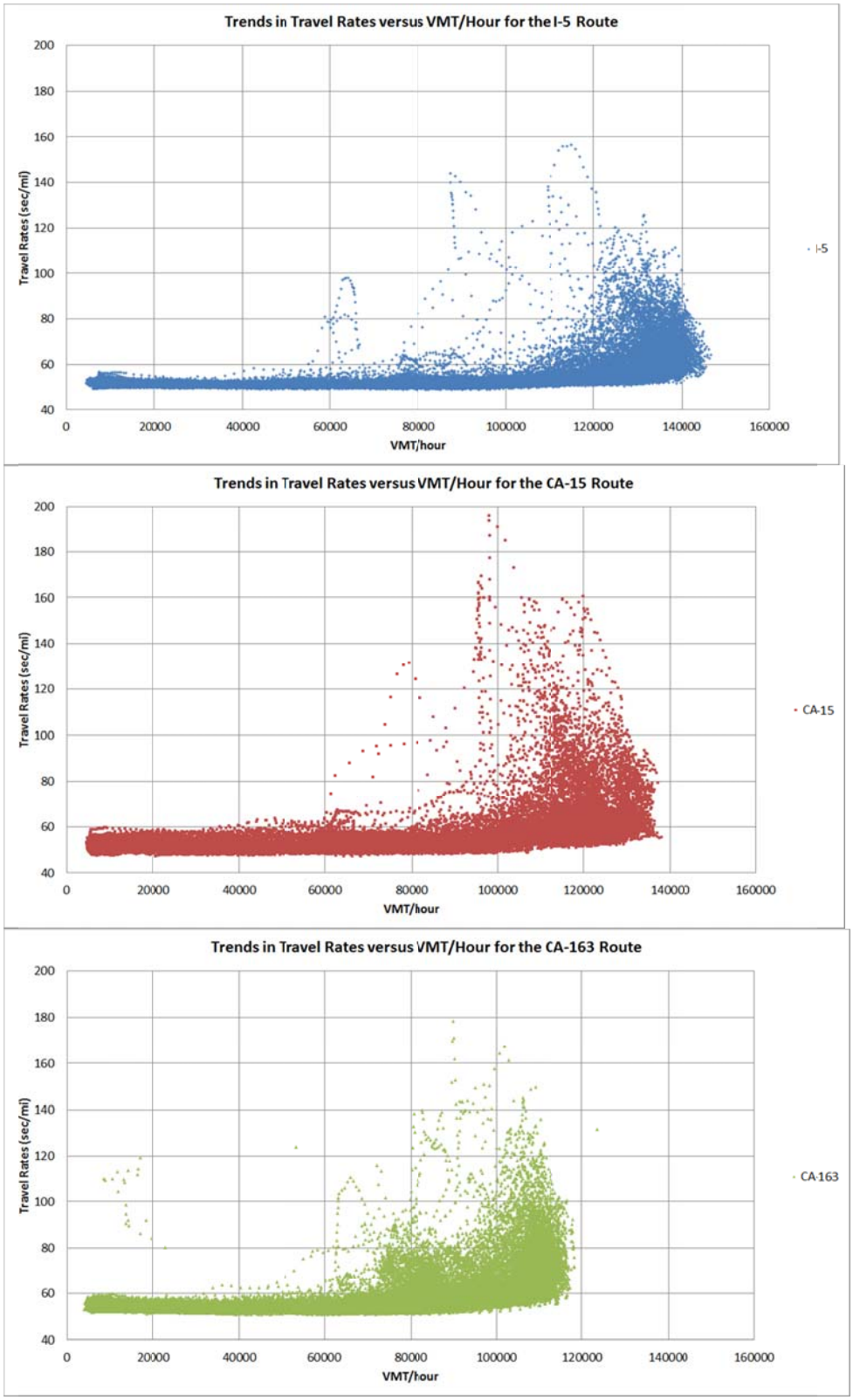
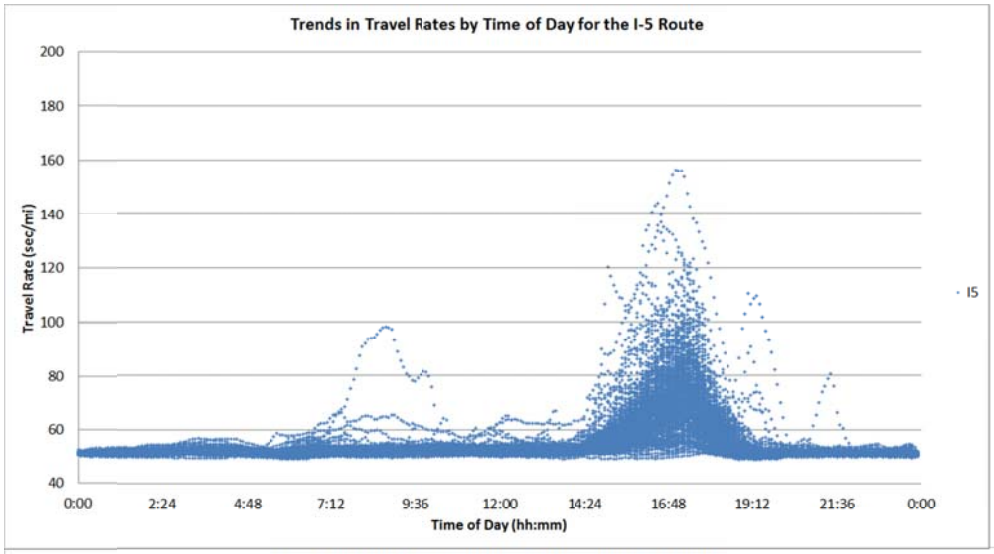
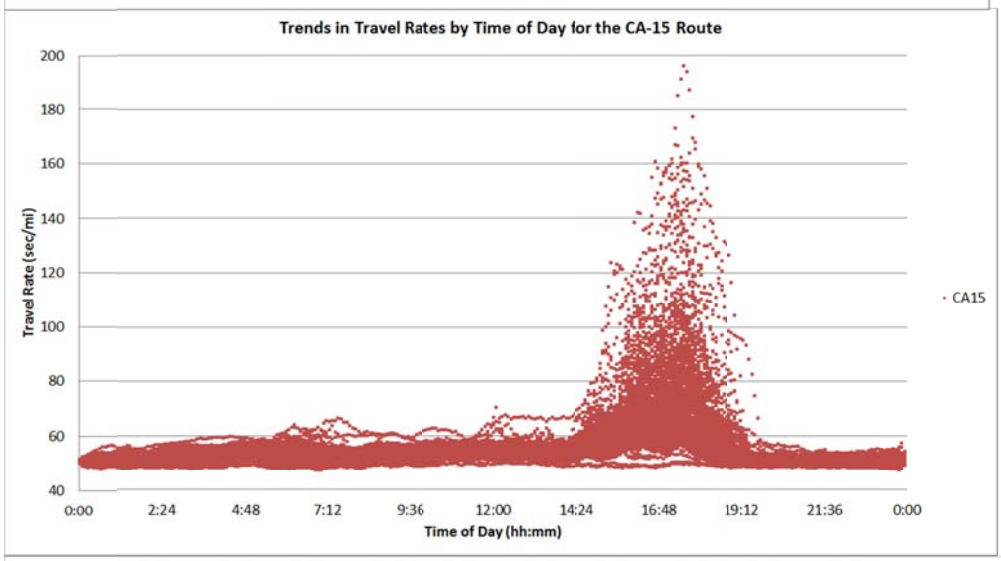


Exhibit D-3: Five-Minute Average Weekday Travel Rates plotted against VMT/Hour for Three Routes in San Diego

Step 4 involves labeling each observation – all 216,000 in this case – in terms of the regime that was operative for each observation. A regime is a combination of nominal system loading (e.g., VMT/hour) and a non-recurring event, as explained in the Guidebook. The technique for adding these labels involves two sub-steps. The first is to add a non-recurring event designation – if any. If these events have been tracked in real time and fields that describe them are already in the database, then this sub-step is done automatically. (The Guidebook and Case Studies illustrate how this can be done and the challenges involved.) If not, they have to be identified by looking for outliers. The data for each route is plotted against time of day and VMT/hour (system loading) as shown in


Trends in Travel Rates by Time of Day for the I-5 Route
Travel Rate (sec/mi)
200
180
160
140
120
100
80
60
40
0:00
2:24
4:48
7:12
9:36
12:00
14:24
16:48
19:12
21:36
0:00
Time of Day (hh:mm)
I5


Trends in Travel Rates by Time of Day for the CA-15 Route
Travel Rate (sec/mi)
200
180
160
140
120
100
80
60
40
0:00
2:24
4:48
7:12
9:36
12:00
14:24
16:48
19:12
21:36
0:00
Time of Day (hh:mm)
CA15

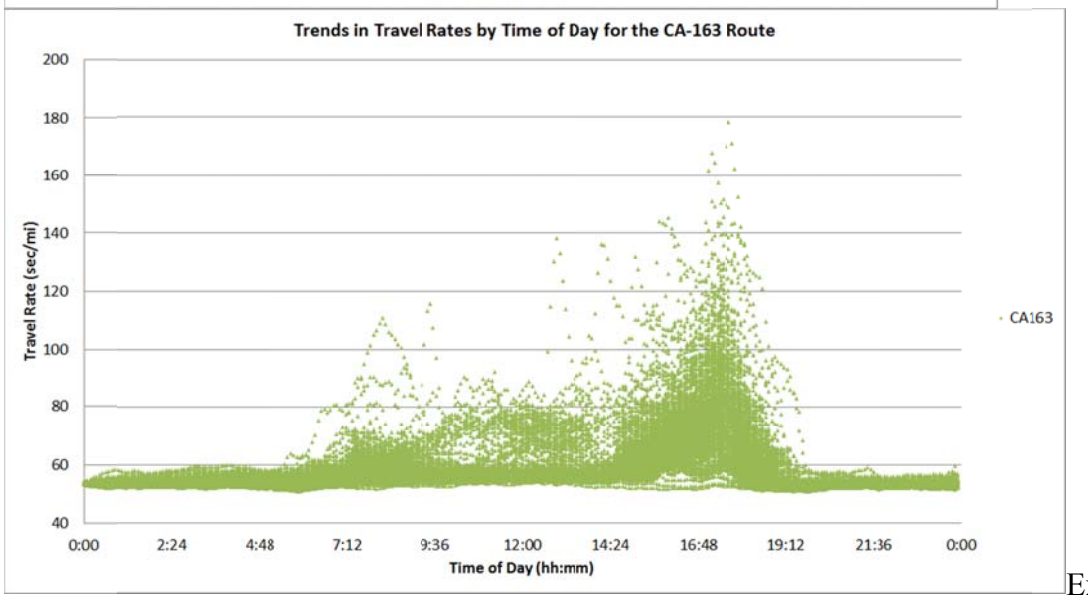

Trends in Travel Rates by Time of Day for the CA-163 Route
Travel Rate (sec/mi)
200
180
160
140
120
100
80
60
40
0:00
2:24
4:48
7:12
9:36
12:00
14:24
16:48
19:12
21:36
0:00
Time of Day (hh:mm)
CA163

Exhibit D-2

and **Error! Reference source not found.** respectively.[1] Starting with the most extreme (largest) outliers first, web-based databases are queried to see if explanatory non-recurring events can be identified for the dates/ times when the unusual travel rates occurred. For this particular system, the types of non-recurring events were: Incidents, Weather, Special Events, and Demand. An Incident was an accident or some other disruptive traffic event – recorded in the PeMS database or some other source; Weather was an inclement weather event; Special Event was an unusual event – often sports-related; and Demand was a condition when the VMT (implicitly, the traffic flows) was higher than normal for the time-of-day at which the high travel rate arose. Data points not falling into any one of these categories remained in a "Normal" category. (A weakness of this approach is that non-recurring events that do not create outliers might be missed.)

Comments about the "Demand" category are useful before going further. First, a "Demand" designation was always the last one added. That is, explanations were sought related to Weather, Special Events, or Incidents before using "Demand" as the explanation. Moreover the former three categories always trumped the "Demand" designation. Hence, values in the "Demand" category were extracted from those remaining in the "Normal" category after those explained by Weather, Special Events, Incidents, or other non-recurring events (e.g., work zones) are removed. Moreover, this removal process was *iterative*; there was nothing permanent about the "Demand" designation, unlike the other three. Second, the identification of the "Demand" category data points had two facets. The first involved comparing the VMT/hr value for a given 5-minute observation with the average for that 5-minute time period. If the value was more than two standard deviations above the mean, it was given a "Demand" designation. Then, because this technique did not work during the highly congested time periods when VMT/hr was constrained by capacity—because the VMT/hr cannot be higher—a second analysis was conducted. Sequences of 5-minute time periods should be sought when: the VMT/hr was high *and* the travel rate was high. (Effectively these were conditions when the D/C ratio was higher than the V/C ratio; implying there were standing queues in the system.) In this particular instance the values used were 75,000 VMT/hr, 80 sec/mile, and 30 minutes. That means that 5-minute time periods were labeled as being in the "Demand" category if their VMT/hr exceeded 70,000 VMT/hr, their travel rate was greater than 80 sec/mile, and at least the next five 5-minute time periods (30 minutes total) were in the same condition.[2]

The second sub-step (in Step 4) involves labeling each observation based upon the nominal loading of the system expected for each observation. This is done by analyzing the observations that remain once the non-recurring events have been removed.

The purpose of the congestion level designations is to differentiate the observations based on the reliability performance to be expected based on system loading, e.g., congestion. Many

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[1] Hourly VMT data (effectively VMT/hour) were obtained from PeMS. The actual hourly values were assigned to the 6th five-minute observation in each hour (25 minutes) and the other 5-minute values were generated by interpolating between these values.

[2] Obviously, changing these criteria affects the selection process. Basically, it changes the separation between observations that are considered normal, high congestion and those that are attributed to high demand on top of high congestion. The values were chosen because: 70,000 VMT/hr, especially for the CA-163 route, was the point at which there was a step change in the variability of the travel rates; 80 sec/mile is the same as 45 mph, which is often the speed that arises when freeways are operating at capacity; and 30 minutes was deemed to be a reasonable system recovery time. It is effectively how long one assumes it takes the system to recover from normal high demand and return to a status where the travel rate is less than 80 sec/mile). Higher values imply that it is OK for the system to take longer; shorter values assume it should take less time. Setting it at 0, for example, would imply that the system should be able to recover from travel rates above 80 sec/mile in five minutes.

metrics could be used to assess this impact, such as the buffer time index, the planning time index, or the travel time index, but the L02 team felt a better choice would be the semi-variance measure. This is because the semi-variance is sensitive to how the data are distributed above the minimum value. As explained in the methodological description, the semi-variance σ_r^2 is a one-sided variance metric that uses a reference value *r* instead of the mean as the basis for the calculation and only observations x_i that are greater than (or less than) that reference value are utilized:

$$\sigma_r^2 = \frac{1}{n}\sum_{i=1}^{n}\left(x_i - r\right)^2 \quad and \quad \sigma_r = \sqrt{\sigma_r^2} \quad \exists\, x_i \geq r$$

In this instance, semi-variance values were computed for every five minute interval for each of the three routes. **Error! Reference source not found.** presents the result. The value of *r* employed for each route was the minimum travel rate observed for the entire year. Moreover, because the number of observations varied from one five-minute period to another, the semi-variances were divided by the number of observations by *n* as shown in the equation above (effectively creating an average per observation so that the results would be comparable among the five-minute time periods.

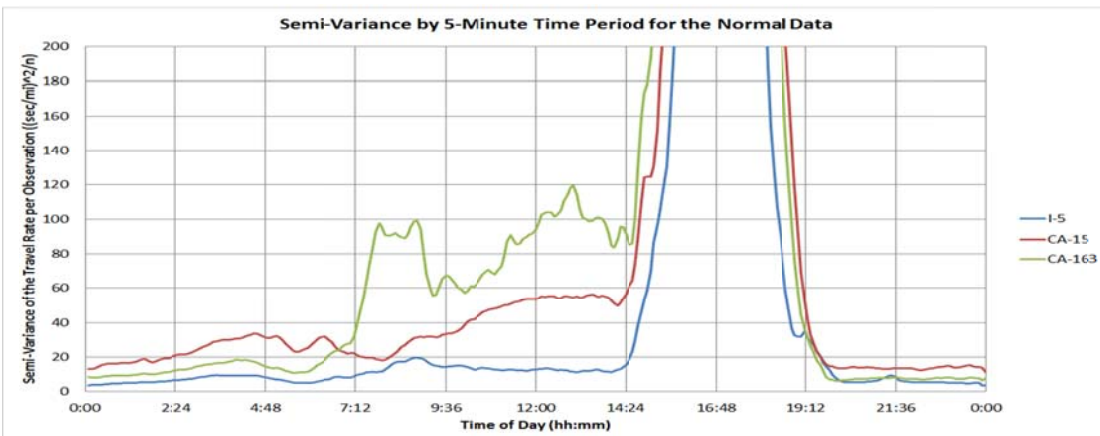


Exhibit D-4: Semi-Variance Values for Every Five-Minutes / Weekday Average Travel Rates for the Normal Condition for Three Routes in San Diego

Notice that reliability becomes worse as the traffic levels increase. This should be expected: reliability should be best when the traffic volumes are low – like late at night or early in the morning. It should be poorer during when the traffic volumes are higher – when the vehicles interact more, like during the midday, and it should be poorest when the traffic volumes are the highest, as in the PM peak, when the varying lengths of the standing queues has an impact. The maximum semi-variance values, which are not shown in the exhibit, reach about 1,000.

While no "right" answer exists for the number of categories to use, four were selected here: Uncongested, Low, Moderate, and High. Uncongested meant the semi-variance was below 20; Low meant 20 to 40; Moderate, 40 to 120; and High, above 120. Thus, the I-5 route was classified as Uncongested all day except from 14:15 to 18:50 when it was classified as High. The CA-15 route was classified as Uncongested from midnight to 2:10; Low from 2:15 to 6:45; Uncongested from 6:50 to 8:15; Low from 8:20 to 9:05; Moderate from 9:10 to 14:10, High from

14:15 to 19:20 and Uncongested from 19:25 to midnight. The CA-163 route was classified as Uncongested from midnight to 6:45, Moderate from 6:50 to 14:15, High from 14:20 to 19:20, and Uncongested from 19:25 to midnight.

Step 5 involves developing TR-CDFs for each regime, that is, each combination of nominal loading (from the analysis above) and non-recurring event (from the first categorical analysis), including “none”. The TR-CDFs are created by appropriately binning the 5-minute travel time observations.

Exhibit D-5 presents the results.

Step 6 involves interpreting the results in terms of the effects on reliability of the various factors. But since that overlaps with the next use case, the results are presented there.

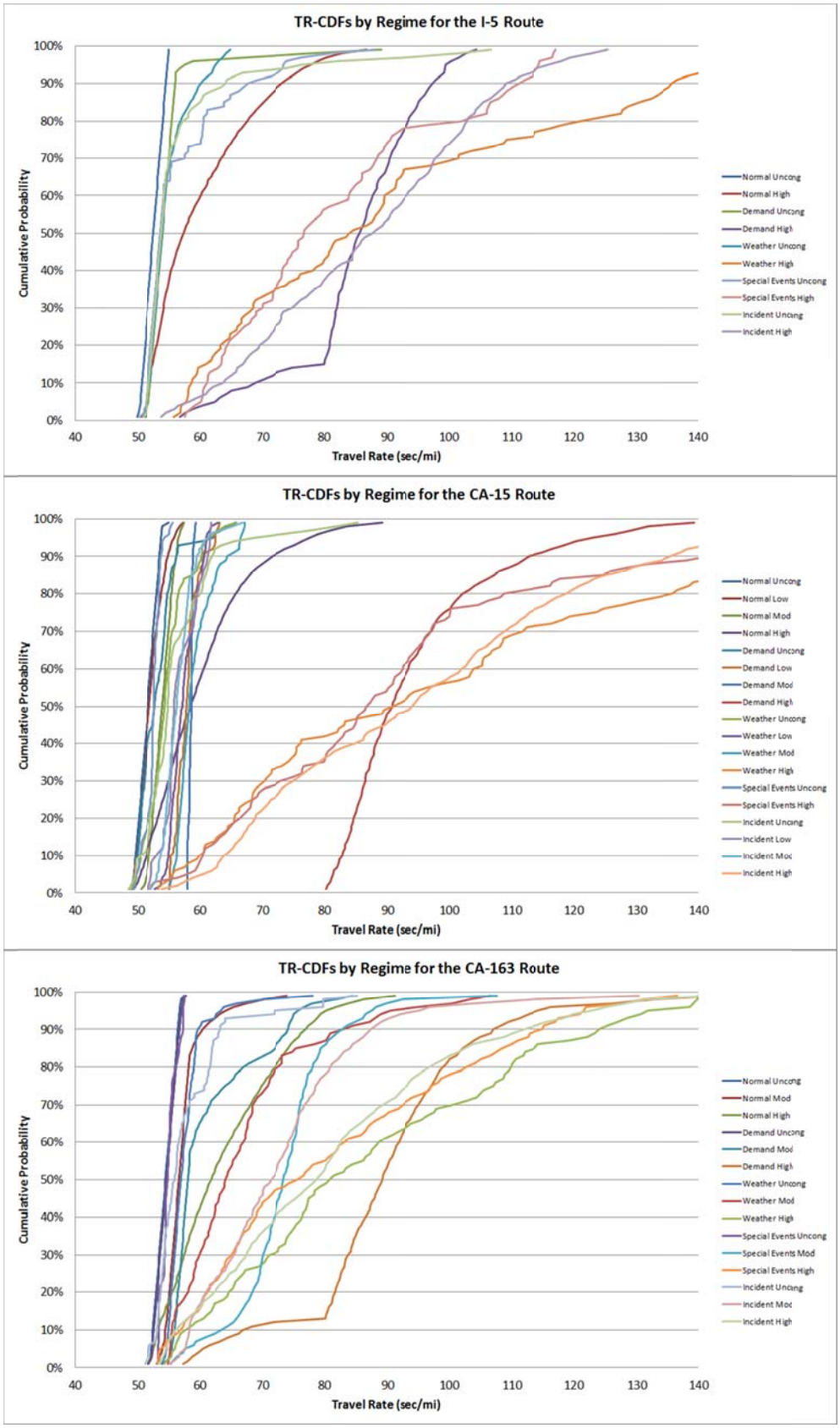


Exhibit D-5: CDFs by Regime for the Three Routes in San Diego

Assess the Contributions of the Factors (AE2)

The objective in this use case is to determine how various factors affect system reliability. Such information helps inform decisions about how to improve performance: geometric treatments, capacity enhancements, operational changes, better signage, improved roadway striping, resurfacing, or better lighting. It can also help managers determine which facilities need better real-time traveler information (such as Changeable Message Signs displaying alternate routes and travel times).

Table D-5: Assess the Contributions of the Factors (AE2)

User	Agency Administrator
Question	How do Various Factors Affect System Reliability?
Steps	1. Select the system of interest (facilities, routes, etc.) 2. Select the timeframe for which the analysis is to be conducted. 3. Assemble travel rate data for each facility. 4. Create TR-PDFs (rates) for each facility and regime – i.e., combinations of system loading and non-recurring event. 5. Study the TR-PDFs and determine the extent to which the facilities are affected by the various factors. 6. Rank order the facilities based on the relative impacts so that those most affected can receive mitigating treatments.
Inputs	A database of TR-PDFs with each observation labeled based on the regime to which it belongs (i.e., system loading and non-recurring event).
Result	A rank ordered list of the facilities based on the TR-PDFs by regime.

Step 1 involves selecting the system of interest. In this case, it is the same three routes in San Diego that were studied in the previous use case.

Step 2 involves selecting the timeframe for which the analysis is to be conducted. Again, consistent with the previous use case, for this analysis it is 2011, weekdays, all hours.

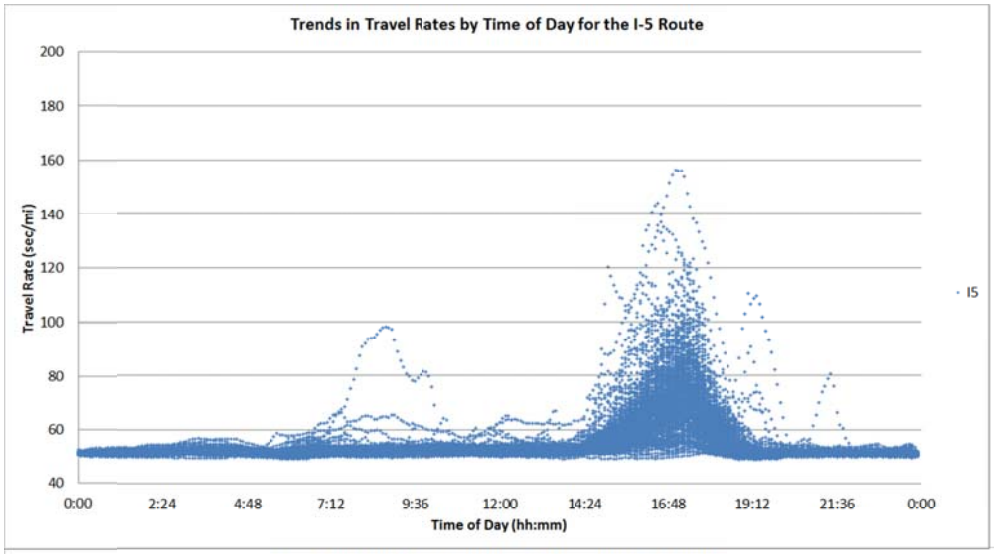
Steps 3 and 4 involve assembling the data and creating the TR-PDFs for the system in each regime. (In this case that means, for each route and regime.) Moreover, travel rates need to be used to create comparability because the facilities are of different lengths.

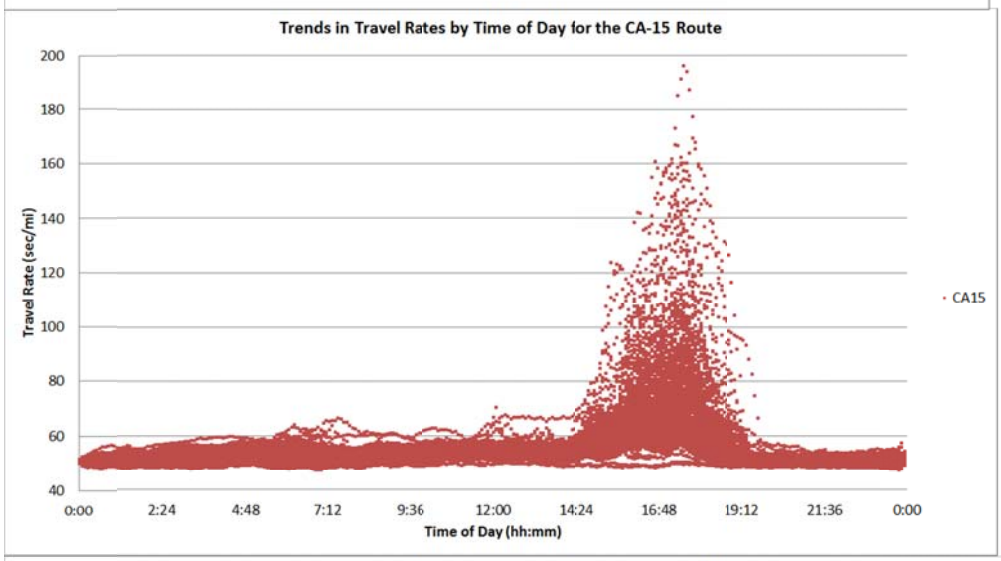
Step 5 aims to determine the extent to which the facilities are affected by various factors. **Error! Reference source not found.** and

Exhibit D-5 can be studied to develop these insights.

Error! Reference source not found. shows that the three routes have somewhat different daily patterns of reliability. The I-5 route has high reliability (a low semi-variance value) throughout the day except during the PM peak. In contrast, the CA-15 route has an increase in its semi-variance (a drop in reliability) across the midday (a higher semi-variance). The CA-163 route has an even more dramatic increase in its semi-variance across the midday but a lower semi-variance during the early morning hours. In addition, the CA-163 route has a discernible AM peak while the other two routes do not.

From an interpretation standpoint, this means the I-5 route is probably the most reliable. It is still challenged during the peak, but consistently has the lowest semi-variance values except for a few 5-minute periods around 7-9pm. Interestingly, this means that even though





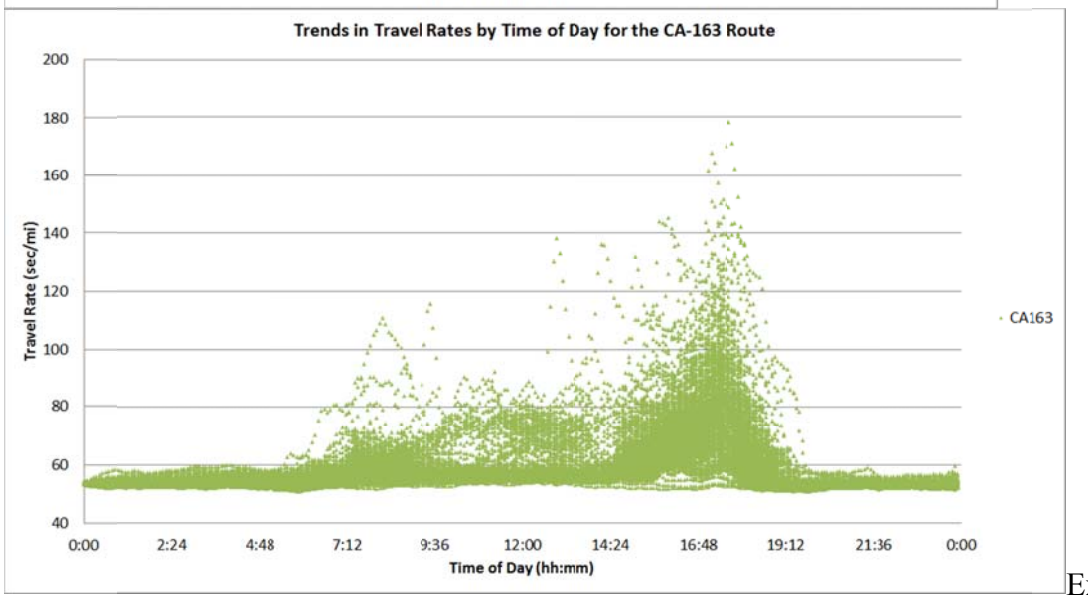


Exhibit D-2 suggests the CA-15 route may have the lowest average travel rates most of the day, the most

reliable route is a different one, namely I-5.

Error! Reference source not found. also suggests that CA-163 is the least reliable route. It has the highest semi-variance during the day – except in the early morning when the CA-15 route has higher values – and its semi-variance is significantly higher – especially during the morning and midday time periods.

Exhibit D-5 provides additional insights. While the plots are rather dense, they do tell a story about the performance of these three routes. Looking at I-5 first, its TR-CDF for the uncongested/normal condition is at the far left and it is almost vertical. This means it is very reliable travel rates during this condition. Moreover, during these uncongested conditions, even the non-recurring events affect only the top 30% of the 5-minute periods and in the worst case double the travel rate at the 100th percentile from about 50 sec/mile up to 100 seconds per mile – the fourth from the left and the most jagged of the group – related to incidents.

I-5's performance during the congested conditions is quite different. Even when there are no identifiable non-recurring events, larger travel rates are involved as can be seen by the smooth red-colored CDF having travel rates from about 50 to 100. Moreover, when non-recurring events occur during high congestion, the impacts are "severe": the travel rates are substantially higher than for normal, high-congestion conditions. The TR-CDFs for three of these conditions largely overlap for incidents, special events, and weather, and no one CDF dominates the other. However, the TR-CDF for the Demand condition (under high congestion) is strikingly different. It has much larger travel rates even at low percentiles, a kink at about 82 sec/mile when the Demand events during high-condition begin to have an impact on the CDF, and a maximum value that is substantially smaller than that for the other three non-recurring categories. The implication is that Demand needs to be a cause for concern, and reducing the rates for low percentile values may be possible through geometric improvements. Reducing the tail may not be that important; rather, it may be more important to focus on the tail for the three other conditions that involve much higher travel rates, even above the 50th or so percentile.

The story for the CA-15 route is similar. Almost all of the regimes involving no or low congestion have similar TR-CDFs. There is some spread between 50 to 60 sec/mi, but the TR-CDFs are all nearly vertical; not much variation in the travel rate occurs. The one notable exception is the TR-CDF for uncongested conditions when incidents arise. As with the I-5 TR-CDFs, the incidents produce a major shift for the travel rates at the higher percentile values, in this case above about 90%. The TR-CDF for high congestion during Normal conditions is the very smooth curve on the right-hand edge of the large cluster. Like I-5 it involves a much larger range of travel rates, from 50 to 85, and more change in the travel rate as the percentiles increase.

The four TR-CDFs that are strikingly different are those for incidents, special events, weather, and demand during periods that would normally involve high congestion. This is not surprising, but it does reinforce the importance of taking actions that help manage the severity of these events when they occur during congested operation. (In this case, for the Demand conditions there is a significant shift in the travel rates from 50 to 80 sec/mile even at the 0th percentile.)

The story for the CA-163 route is quite different. It obviously has problems. Its TR-CDFs are widely scattered, and non-recurring events have an impact under all levels of congestion. The most important details to notice are that: 1) the most significant impacts (the CDFs furthest to the right)—all during high congestion—come from (right to left) weather, special events, and incidents; 2) the next two (light blue and dark red) are for weather under moderate congestion

and demand during high congestion; and 3) the next three (right to left) are incidents, special events, and demand under *low* congestion conditions, not moderate.

With these differences noted, this route's reliability performance is otherwise similar to the other two. More specifically, it has a travel rate performance very similar to the other two routes under uncongested-normal conditions, but it struggles to maintain that performance either when the congestion levels get higher or non-recurring events take place.

The fact that the CA-163 route has more significant shifts in the TR-PDFs for various conditions leads to a conclusion that there are problems with this route between I-805 and I-5. It is not too difficult to see why by "driving" the route, either physically or virtually, and observing its physical features and congestion. The highway has many curves, its geometry is tight, and there are closely spaced interchanges. Particularly, between I-8 and I-5, it has tight geometry common to older freeway facilities and is only two lanes wide in each direction. While it is not the purpose of L-02 to determine what geometric and other treatments that would help alleviate reliability problems—that is the focus of other SHRP2 projects like L-07—it is obvious that this section of CA-163 is one where geometric improvements and expedient response to incidents would be likely to have a significant impact on reliability.

Step 6 involves rank ordering the facilities based on the relative impacts so that those most affected can receive mitigating treatments.

Exhibit D-6 provides a way to develop the rankings. Columns 3-12 report the average semi-variance values (SV) for each regime as well as the frequency (n) with which that regime occurs. The 13th column shows the semi-variance totals for each congestion condition (e.g., 573,000 for I-5 during uncongested conditions and 4,705,000 during congested conditions). These are based on the sum-product of the SV and *n* values. The last column in the top table reports the total semi-variance in the travel rate for the year (Facility Total).

Inspection of the facility totals suggests that the least reliable facility is CA-163. This is consistent with the impression one gains from the scatterplots shown in **Error! Reference source not found.** and **Error! Reference source not found.**. The CA-15 route is the next most unreliable (9465 versus 9561), but its distribution of the semi-variance is slightly different. As the bottom table shows, a higher percentage can be attributed to incidents and special events during nominally high congestion conditions.

A summary of this analysis might be: all three of the routes exhibit variations in reliability depending upon the recurring congestion condition and non-recurring event. Evidence of these differences is most significant for the CA-163 route, and it seems apparent the "problems" it has are due to the geometric conditions on the section of CA-163 from I-805 to I-5. All three routes are significantly affected by high congestion, even under normal conditions; the TR-CDF for that condition is dramatically different from the CDFs for normal operation under lesser congestion conditions. And incidents, weather, special events, and higher-than-normal demand all have a significant effect on reliability during highly congested conditions. Finally, it is clear that these TR-CDFs provide guidance about actions that might be useful to help fix the reliability problems.

Route	Cond	Normal		Demand		Weather		Special Events		Incidents		Σ(SV*n) (000)	Facility Total
		SV	n	SV	n	SV	n	SV	n	SV	n		
I-5	Uncong	7	55533	60	1250	46	797	111	135	172	285	573	5278
	High	205	12783	1415	472	2563	175	1399	104	1769	466	4705	
CA-15	Uncong	15	24491	47	147	68	229	29	77	139	55	400	9465
	Low	27	15931	118	102	106	193	0	0	97	25	457	
	Mod	46	14863	127	13	151	271	0	0	93	103	740	
	High	241	13918	2415	665	3751	162	3113	168	3032	587	7868	
CA - 163	Uncong	11	32823	13	1019	61	277	21	29	54	102	386	9561
	Mod	56	20950	169	519	399	333	601	344	684	354	1841	
	High	261	12764	1789	1028	1924	254	1424	243	1385	961	7333	

Route	Cond	Normal	Demand	Weather	Special Events	Incidents	Σ(SV*n) (000)	Facility Total
I-5	Uncong	8%	1%	1%	0%	1%	11%	1
	High	50%	13%	8%	3%	16%	89%	
CA-15	Uncong	4%	0%	0%	0%	0%	4%	1
	Low	4%	0%	0%	0%	0%	5%	
	Mod	7%	0%	0%	0%	0%	8%	
	High	35%	17%	6%	6%	19%	83%	
CA - 163	Uncong	4%	0%	0%	0%	0%	4%	1
	Mod	12%	1%	1%	2%	3%	19%	
	High	35%	19%	5%	4%	14%	77%	

Exhibit D-6: Semi-Variances for Each Regime for Three Routes in San Diego

View the Travel Time Reliability Performance of a Subarea (AE3)

In this use case, the agency administrator wants to review the travel time reliability performance of a subarea of the network. Subarea aggregations support transportation network planning and operations decisions for large-scale metropolitan networks.

Table D-6: View the Travel Time Reliability Performance of a Subarea (AE3)

User	Agency Administrator
Question	What is the reliability performance of a sub-area?
Steps	1. Define the boundary of the subarea of interest. 2. Choose the spatial aggregation method: windowing or focusing approach. 3. Select the date range, days of the week, and times of day over which to aggregate data. 4. Assemble TR-PDFs (rate) for the subarea differentiated by facility type, operating condition, time-of-day, etc. 5. Develop a picture of the reliability of the region that reflects the importance of each of the facility types, operating conditions, and times-of-day.
Inputs	TR-PDFs (rates) for the subarea differentiated by facility type, operating condition, time-of-day, etc.
Result	TR-PDFs for the region and selected routes (as shown by the red lines in Exhibit D-7) that reflect the importance of each of the facility types, operating conditions, and times-of-day.

As shown in Exhibit D-7, two different spatial aggregation approaches can provide users with subarea travel time reliability statistics:

1) *A Windowing Approach*, which isolates the subarea and focuses only on routes entirely within the subarea's boundary. This allows for the evaluation of the reliability impacts of policies enacted within a specific subarea and the analysis of subarea boundary-to-boundary travel time reliability measures.
2) *A Focusing Approach*, which is aimed at reliability measures for all of the routes that pass through the subarea. This allows linkages and relationships to be maintained between a subarea and its surrounding districts. It can generate statistics on the reduced subarea networks without losing reliability information at origin-destination level for long-distance trips.

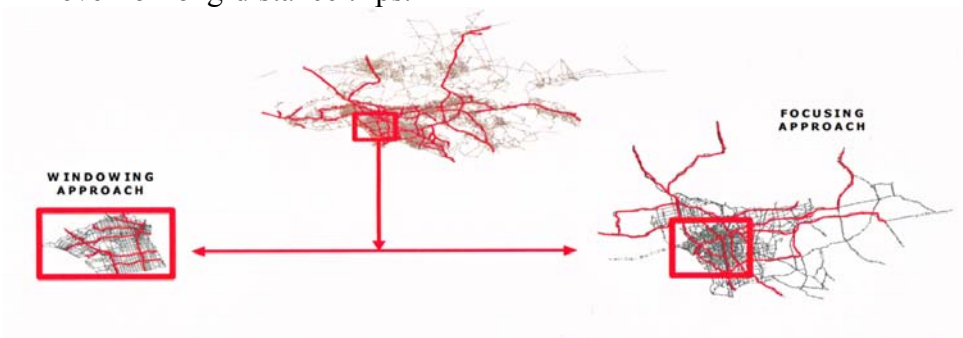


Exhibit D-7: Subarea Aggregation Approaches

Step 1 involves selecting the subarea of interest. In this case it is the same portion of San Diego metropolitan area shown in Exhibit 3-2.

Step 2 is to choose the aggregation method. In this particular instance, a windowing approach is employed, studying the reliability performance of the same three routes from A to B considered in the previous use case: I-5, I-805/ CA-15/I-5, and I-805/CA-163/I-5.

Step 3 is to select the date range, days of the week, and times of day over which to conduct the analysis. As with the prior use case, 2011 has been chosen, all weekdays, and all 24 hours.

Step 4 involves assembling the TR-PDFs differentiated by facility type, operating condition, time-of-day, etc. In this case the same regimes used in the previous use case are fine: the nominal loading (uncongested, or low, moderate, or high congestion) and non-recurring event (incident, special event, weather) including normal (no unusual non-recurring condition). Hence the TR-CDFs presented in

Exhibit D-5 still pertain.

Step 5 focuses on developing a picture of the reliability of the region that reflects the importance of each of the facility types, operating conditions, and times of day. For this purpose, the data presented in

Exhibit D-6 can be used, repurposed.

Assume that the three routes represent all the significant facilities in the region and that a picture of their combined contributions to unreliability is to be developed. The average semi-variance values can be converted into totals and then summed to gain a sense of the answer.

Exhibit D-8 presents the result.

The table shows that the regime involving high congestion and "no" non-recurring event (i.e., normal conditions) contributes most to the total semi-variance. It is followed by (high

congestion, demand) and (high congestion, incidents). The contributions from the regimes are individually under 10%. (High congestion, weather) contributes 6%; and (normal, uncongested), 5%.

Cond	Normal	Demand	Weather	Special Events	Incidents	Total
Uncong	5%	0%	0%	0%	0%	6%
Low	2%	0%	0%	0%	0%	2%
Mod	8%	0%	1%	1%	1%	11%
High	38%	17%	6%	4%	16%	82%
Total	52%	18%	7%	5%	17%	100%

Exhibit D-8: Semi-Variances Each Regime for Three Routes in San Diego

To gain a more detailed sense of the similarities and differences among these regimes, one tracks backward to

Exhibit D-6 and examines the average semi-variances. For example, the CA-15 route has many of the highest average SV values (e.g., 3,751 for weather under high congestion; 3,032 for incidents under high congestion) and semi-variances for these regimes contribute substantially to the total (17% and 19% respectively). Digging deeper leads to

Exhibit D-5 where one can see that the CDFs for those two situations are still climbing through the 70th and 80th percentiles at the maximum travel rates plotted (130-140 sec/mi). Clearly, these are the conditions where factors have the greatest impacts on reliability.

Assist Planning and Programming Decisions (AE4)

In this use case, the user wants make planning and programming decisions based on inputs from the TTRMS.

Table D-7: Assist Planning and Programming Decisions (AE4)

User	Agency Administrator
Question	What agency actions are having significant impacts on travel time reliability?
Steps	1. Select routes and subareas for analysis. 2. Assemble TR-PDFs for routes and areas for before/after traffic conditions under equivalent operating conditions. 3. Analyze the before/after changes in reliability along those routes and in those subareas and relate those changes to the actions taken as part of the transportation improvement projects. 4. Find the trends in the efficacy of different types of transportation improvement projects. 5. Use the results as input into decision-making associate with future agency planning and programming decisions.
Inputs	TR-PDFs for each route and area under the before and after conditions for similar network operating conditions associate with the travel rate observations information about the transportation improvement project actions that were taken.
Result	Both results of the before/after cause-and-effect analysis of the improvement actions taken as well as a process for conducting the assessment.

A description of the use case can build off AE1. Imagine a hypothetical situation in which the conditions portrayed for CA-163 are the status of that route at the end of 2009; the CA-15 conditions are for that same route (CA-163) at the end of 2010; and the conditions for I-5 are the status of that route (CA-163) at the end of 2011. Admittedly, such change would be remarkable progress, but that is actually useful here because it makes the differences clear.

Step 1 is to select the routes and subareas of interest. In this case it is the same portion of San Diego metropolitan area shown in Exhibit D-1 and the route of interest is the one involving CA-163.

Step 2 is to assemble TR-PDFs for routes and areas for before/after traffic conditions under equivalent operating conditions. In the context of the hypothetical situation described above, this has already been done and the results are presented in

Exhibit D-5. (Only those results have to be interpreted in as reflecting the performance of the CA-163 route in reverse chronological order with the most recent performance presented first.)

Step 3 involves analyzing the before/changes in reliability along the routes in the sub area and relating those changes to the actions taken as part of transportation improvement projects. Hence in the context of hypothetical situation described in Step 2 above, there are remarkable changes to assess.

Step 4 involves finding trends in the efficacy of different types of transportation improvement projects.

Exhibit D-9 presents the findings consistent with the hypothetical construct presented earlier. It shows that the agency actions are improving the reliability of the facility under normal conditions – dropping the SV under uncongested conditions from 11-7, eliminating the existence of a "Moderate" congestion condition, and reducing the SV during high congestion from 261 to 205. The SV trend under the other conditions is less clear. In some cases there is improvement; in other cases there is not. Of course, generating clear trends in these other categories is somewhat difficult to do because the severity of the non-recurring events can be different in one year versus another.

Cond	Year	Normal		Demand		Weather		Special Events		Incidents	
		SV	n	SV	n	SV	n	SV	n	SV	n
Uncong	X	11	32823	13	1019	61	277	21	29	54	102
	Y	15	24491	47	147	68	229	29	77	139	55
	Z	7	55533	60	1250	46	797	111	135	172	285
Mod	X	56	20950	169	519	399	333	601	344	684	354
	Y	73	30794	244	115	257	464	0	0	190	128
	Z	0	0	0	0	0	0	0	0	0	0
High	X	261	12764	1789	1028	1924	254	1424	243	1385	961
	Y	241	13918	2415	665	3751	162	3113	168	3032	587
	Z	205	12783	1415	472	2563	175	1399	104	1769	466

Exhibit D-9: Changes in Reliability over Time for a Hypothetical Route

Even though the agency may be doing a better job of managing the consequences of the events, the distribution of the severity of the events may make it difficult to see the impacts in a simple measure like the SV. Notice in

Exhibit D-9 that the SV values for the Special Event and Incident events show increases in the SV values from year X to Y and then decreases from year Y to Z. Whether progress has been made is unclear. However, in Exhibit D-10, the progress with Special Events becomes clearer. Notice that the TR-CDF for year Z has upper percentile values that are better than in either years X or Y; so, while the lower percentiles are not particularly improved, the higher percentiles are. The same is true for Incidents.

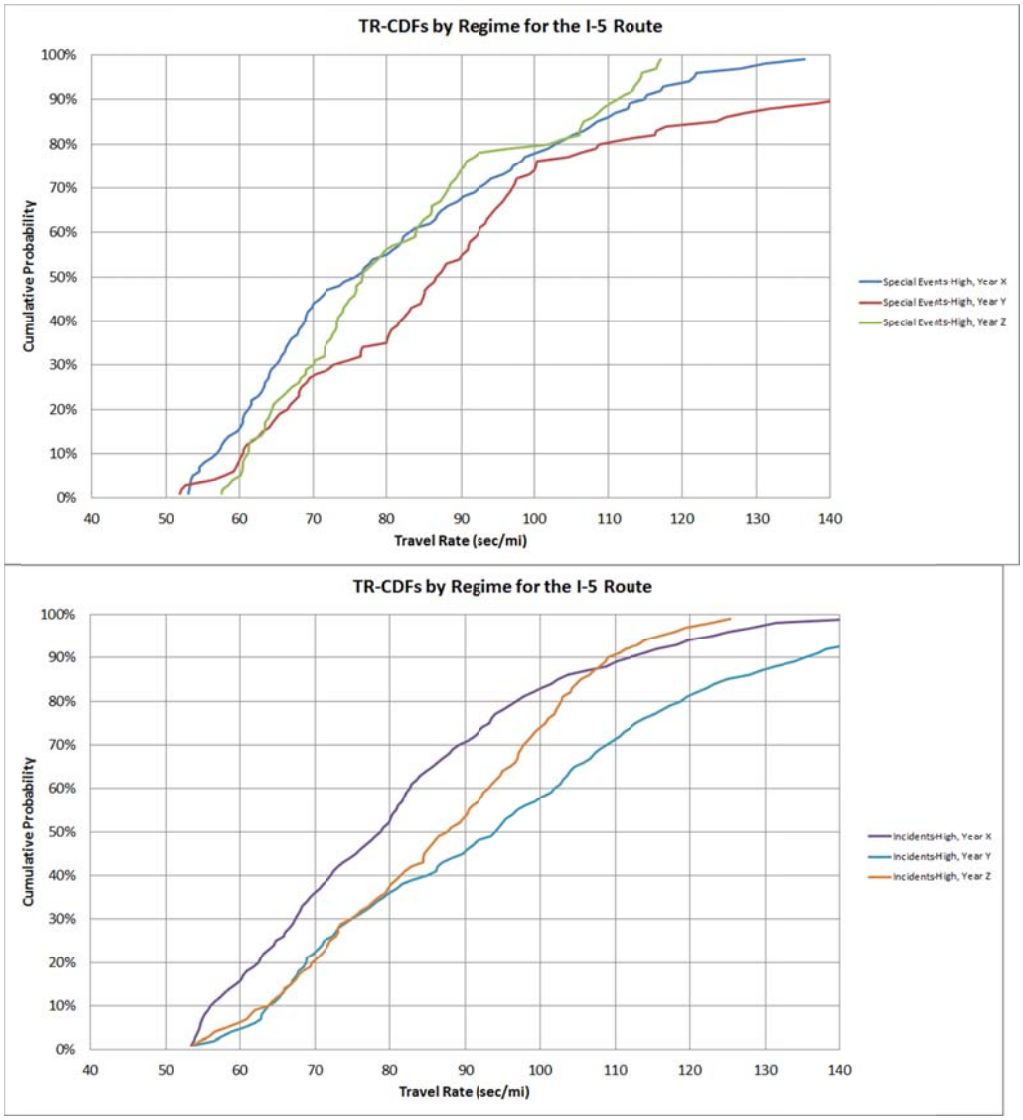


Exhibit D-10: Using TR-CDFs to Analyze Performance Changes

While the performance for lower percentiles in Year Z is not better than in Year Y (but better than or the same as in Year X), it is better for the higher percentiles, at about the 88th percentile and above. Hence, an improvement in reliability has been accomplished. Of course, while improvements have been made in the higher percentiles, further improvement can be made in the lower ones (for the high congestion condition). Putting more resources into special event management and incident clearance would help improve performance further.

Step 5 is focused on using the results as input into decision-making associate with future agency planning and programming decisions. The aggregate semi-variances do not portray the picture as completely as the CDFs, but they are more succinct and convey a general sense of the situation. For example, the "Normal" condition occurs a lot, as would be expected, but the semi-variances are all quite small. The largest values occur during high congestion and range from 200 to 300. By comparison, the semi-variances for the less frequent conditions range up to almost 4,000.

Exhibit D-11 plots the semi-variances against the occurrence frequencies for events that occur 1500 times per year or less. The "Normal" data points are not present because their frequencies of occurrence are much larger, but as can be seen, their semi-variances are quite low as well, relatively speaking. The exhibit shows that there are a few conditions that merit significant attention—those located on the outer boundary of the plot—in terms of mitigating low-probability, high-consequence events.

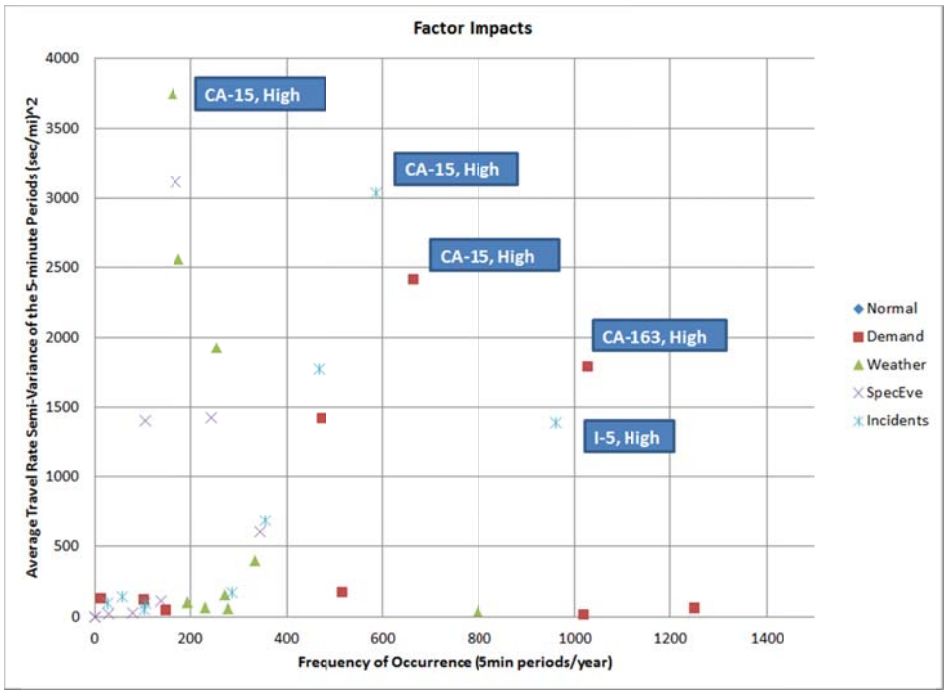


Exhibit D-11: Relative Importance of Different Conditions

As

Exhibit D-11 shows, these are demand events on CA-15 and CA-163 under nominally high congestion conditions; incident events on I-5 and CA-15 under nominally high congestion conditions, and weather events on CA-15 under nominally high congestion conditions. These would be situations for which mitigating strategies would have a significant payoff. Interestingly, and perhaps unexpectedly, it is the CA-15 route, and not the CA-163 route that may deserve the most attention in terms of managing significant consequences of non-recurring events. (That is, while the CA-163 route certainly has reliability "problems", it does not surface in

Exhibit D-6 as being the route that produces the most significant reliability problems.)

Document Agency Accomplishments (AE5)

In this use case, an agency administrator wants to document recent accomplishments. These can be helpful for comparing past years with the current one.

Table D-8: Document Agency Accomplishments (AE5)

User	Agency Administrator
Question	What has the agency accomplished in terms of travel time reliability improvements?
Steps	1. Select routes and subareas for analysis. 2. Assemble TR-PDFs for routes and areas for before/after traffic conditions under equivalent operating conditions. 3. Analyze the before/after changes in reliability along those routes and in those subareas and relate those changes to the actions taken as part of the transportation improvement projects. 3. Find the trends in the efficacy of different types of transportation improvement projects. 4. Use the results as input into decision-making associate with future agency planning and programming decisions.
Inputs	TR-PDFs for each route and area under the before and after conditions for similar network operating conditions associate with the travel rate observations information about the transportation improvement project actions that were taken.
Result	Both the results of the before/after-based cause-and-effect analysis of the agency actions taken as well as a process for conducting the assessment.

Exhibit D-9 and Exhibit D-10 can be used again for this purpose. Assuming the same hypothetical situation previously described, these two exhibits show how the performance of this hypothetical facility has changed in response to agency treatments.

Exhibit D-9 uses the semi-variance values to show the changes. Exhibit D-10 uses the TR-CDFs. Exhibit D-10 provides added detail because it shows how the performance has changed (improved) for all percentiles of the TR-CDF; so it can be used for detailed presentations and analyses.

Exhibit D-9 is suitable for broad-brush analyses and for gaining a general sense of how reliability has changed.

The use case is focused on determining the sources of unreliability for a given set of facilities and timeframe of interest. There is no one right way to do this analysis, but a logical one is to focus on the delays caused by unreliability. In principle, a facility or system's performance would be completely "reliable" if all the travel times were the same, that is, at the minimum travel time. Clearly, this is an "ideal" condition, but it is a standard—a goal—against which the facility or system's performance can be measured.

Step 1 involves selecting a region or facility for analysis. As with the prior use cases, San Diego will be selected using the same three routes.

Step 2 is to select the date range over which to view the data as well as the days of the week and times of day to include. As before, 2011 is examined, all weekdays, all hours.

Step 3 involves assembling travel time and/or rate and traffic volume information. In this instance, travel rate and VMT data were employed.

Step 4 involves analyzing the contributions to unreliability from the various sources. In this instance the following procedure was used. First, the vehicle hours of delay was computed for every five minutes by multiplying the difference between the travel rate and the minimum rate by the VMT/hour and then dividing by 12 (to get VMT/5-minutes). Then these results were summed for each combination of nominal congestion condition (uncongested….high congestion) and non-recurring event (incident, demand, special event, weather) including "normal". Finally, the percentage breakdown was computed among these conditions.

Error! Reference source not found. shows the results for each of the three routes. The "Normal" conditions are the main contributors to unreliability – for the high congestion condition on CA-15 and CA-163 and the Uncongested condition for I-5 (because I-5 does not spend time in either Low or Moderate congestion conditions.) Clearly, focusing on improving performance during "Normal" operation will reduce the vehicle-hours of delay due to unreliability. In fact, the vehicle-hours of delay in all the other categories are no more than 3% of the total for any facility.

For the non-recurring conditions other than "Normal", the next most significant source of delay is during "Demand" conditions when the facility would normally be in high congestion. The second most significant category is "Incidents" during high congestion. Hence, to have the most significant impacts on delay due to unreliability, the priorities would be 1) Normal conditions during high congestion, 2) the other Normal conditions during other levels of congestion, 3) Demand during high congestion, and 4) Incidents during high congestion. This covers the conditions that contribute more than 1% except for Demand during Uncongested operation for I-5 and Demand during moderate congestion for CA-163.

Congestion Level	Non-Recurring Event	Percent of all Veh-Hrs of Delay		
		I-5	CA-15	CA-163
High	Normal	31.7%	35.8%	30.0%
	Demand	1.2%	1.9%	2.6%
	Incidents	1.2%	1.5%	2.2%
	Weather		0.4%	0.5%
	Special Events	0.3%	0.4%	0.6%
Mod	Normal		25.7%	39.1%
	Demand		0.0%	1.1%
	Incidents		0.2%	0.7%
	Weather		0.4%	0.6%
	Special Events		0.0%	0.6%
Low	Normal		10.0%	
	Demand		0.0%	
	Incidents		0.0%	
	Weather		0.1%	
	Special Events		0.0%	
Uncongested	Normal	62.7%	23.0%	20.9%
	Demand	1.2%	0.1%	0.7%
	Incidents	0.4%	0.1%	0.1%
	Weather	0.8%	0.2%	0.2%
	Special Events	0%	0%	0.0%

Exhibit D-12: Contributions to Unreliability

Assess Progress toward Long-Term Reliability Goals (AE6)

An administrator wants to determine if the agency is meeting its long-term reliability improvement goals by viewing changes to travel time variability over time. The agency

administrator might use this information to see how well the agency is meeting the established goals and report the progress observed to the public.

This use case is identical to AE4 and/or AE5 except that the focus is on a region or system instead of a route. The steps in the analysis are effectively the same; and the results would be interpreted in the same manner.

Table D-9: Assess Progress toward Long-Term Reliability Goals (AE6)

User	Agency Administrator
Question	What progress has been made toward achieving long-term reliability goals?
Steps	1. Select a region for analysis. 2. Select the date range over which to view the data as well as the days of the week and times of day to include in the analysis. 3. Select a granularity for the analysis (e.g., year, quarters, seasons). 4. Assemble TR-PDFs for routes and subareas and the region so that trends in the TR-PDFs can be observed. 4. Determine what changes and rates of change in reliability have been occurring by examining the rates at which various percentiles of the TR-PDFs are changing.
Inputs	TR-PDFs for each route and area across time for the date range and other specifications desired.
Result	An assessment of the trends in changes of the percentile values of the TR-PDFs.

Assess Reliability Impact of a Specific Investment (AE7)

The agency administrator wants to see if a specific agency investment, improvement action, or policy has had a positive impact on travel time reliability. He or she wants to evaluate the impacts of past decisions, to decide if the action has been effective, and to report this information to the public.

Table D-10: Assess Reliability Impact of a Specific Investment (AE7)

User	Agency Administrator
Question	What has been the impact on reliability of a specific investment?
Steps	1. Select the area or routes on which the change was implemented. 2. Select the date that the change was implemented as well as the date ranges for the pre-change and post-change analyses. 3. Select the conditions under which the change will be assessed (e.g., peak hours, weekdays). 4. Assemble TR-PDFs for the areas and routes where the change was implemented for the pre-change and post-change date ranges for the operating conditions of interest. 4. See if significant changes in the TR-PDFs have occurred in one or more instances.
Inputs	TR-PDFs for each route and area across time for the date ranges of interest and other specifications desired.
Result	An assessment of the effect on the TR-PDFs caused by the change.

This use case is similar to AE4 and AE6 except that the focus is on the impacts of a specific investment. Of course, compound effects can cloud this analysis, like changes in flow patterns due to a capacity enhancement or increase, but if the change is substantial enough that the impact can be seen in spite of these other factors, then the impact can be assessed. The procedure involved is akin to that presented in AE4. As described in Step 4, assemble TR-PDFs for the areas and routes where the change was implemented for the pre-change and post-change date ranges, as is done in safety treatment impact analyses, and see what improvement in reliability has arisen. If the changes from year to year are due to specific actions being taken, then the changes in reliability are attributable at least in part to those actions. Simulation (microscopic traffic simulation) is a useful tool here in that it allows the impacts of such changes to be assessed one at a time, removing the compound effects.

Agency Planners

This group of use cases shows how the TTRMS can be used by highway agency planners to understand the reliability performance of their system.

Find the Facilities with the Highest Variability (AP1)

In this use case, the agency planner wants to determine which regional facilities experience the highest travel time variability. She or he can use this information to determine which facilities need further reliability analysis to develop appropriate policy or investment actions.

Table D-11: Find the Facilities with Highest Variability (AP1)

User	Agency Planner
Question	What facilities have the most travel time variability?
Steps	1. Select the facilities of interest (could be all of them). 2. Determine the metric by which the variability is going to be assessed (e.g., the semi-variance). 3. Assemble TR-PDFs (rates) for each facility under equivalent operating conditions (could be more than one or all together or the same number of observations of time periods spent in each condition). 3. Rank order the facilities based on the variability metric.
Inputs	A database of TR-PDFs (rate) for each facility under equivalent operating conditions (could be more than one or all together or the same number of observations of time periods spent in each condition).
Result	A rank ordered list of the facilities based on the variability in travel times.

The question posed is effectively the same as AE2. It seeks a rank ordering of selected facilities based on reliability. The aim is to identify appropriate corrective treatments.

Exhibit D-6, presented as a part of AE2, responds directly to the question. As can be seen in the top half of the exhibit, the CA-163 route has the greatest variability in its travel times. It should be ranked first. It is followed closely by CA-15, and then distantly by I-5 (with a variability which is half as large). Digging further, and examining individual regimes, one can see that focusing on the CA-15 might be a better choice than CA-163, even though it is not top ranked. The reason is: it has the highest average semi-variances during: (high congestion and weather), (high congestion and special events), and (high congestion and incidents). For the CA-163 route, the most important target seems to be (high congestion and weather) – which might be addressed by improvements on the section of CA-163 between I-8 and I-5.

Assess the Reliability Trends over Time for a Route (AP2)

An agency planner wants to see how the travel time variability is changing over time for a route. The planner could use this information to monitor reliability trends for a route. If the travel time variability is increasing over time, the planner could monitor the situation and determine when a policy or improvement intervention would be valuable.

Table D-12: Assess the Reliability Trends over Time for a Route (AP2)

User	Agency Planner
Question	What is the trend in reliability over time for a route?
Steps	1. Select a route for analysis. 2. Select the date range over which to view the data as well as the days of the week and times of day to include in the analysis. 3. Select a granularity for the analysis (e.g., year, quarters, seasons). 4. Assemble TR-PDFs for the route for the days, times of day, etc., of interest. 4. Determine what changes in reliability have occurred by examining the changes in the various percentiles of the TR-PDFs.
Inputs	TR-PDFs for the route across time for the date range and other specifications desired.
Result	An assessment of the trends in changes of the percentile values of the TR-PDFs.

This use case is very similar to AE4. Reflecting back to its discussion,

Exhibit D-9 shows changes in reliability over time for a hypothetical route. That same information would be developed to answer the question posed here. The analysis would be the same as would the conclusions drawn.

Assess Changes in the Hours of Unreliability for a Route (AP3)

This is a different type of use case. It focuses on how long (for how many hours) a route's performance is unacceptable. Further, the agency planner wants to see how this percentage has changed over time. This information would help the planner determine if travel time variability is increasing, meaning that periods of high variability are lasting longer and impacting more travelers. For routes with lengthening periods of variability, the planner might want to perform further analysis to find the cause and determine what mitigating actions can be taken.

The data used in AE4 can be re-purposed here to answer the question posed. As was indicated there,

Exhibit D-9 shows the average semi-variance values by regime for each of three years for a hypothetical facility. What is not shown explicitly is the number of hours that the facility operated in each regime. The number of five-minute time periods is shown.

Error! Reference source not found. re-presents the data from

Exhibit D-9 in a slightly different format. The average semi-variance values are still shown, but the counts of five-minute time periods have been replaced by the number of hours that the facility was operating in regimes where the semi-variance value was 100 or greater.

Table D-13: Assess Changes in the Hours of Unreliability for a Route (AP3)

User	Agency Planner
Question	What is change in the number of hours for which the route has an unreliable travel time?
Steps	1. Select the route for which the change assessment is desired. 2. Determine how unreliable performance is defined (e.g., the spread between the 80th and 20th percentile travel rates divided by the 50th percentile travel rate). 3. Select a value of the metric which is deemed to be representative of reliable travel times. 4. Determine the period of time for which the hours will be counted (e.g., a year, a quarter, a season, only weekdays). 5. Select the date ranges for the before and after conditions. 6. Select the operating conditions under which the change will be assessed (e.g., peak hours, weekdays, all times). 7. Assemble TR-PDFs for the route for the before and after date ranges and for the system operating conditions of interest. 8. Determine the number of hours that the travel rate is unreliable (per unit time) for the before and after conditions. 9. Determine the change in the number of hours of unreliable travel time (per unit time).
Inputs	TR-PDFs for the route and across time for the date ranges of interest and other specifications desired.
Result	An assessment of the extent to which the number of hours of unreliable operation has changed.

Notice that almost all of the hours of unreliable operation are during the (high congestion, normal) regime. Moreover, those hours are largely unchanged across the years.

Hours of Unreliability												
Cond	Year	Normal		Demand		Weather		Special Events		Incidents		Total
		SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs	
Uncong	X	11	0	13	0	61	0	21	0	54	0	0
	Y	15	0	47	0	68	0	29	0	139	5	5
	Z	7	0	60	0	46	0	111	11	172	24	35
Mod	X	56	0	169	43	399	28	601	29	684	30	129
	Y	73	0	244	10	257	39	0	0	190	11	59
	Z	0	0	0	0	0	0	0	0	0	0	0
High	X	261	1064	1789	86	1924	21	1424	20	1385	80	1271
	Y	241	1160	2415	55	3751	14	3113	14	3032	49	1292
	Z	205	1065	1415	39	2563	15	1399	9	1769	39	1167

Exhibit D-13: Changes in Reliability over Time for a Hypothetical Route

However, the hours spent in the other unreliable regimes decline. The only exception is the (uncongested, incidents) regime where the number of hours increases from 0 to 5 and then to 24. In all other regimes, the total declines. For example, during the (high congestion, demand)

and (high congestion, incidents) regimes, the hours drop from 86 to 55 and then 39 for the first; and 80 to 49 and then 39 for the second. Clearly, the facility's reliability performance has improved.

Assess the Sources of Unreliability for a Route (AP4)

In this use case, an agency planner wants to determine what factors affect the reliability of a route. She or he wants to investigate this to prioritize long-term system improvements. For example, if incidents are creating high and variable travel times along a route, the planner might want to stress safety improvements, such as deploying freeway service patrols at certain corridor locations to clear disabled vehicles more quickly.

Table D-14: Assess the Sources of Unreliability for a Route (AP4)

User	Agency Planner
Question	What are the sources of unreliability for a route?
Steps	1. Select the route of interest. 2. Select the date range over which to view the data as well as the days of the week and times of day to include in the analysis. 3. Label each observation in terms of the regime to which it belongs – its nominal loading condition (congestion level) and non-recurring event – including none. 4. Create TR-PDFs so that the impacts of various factors can be assessed. 5. Analyze the changes in reliability caused by these factors so that the differences in impact severity can be assessed.
Inputs	TT-PDFs for the route for the date range etc. for which the data are desired.
Result	An assessment of the impacts that various factors have on travel time reliability.

The three routes in San Diego employed earlier could be employed to illustrate this use case. However, a new example will be used.

The first step is to select the route of interest. Westbound I-8 in San Diego has been chosen. As shown in

Exhibit D-14, the section being used for analysis lies between La Mesa on the eastern end of the study area and Morena on its western end, or more specifically from Baltimore Drive to the interchange with I-5. The data being used to conduct the analysis are observations of average weekday travel times.

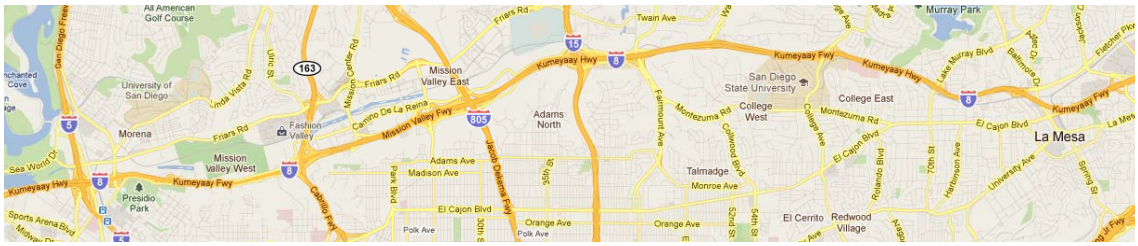


Exhibit D-14: I-8, San Diego

The second step is to select the data range over which to review the data as well as the days of the week and times of day to include in the analysis. In this instance the date range is November 3, 2008 until February 27, 2009; and it is weekdays; and all hours.

The third step involves labeling each of the data points based on the regime to which it belongs, i.e., combinations of nominal loading condition (D/C) and non-recurring event (including none). The procedure used is identical to that described for use case AE1. Plots of the data versus time of day and VMT/hour were prepared and outliers were identified. Explanations were sought for the outliers, and the remaining data points (in the "none" category in terms of non-recurring events) were then analyzed to establish categories of operation in terms of system loading (congestion).

The results are shown in

Exhibit D-15 and

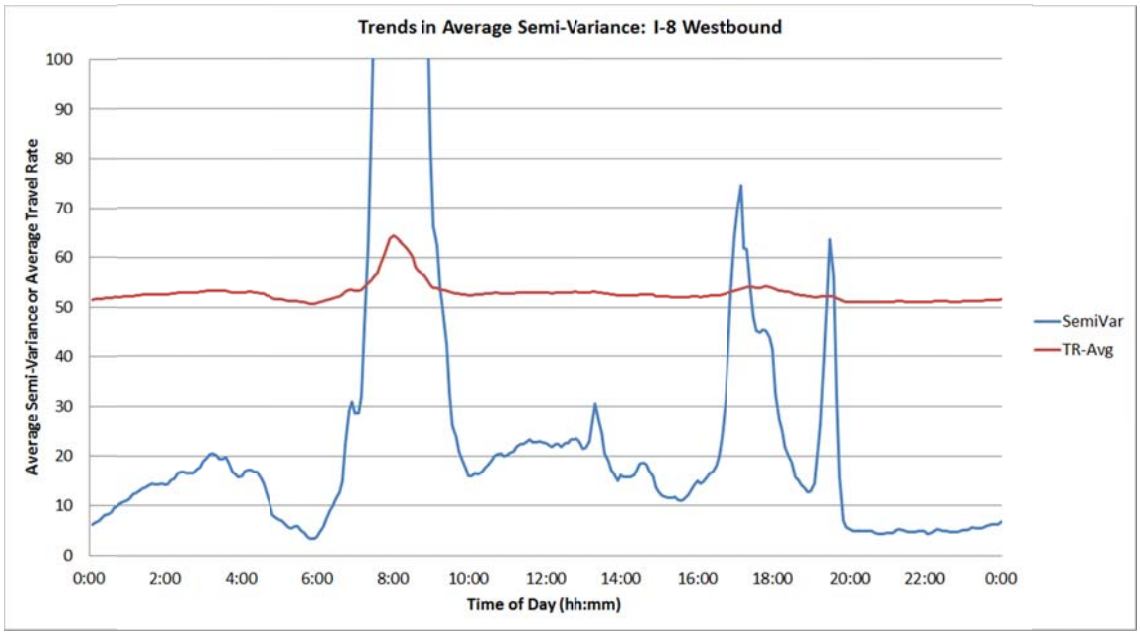


Exhibit D-16.

Exhibit D-15 shows plots of the data against time of day and VMT/hour.

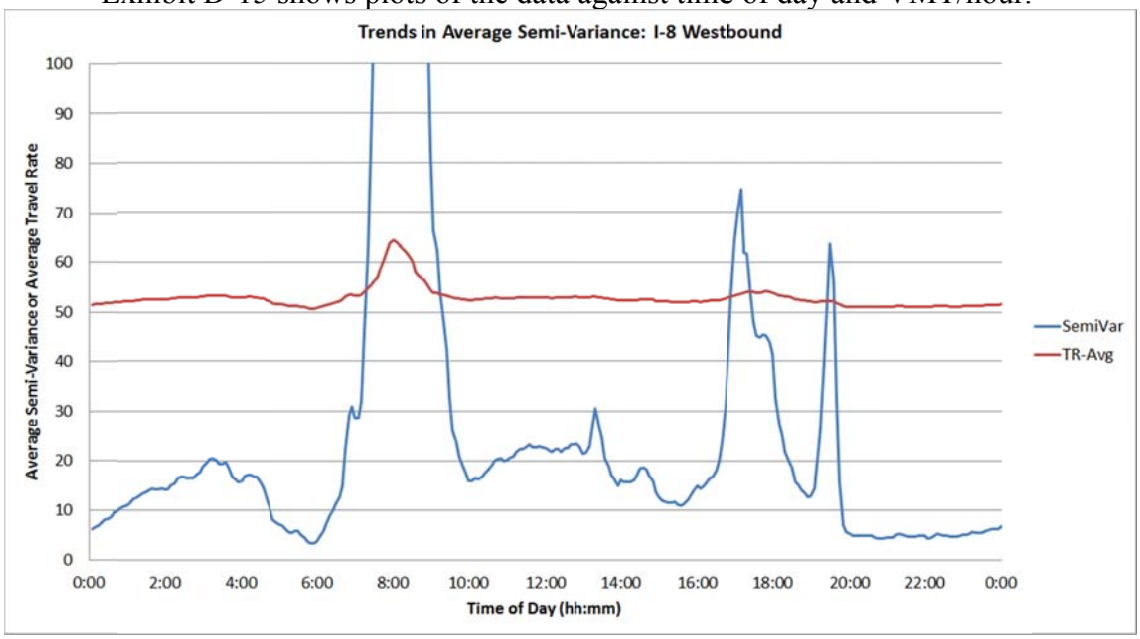


Exhibit D-16 shows the semi-variance trends.

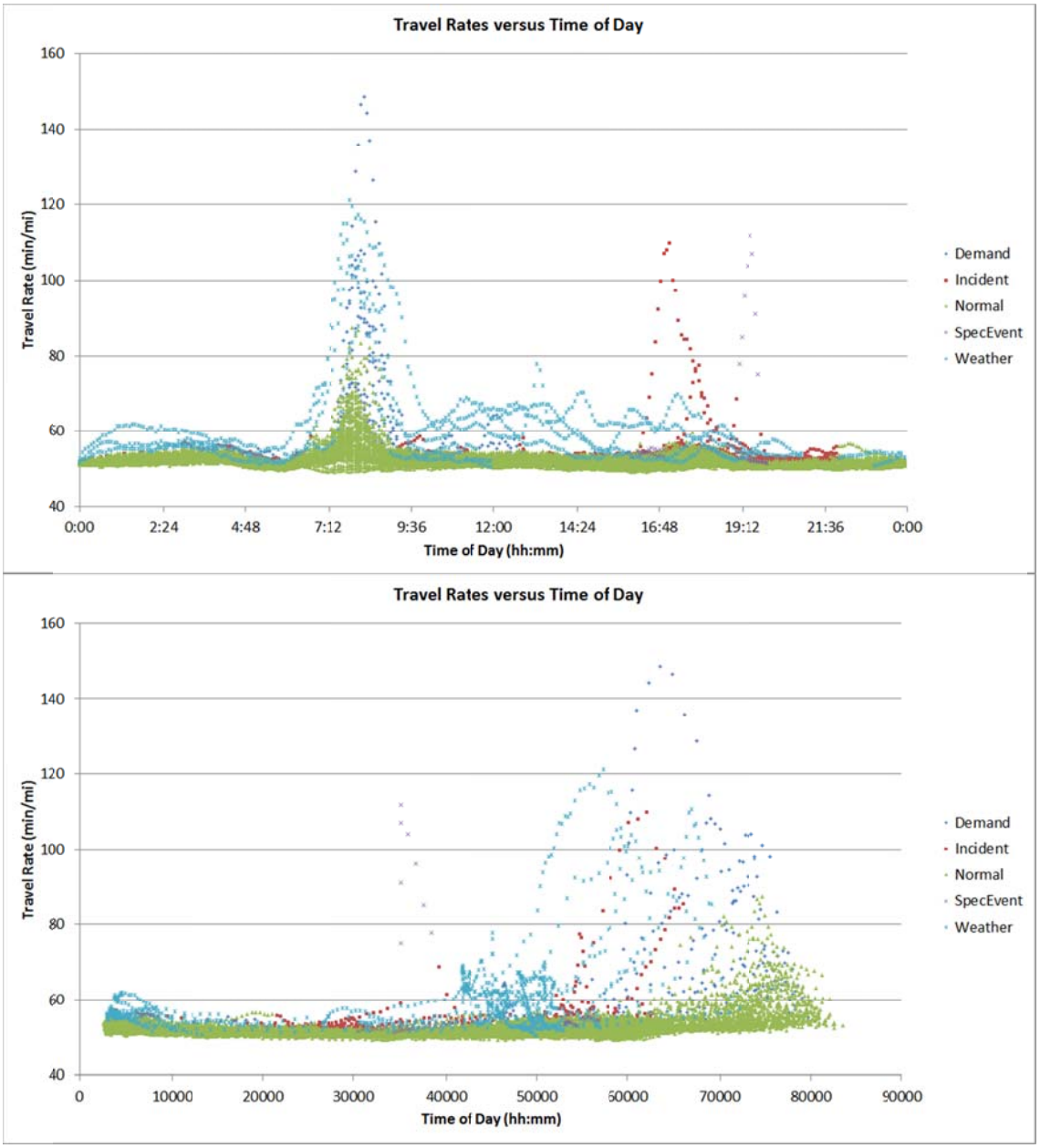


Exhibit D-15: Plots of Average Travel Time against Time of Day and VMT/hour, I-8 Westbound, San Diego

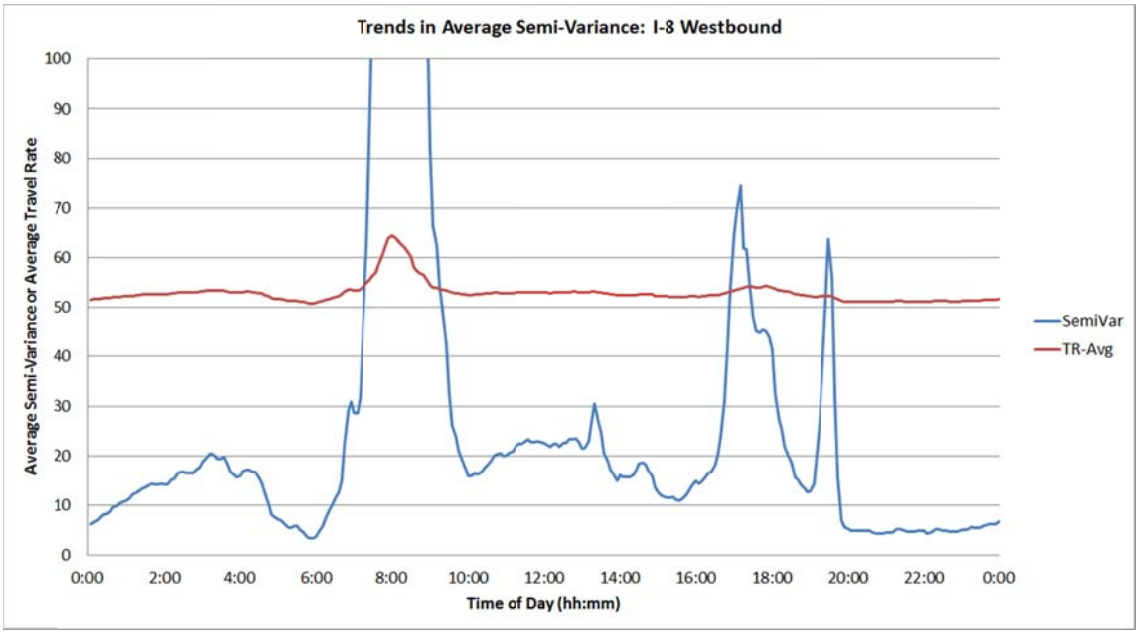


Exhibit D-16: Average Semi-Variance Trends, I-8 Westbound, San Diego

The semi-variance plot in

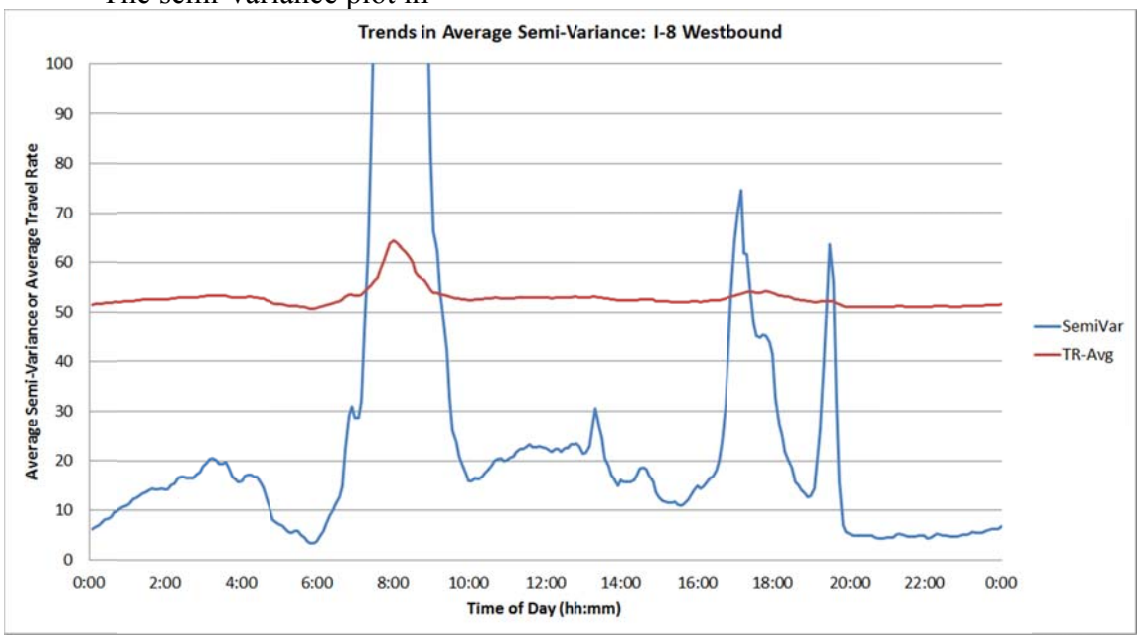


Exhibit D-16 shows that the route has fairly reliable travel times except during the AM peak (about 7:00-10:00am) and then during the PM peak to a much lesser extent (about 16:30 to 20:00). The average travel rate follows a similar trend.

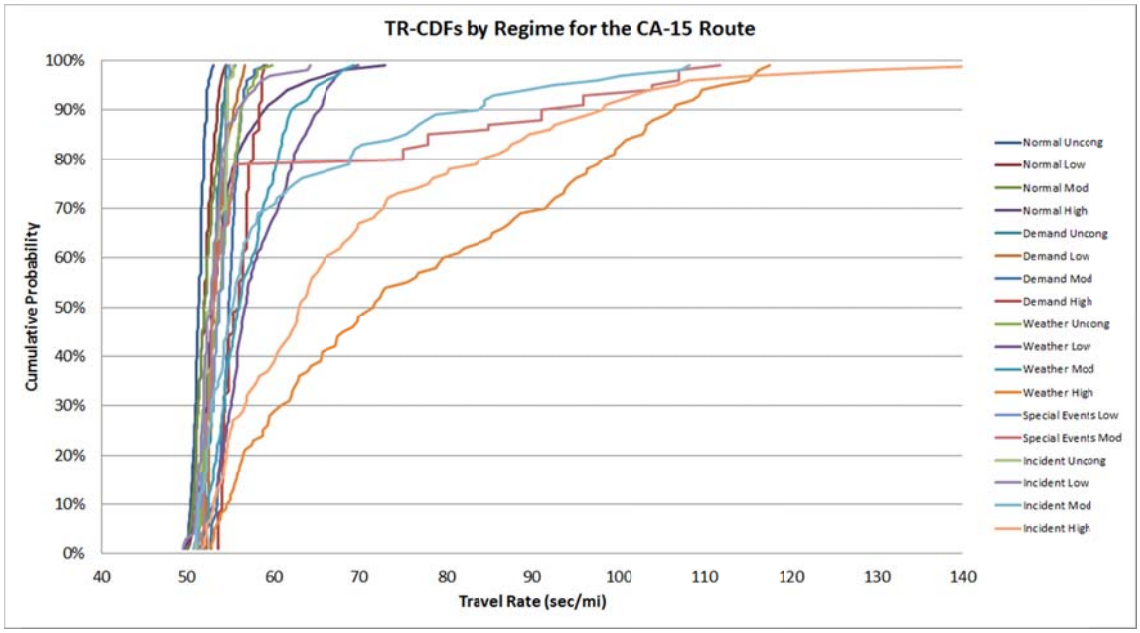


Exhibit D-17 shows the CDFs by regime. The CDFs with the most variation in travel rates are, from right to left, (high congestion, weather), (high congestion, incidents), (moderate congestion, special events), and (moderate congestion, incidents).

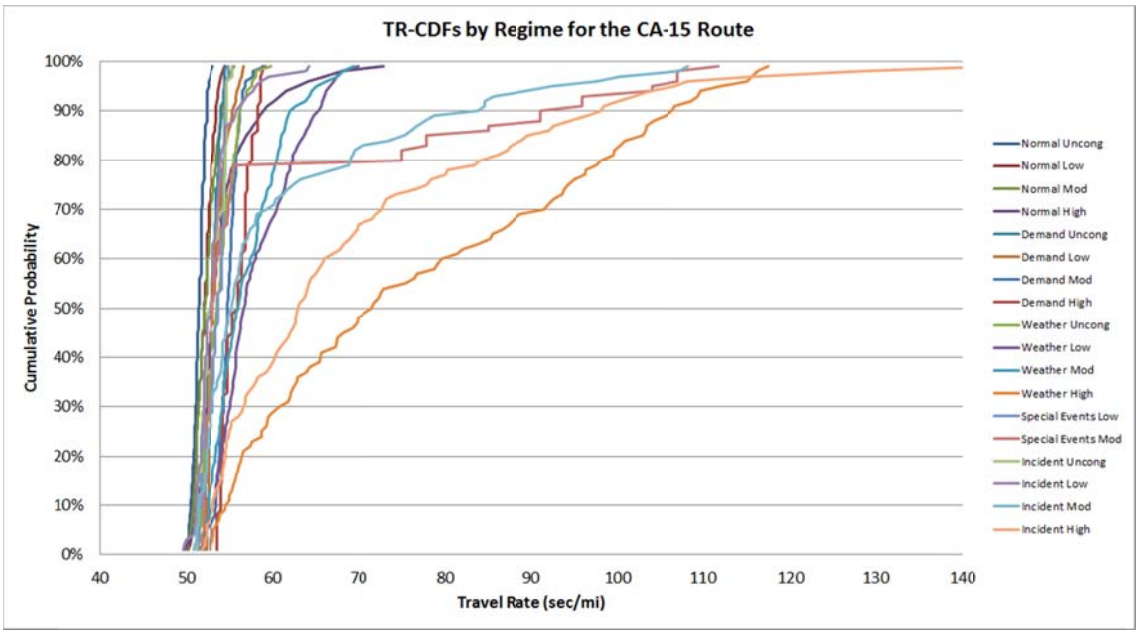


Exhibit D-17: CDFs by Regime for the Average Travel Rate, I-8 Westbound, San Diego

The next three, again right to left, are (low congestion, weather), (moderate congestion, weather), and (high congestion, normal). The CDFs for the remaining regimes are all nearly identical. It is important to note the number of instances in which weather is a significant, non-recurring factor.

Average Semi-Variances and the Number of 5-Minute Time Periods by Regime											
Route	Cond	Normal		Demand		Weather		Special Events		Incidents	
		SV	n	SV	n	SV	n	SV	n	SV	n
I-8 WB	Uncong	5	1973	16	29	27	89	0	0	17	15
	Low	9	12840	21	276	101	610	20	16	24	220
	Mod	11	2633	35	110	80	147	473	37	337	115
	High	45	2916	50	17	1180	176	0	0	805	245

Hours of Unreliable Operation											
Route	Cond	Normal		Demand		Weather		Special Events		Incidents	
		SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs
I-8 WB	Uncong	5	0	16	0	27	0	0	0	17	0
	Low	9	0	21	0	101	51	20	0	24	0
	Mod	11	0	35	0	80	0	473	3	337	10
	High	45	0	50	0	1180	15	0	0	805	20

Exhibit D-18 shows the average semi-variance values and the number of five-minute time periods by regime in the top table and the number of hours for those regimes where the semi-variances exceed 100 in the bottom table.

Average Semi-Variances and the Number of 5-Minute Time Periods by Regime											
Route	Cond	Normal		Demand		Weather		Special Events		Incidents	
		SV	n	SV	n	SV	n	SV	n	SV	n
I-8 WB	Uncong	5	1973	16	29	27	89	0	0	17	15
	Low	9	12840	21	276	101	610	20	16	24	220
	Mod	11	2633	35	110	80	147	473	37	337	115
	High	45	2916	50	17	1180	176	0	0	805	245

Hours of Unreliable Operation											
Route	Cond	Normal		Demand		Weather		Special Events		Incidents	
		SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs
I-8 WB	Uncong	5	0	16	0	27	0	0	0	17	0
	Low	9	0	21	0	101	51	20	0	24	0
	Mod	11	0	35	0	80	0	473	3	337	10
	High	45	0	50	0	1180	15	0	0	805	20

Exhibit D-18: Average Semi-Variances by Regime

Several trends are clear from the exhibit: 1) while a lot of five-minute time periods are spent in the "Normal" condition, the semi-variance is never particularly large, it only reaches 45 in the (high congestion, normal) regime; 2) the regime with the highest semi-variance is (high congestion, weather), followed by (high congestion, incidents), (moderate congestion, special events), (moderate congestion, incidents), and (low congestion, weather). The semi-variances for all other regimes are relatively small; 3) there are 99 hours of operation (out of a total of 1872 hours) for regimes where the semi-variance exceeds 100 (5% of the total hours); 4) the regime with the most hours is (low congestion, weather) with 51 hours. It seems clear that focusing on enhancing facility reliability during inclement weather would be a logical action to take.

Determine When a Route is Unreliable (AP5)

In this use case, the agency planner wants to see when a route's travel time reliability is unacceptable. The planner can use this analysis to determine if travel time variability is an all-day problem, or if it is confined to specific time periods. She or he can use this insight to decide where and when to implement corrective measures like ramp metering that would help mitigate

congestion-induced variability. The analysis can also help planners determine where and when HOV lanes or HOT lanes could be an alternative to provide more consistent travel times for carpools or paying drivers. Planners might also use this analysis to see what can be done in rural areas to mitigate the impacts of beach traffic in the summer or recreational skiing traffic in the winter.

Table D-15: Determine When a Route is Unreliable (AP5)

User	Agency Planner
Question	When does a route have an unreliable travel times?
Steps	1. Select the route for which the reliability assessment is desired. 2. Select a metric to assess reliability and a value to be used to distinguish between reliable and unreliable operation. 3. Determine the timeframe for the analysis (e.g., a year, a quarter, a season, only weekdays; peak hours, weekdays, all times). 4. Assemble TR-PDFs for the route for the time period and system operating conditions of interest. 5. Determine the times when the route has unreliable travel times. 6. Search for reasons why the route might have had unreliable travel times under those conditions (e.g., weather, incidents, work zones). 7. Create a list of those reasons and e**xhibit**s that show the percentage of time during which those conditions exist.
Inputs	TR-PDFs for the route and across time for the date ranges of interest and other specifications desired.
Result	A list of those reasons and **exhibit**s that show the percentage of time during which those conditions exist.

This use case can be addressed using any one of the routes examined before. The metric can again be the semi-variance and the time frames can be those for which data were available: all of 2011 in the case of I-5, I-15, and CA-163; and November 3, 2008 until February 27, 2009 in the case of I-8.

The semi-variance data suggest that:

- I-5 is unreliable only during the PM peak;
- I-15 is somewhat unreliable during midday and significantly unreliable during the PM peak;
- CA-163 is more unreliable during the midday and equally unreliable during the PM peak;
- I-8 is unreliable during the AM peak and to a lesser extent during the PM peak and into the early evening.

The reasons are predominantly:

- High congestion during the PM peak in the case of I-5, I-15, and CA-163; and the AM peak in the case of I-8;

- Weather, which is a significant source of unreliability for all four routes, especially during regimes involving high congestion, but for other regimes as well;
- Incidents, although they predominantly have an impact during regimes involving high congestion; and
- Special events, especially during the early evening on I-8.

Exhibit D-19 provides hour and percentage breakdowns of the times (regimes) when each facility's average semi-variance exceeds 100.

Hour and Percentage Contributions to Unreliable Travel Times

Route	Cond	Normal		Demand		Weather		Special Events		Incidents		Total
		SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs	Hours
I-5	Uncong	7	0	60	0	46	0	111	11	172	24	35
	High	205	1065	1415	39	2563	15	1399	9	1769	39	1167
CA-15	Uncong	15	0	47	0	68	0	29	0	139	5	5
	Low	27	0	118	9	106	16	0	0	97	0	25
	Mod	46	0	127	1	151	23	0	0	93	0	24
	High	241	1160	2415	55	3751	14	3113	14	3032	49	1292
CA - 163	Uncong	11	0	13	0	61	0	21	0	54	0	0
	Mod	56	0	169	43	399	28	601	29	684	30	129
	High	261	1064	1789	86	1924	21	1424	20	1385	80	1271
Route	Cond	Normal		Demand		Weather		Special Events		Incidents		Total
		SV	Pct	SV	Pct	SV	Pct	SV	Pct	SV	Pct	Percent
I-5	Uncong	7	0%	60	0%	46	0%	111	1%	172	2%	3%
	High	205	89%	1415	3%	2563	1%	1399	1%	1769	3%	97%
CA-15	Uncong	15	0%	47	0%	68	0%	29	0%	139	0%	0%
	Low	27	0%	118	1%	106	1%	0	0%	97	0%	2%
	Mod	46	0%	127	0%	151	2%	0	0%	93	0%	2%
	High	241	86%	2415	4%	3751	1%	3113	1%	3032	4%	96%
CA - 163	Uncong	11	0%	13	0%	61	0%	21	0%	54	0%	0%
	Mod	56	0%	169	3%	399	2%	601	2%	684	2%	9%
	High	261	76%	1789	6%	1924	2%	1424	1%	1385	6%	91%

Hours and Percentages of Unreliable Operation

Route	Cond	Normal		Demand		Weather		Special Events		Incidents		Total
		SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs	SV	Hrs	Hours
I-8 WB	Uncong	5	0	16	0	27	0	0	0	17	0	0
	Low	9	0	21	0	101	51	20	0	24	0	51
	Mod	11	0	35	0	80	0	473	3	337	10	13
	High	45	0	50	0	1180	15	0	0	805	20	35
Route	Cond	Normal		Demand		Weather		Special Events		Incidents		Total
		SV	Pct	SV	Pct	SV	Pct	SV	Pct	SV	Pct	Percent
I-8 WB	Uncong	5	0%	16	0%	27	0%	0	0%	17	0%	0%
	Low	9	0%	21	0%	101	52%	20	0%	24	0%	52%
	Mod	11	0%	35	0%	80	0%	473	3%	337	10%	13%
	High	45	0%	50	0%	1180	15%	0	0%	805	21%	36%

Exhibit D-19: Average Semi-Variances by Regime

Notice that the trends are quite different for I-8 versus the other three facilities. I-8 has all of its hours of unreliable operation during non-recurring events – weather, special events and incidents – and none during normal operation while the other three routes have most (more than 76%) of their unreliable operation during (high congestion, normal operation). Moreover, I-8 has no percentages attributable to Demand conditions while the other three do.

Assist Rural Freight Operations Decisions (AP6)

In this use case, an agency planner wants to help out with rural freight operations. He or she wants to understand where and when rural freight delivery times are unreliable. The planner would have to have access to truck-related travel times, which are different from cars and other vehicles. Assuming that is the case, this type of analysis would help the planner make decisions about how to help rural freight operations – such as special climbing lanes, snow removal, and highway geometry – especially in areas with little/no real time traffic data.

Table D-16: Assist Rural Freight Operations Decisions (AP6)

User	Agency Planner
Question	Where and when are rural freight travel times unreliable?
Steps	1. Select the routes and areas of interest. 2. Select the time periods and network operating conditions of interest (could be all). 3. Assemble TR-PDFs for freight trips for the routes and areas of interest and the time periods and network operating conditions of interest. 4.Search for reasons why the routes and areas might have had variations in the travel rates under those conditions (e.g., weather, incidents, work zones). 9. Create a list of the reasons why the travel rates might be more variable and a pie chart showing the percentage of time during which those conditions exist.
Inputs	TR-PDFs for the routes and areas of interest and across time and for the system operating conditions of interest.
Result	A list of the reasons why the travel rates might be more variable and a pie chart showing the percentage of time during which those conditions exist.

The Bluetooth data from US-50 between Placerville and South Lake Tahoe provide an excellent basis for examining this use case. Travel times along US-50 were monitored by

CalTrans using a set of Bluetooth detectors. The area is rural; no system detectors exist.

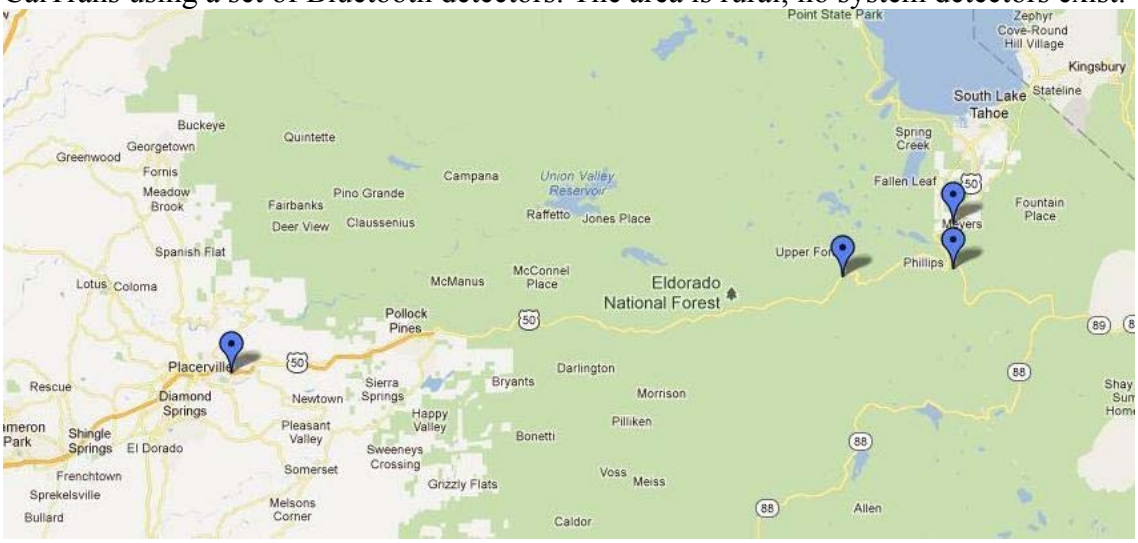


Exhibit D-20 gives a sense of where the detectors were placed. Four are shown. For purposes of this analysis, the Placerville Bluetooth sensor is the pushpin furthest to the left (west); the South Lake Tahoe sensor is the one furthest to the right (east). The distance between the sensors is about 50 miles; the highway is four lanes wide – two lanes in each direction - undivided. The travel time under good weather conditions is about 50 minutes.

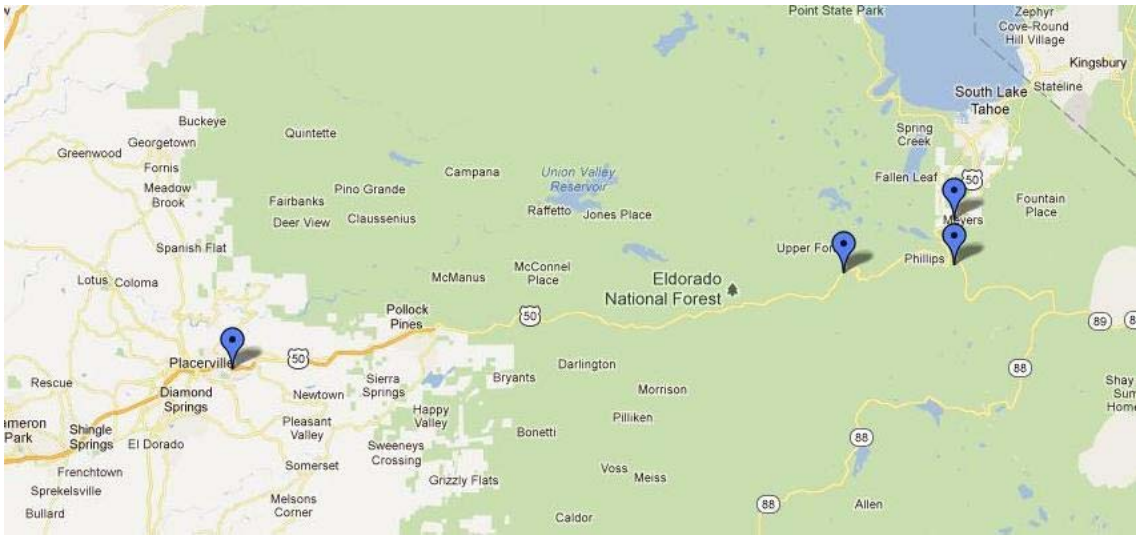


Exhibit D-20: Placerville to South Lake Tahoe

From 1/28/2011 until 4/21/2011, 29,533 observations of trip times were observed on 82 days; or about 360 observations per day. All of the observations are displayed in Exhibit D-21. One can see that the observations are a combination of trip times and travel times – some of the observations range up to 400 minutes (the time difference limit used for matching the Bluetooth pings).

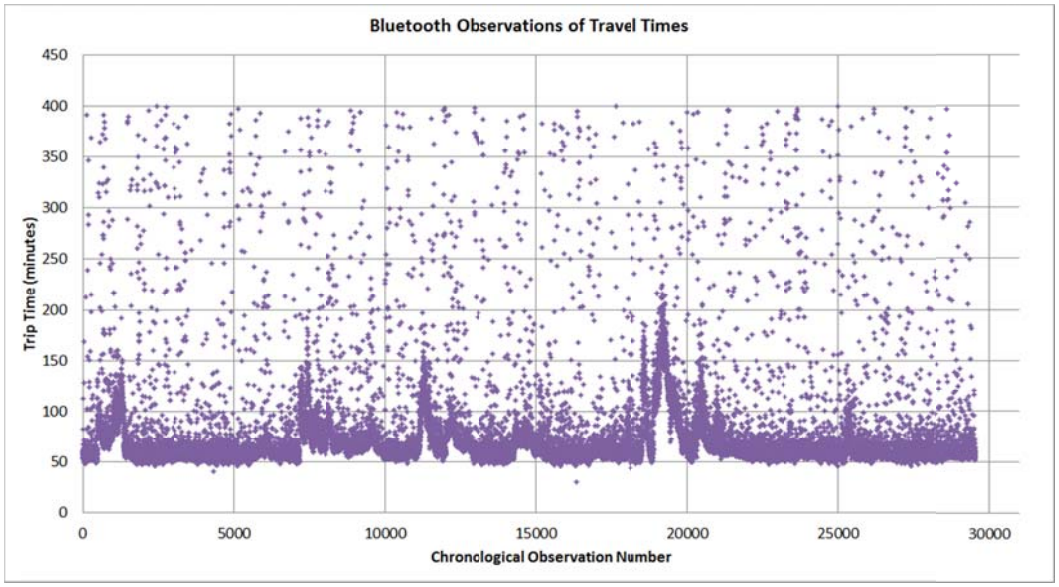


Exhibit D-21: Observations of Trip Times, Placerville to South Lake Tahoe

The observations, filtered and plotted against date and time are shown in

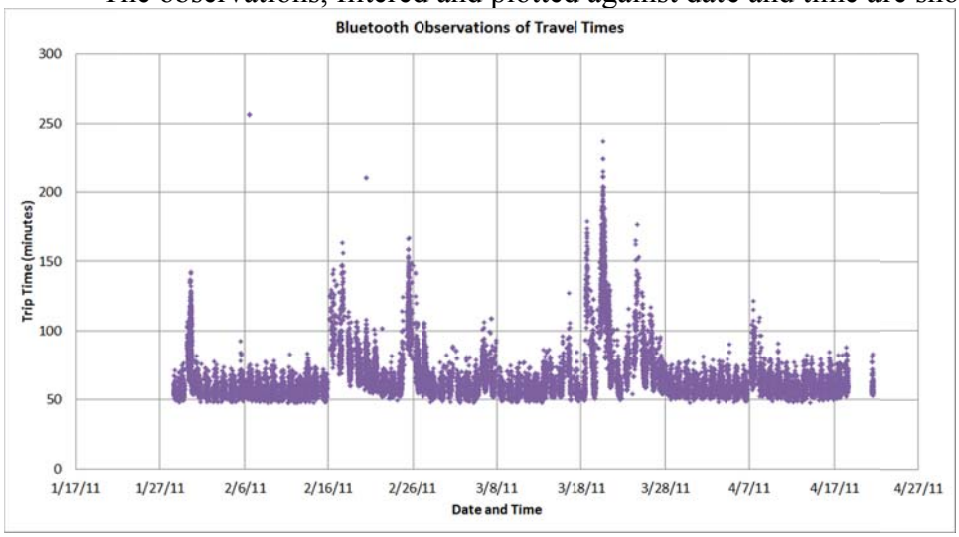


Exhibit D-22. Clearly, there were some days when the travel times were very large – ranging up to 250 minutes during a heavy snow storm. On days when conditions were good, the times ranged from 50-75 minutes.

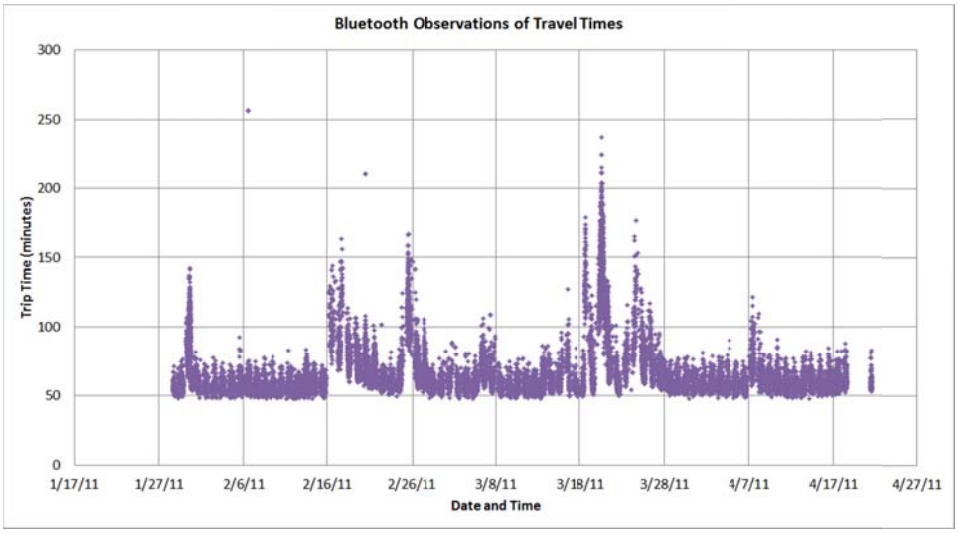


Exhibit D-22: Filtered Observations of Trip Times, Placerville to South Lake Tahoe

To address the use case, Step 1 is to select the route and area of interest. In this instance, it is US-50, from Placerville to South Lake Tahoe. Step 2 is to select the time period and network operating conditions of interest. In this instance it is 1/28/2011 to 4/21/2011, or the duration of time during which the detectors were installed, and all conditions. Step 3 is to assemble TR-PDFs for freight trips. Since no vehicle classification data was associated with the Bluetooth observations, it will be assumed that *all* the observations are for freight vehicles (clearly, not true). Step 4 is to search for reasons why there were variations in the travel rates. For this purpose, two data sources were employed: the incident data contained within PeMS and weather data. The most useful weather information related to precipitation, fog, and wind gusts. It was perceived that these three would have the most effect on travel conditions. All incidents within the monitored section were deemed to be noteworthy; none were omitted. And care was taken to associate the incidents, given their locations, with those trips most likely to be affected. Trips were presumed to be affected if they would have been at about the location of the incident at the time when it occurred given the time at which they passed by the Placerville sensor (going east) or the South Lake Tahoe sensor (going west). A speed of 60mph was assumed to estimate the travel time to the incident location.

A disappointing aspect of the incident data was that some of the durations appeared to be spurious. They were often zero minutes. Consideration of the non-zero values suggested that 30 minutes would be sensible default. That value was used in lieu of the recorded information if the recorded value was smaller. In summary, weather- and incident-related non-recurring event information was added to each record.

Exhibit D-23 presents a summary of the travel times for each condition. One can see that the three most adverse conditions—in the absence of incidents—are heavy snow, snow and fog, and freezing fog. The worst is heavy snow, for which the average travel time is 125 minutes instead of 61 under normal conditions. Incidents raise the average to 133. Highlighted in grey are the conditions with the largest values for the four trip time metrics.

Condition	#Obs	Trip Time			
		Min	Avg	Max	StdDev
Normal	16683	47.5	61.3	256.7	9.9
Gusts	5286	47.7	60.2	176.7	9.7
Rain	908	48.1	64.3	93.8	7.9
Light Snow	2066	50.9	83.7	203.4	24.8
Limited Visibility	25	58.6	85.7	128.4	23.1
Snow	136	56.3	97.3	143.2	16.5
Freezing Fog	27	54.1	112.4	153.2	26.6
Snow and Fog	276	63.5	125.7	237.2	39.9
Heavy Snow	298	59.9	125.5	200.0	27.7
Incidents Alone	191	52.0	81.6	136.8	25.7
Incidents with Rain	18	53.3	56.1	65.6	3.0
Incidents with Gusts	107	48.5	62.3	136.2	16.3
Incidents with Light Snow	78	58.8	80.9	125.1	16.5
Incidents with Snow	105	64.2	106.0	153.8	18.5
Incidents in Freezing Fog	11	93.4	113.5	141.2	16.0
Incidents with Snow and Fog	49	72.4	123.6	179.1	27.7
Incidents with Heavy Snow	89	106.3	133.1	173.6	14.6

Exhibit D-23: Trip Time Impacts from Adverse Conditions

Exhibit D-24 presents the CDFs for the various conditions listed in Exhibit D-23. As can be seen from the labeling, the six distributions furthest to the right are (incidents, snow), (freezing fog), (incidents, freezing fog), (incidents, heavy snow), (incidents, snow), (incidents, snow & fog), (heavy snow), and (snow & fog). Furthest to the left are a set of density functions lying to the left of the "Normal" label: (incidents, gusts), (rain), (gusts), (light rain), (incidents, light rain), (normal), and (incidents), and (heavy rain).

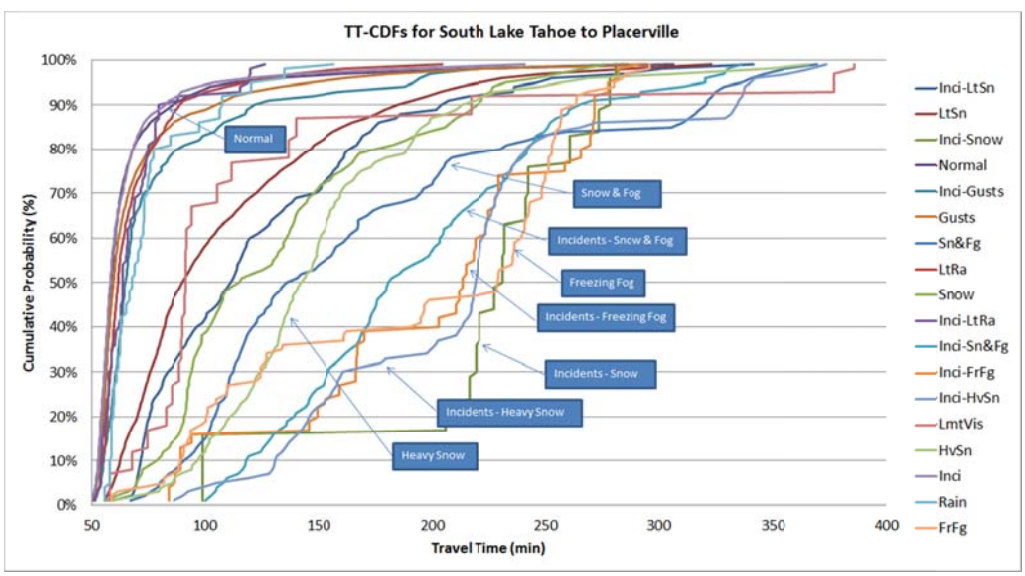


Exhibit D-24: CDFs for Trip Times during Adverse Conditions

Based on the data in Exhibit D-23 and

Exhibit D-24, the guidance one might give to freight operators would be that: 1) under normal conditions, the travel time should be about 61 minutes; 2) gusty wind and rain do not seem to have a significant effect. Light snow adds about 10 to 20 minutes as does limited visibility; 3) heavy snow, snow and fog and fog with freezing conditions adds another 40 to 50 minutes and can make the trip as long as two hours. Incidents do have an impact, but often not a substantial one. The exception is incidents that occur under normal conditions. They can add 20 or more minutes to the travel time.

HIGHWAY SYSTEM OPERATORS AND USERS

This section focuses on questions that might be asked by people who both manage (supply side) and use (demand side) the highway network. Each use case is defined followed by a description of the context in which it is applied and then the results obtained. The order is consistent with the table presented in Table D-1.

ROADWAY SYSTEM MANAGERS

Roadway system managers need to make decisions about how to operate the system. They are directly responsible for maintaining and improving reliability. These people often work for Transportation Management Centers (TMCs), metropolitan agencies, and state DOTs. Reliability information helps them better manage the network's operation. For example, a roadway system manager might use reliability information to determine what actions to take when conditions are awry and set goals for reliability improvements. Such people might also use reliability information to determine how to respond to incidents and other events.

View Historical Reliability Impacts of Adverse Conditions (MM1)

In this use case, a system manager wants to know how adverse conditions affect travel time reliability. Knowing the impacts of special events, bad weather, incidents, lane closures and so forth can help him or her manage the system better. For example, it helps provide better real-time information to the public, such as updating Variable Message Signs with expected delay information. Knowing the impacts also helps the operator provide better pre-trip information such as anticipated speeds and delay times and encourage people to plan ahead or take alternate routes or modes.

Table D-17: View Historical Reliability Impacts of Adverse Conditions (MM1)

User	Roadway System Manager
Question	What are the historical reliability impacts of different adverse conditions?
Steps	1. Select the network area of interest. 2. Select the adverse conditions of interest. 3. Assemble a historical database of normal and adverse conditions for segments in the study area that have been adversely affected. 4. Determine the relative impacts of the adverse conditions.
Inputs	Historical TT-PDFs for the segments in the study area under various normal and adverse conditions.
Result	A table that shows the range of reliability impacts that has arisen due to the various adverse conditions.

As will shortly be seen, answering this question is complicated. It gets at the heart of the difference between travel time reliability viewed from an operator's perspective versus a user's. To see the difference, one needs to examine both system detector data and individual vehicle data. Fortunately, both were collected simultaneously in the Lake Tahoe case study for I-5 in Sacramento; so those data are used here.

Following the steps sequentially, Step 1 involves selecting the network area of interest. In this case it will be I-5 in Sacramento, just south of the junction with US-50. Exhibit D-25 shows the location of the study area. The four pushpins indicate the locations where Bluetooth readers were set up to record vehicles moving both northbound and southbound. The use case will focus on travel times between the first and last reader.

Exhibit D-25: I-5 in Sacramento

Step 2 involves selecting the adverse condition of interest. Rain is a good choice. It has a significant impact on the travel time, as will be seen shortly.

Step 3 is focused on assembling the data for the location and condition of interest. In this instance, the timeframe will be 1/24/2011 until 3/16/2011, the dates during which the Bluetooth data were collected.

Four datasets will be used: 1) the Bluetooth data; 2) PeMS system detector data; 3) PeMS incident data; and 4) weather data. These four datasets are combined to create a unified database in which each Bluetooth observation can be cross referenced to the weather conditions and incidents. The same is true for the PeMS 5-minute travel times.

Step 4 involves determining the impacts of the adverse condition; in this case, rain. It makes sense to begin exploring the impacts with a broad-brush perspective.

Exhibit D-26 shows the daily trends in the 5-minute system detector-based travel times for the southbound direction. Clearly, weather does have an adverse impact as do incidents during adverse weather conditions. In addition, there is an afternoon peak, but its impact on the travel times is not that significant; it boosts the times from 4 to 5 minutes up to about 7 minutes.

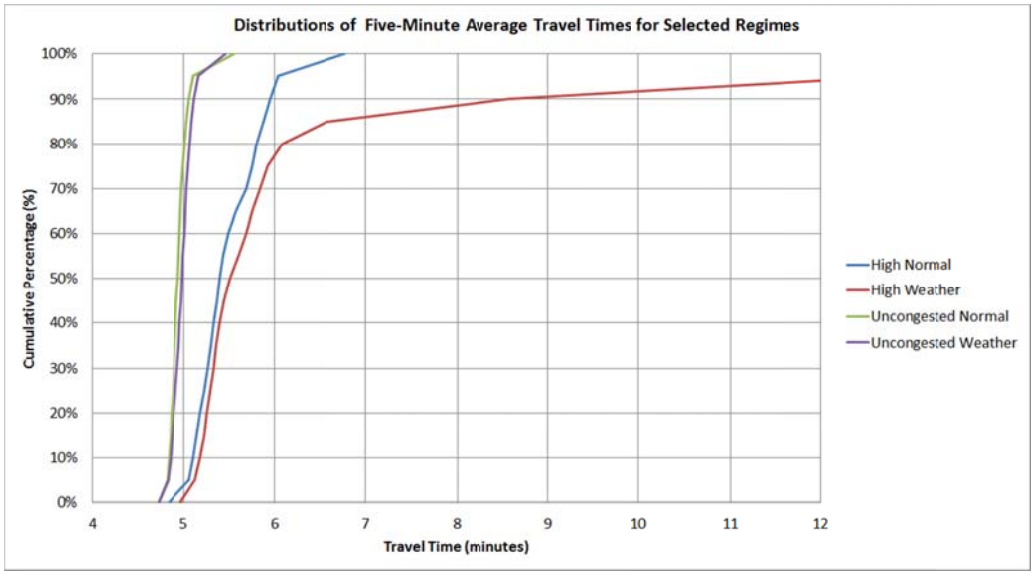


Exhibit D-27 shows the CDFs for the 5-minute travel times in the southbound direction under four regimes: (high congestion, normal), (high congestion, weather), (uncongested, normal) and (uncongested, weather). Not enough data points exist for weather combined with incidents to produce meaningful CDFs.

It is apparent that weather does have a significant impact on the travel times when the congestion is high; but not otherwise. Hence, one answer to the question is that I-5 does become unreliable when weather is the adverse condition.

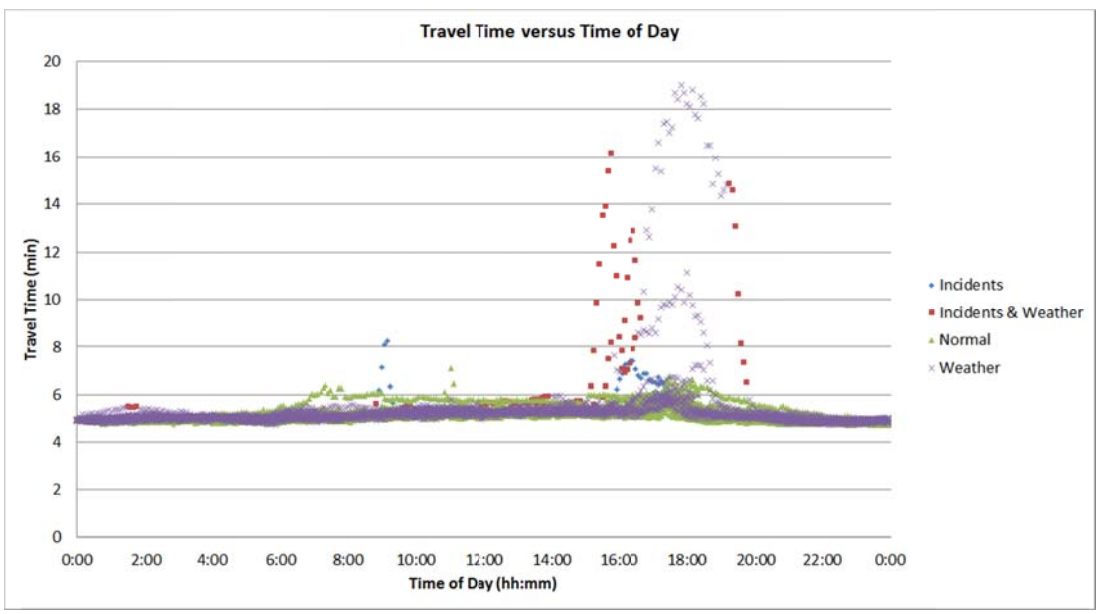


Exhibit D-26: Daily Trends in the 5-Minute Average Travel Times – I-5 Southbound

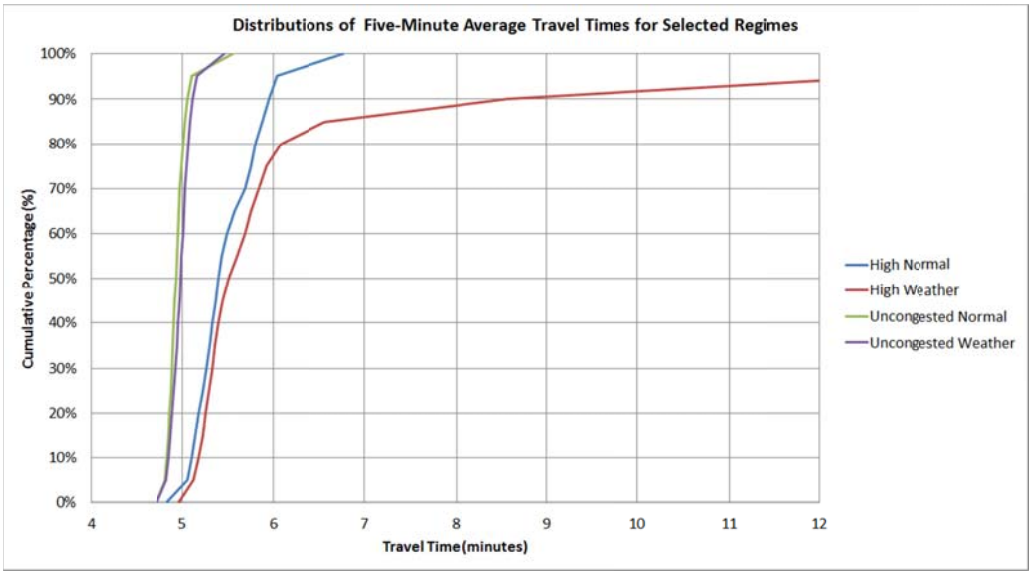


Exhibit D-27: CDFs of the 5-Minute Average Travel Rates for Four Regimes – I-5 Southbound

Even though the question has been answered, the individual vehicle travel times lend a slightly different perspective. In this case, the question is: by how much do the individual vehicle travel times vary when the conditions are adverse?

To see what the impacts are, it is useful to begin with a high-level examination of the data.

Exhibit D-28 shows daily weekday trends in the travel times experienced by individual vehicles on I-5 Southbound. Plotted are data points for 119,528 weekday trips across the three-month time period (out of 156,855 observations total). These travel time trends can be directly compared with Exhibit D-25, which displayed the 5-minute average travel times based on the system detectors.

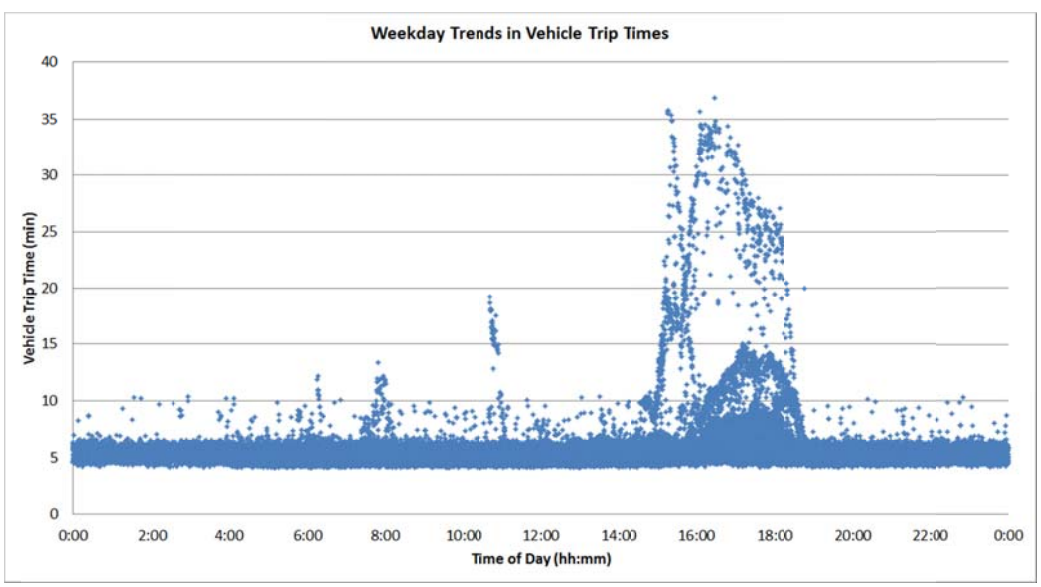


Exhibit D-28: Daily Trends in Individual Vehicle Travel Times – I-5 Southbound

It is clear that when the freeway is uncongested, the travel times range from just under 5 minutes (about 4.2 minutes) to about 7 minutes, with some times reaching up to 10 minutes. (These might be outliers.) However, during the peak (high congestion), even though there are days when vehicles still experience travel times of 5 minutes, there are days when the travel times reach up to 10. There are a few (due to non-recurring events) when the travel times range up to 35 minutes.

But are these data scattered on a given day, or are there trends? **Error! Reference source not found.** shows in the top graph the 10,000 travel times observed between 2/16/2011 at 01:14 to 2/21/2011 at 16:33. A short, abrupt transient can be seen followed by a much longer less dramatic one. Several other smaller transients are also evident. The major transient was due to rain on 2/18/2011 and the short blip was due to an incident that same day.

The second graph in **Error! Reference source not found.** zooms in on the roughly 1,500 observations from 2/18/2011 during the two major events. While there is still some over-plotting, the dots from individual trip times can be seen. Mid-morning it began to rain (at about observation 46,000). Then, about 11:00 there was an incident (at about observation 46,110). The rain had no effect on the travel times. At about 13:30 there was another incident (at about observation 46,500). It also had no impact on the travel times. Then, at about 14:40 there was another incident (at about observation 46,700). While at first it had a small impact, at about 15:00 it had a major impact. The travel times rose dramatically to about 35 minutes. Then, by 16:00 the travel times dropped back to about 9 minutes. They began climbing again (at about observation 47,000) and peaked at about 15 minutes. While this was underway, at about 17:40 there was another incident; but it did not have a discernible impact. Hence, the long transient seems to have been due to the rain. By 18:45 with the peak over the travel times were back down to 5-6 minutes (about observation 47,700).

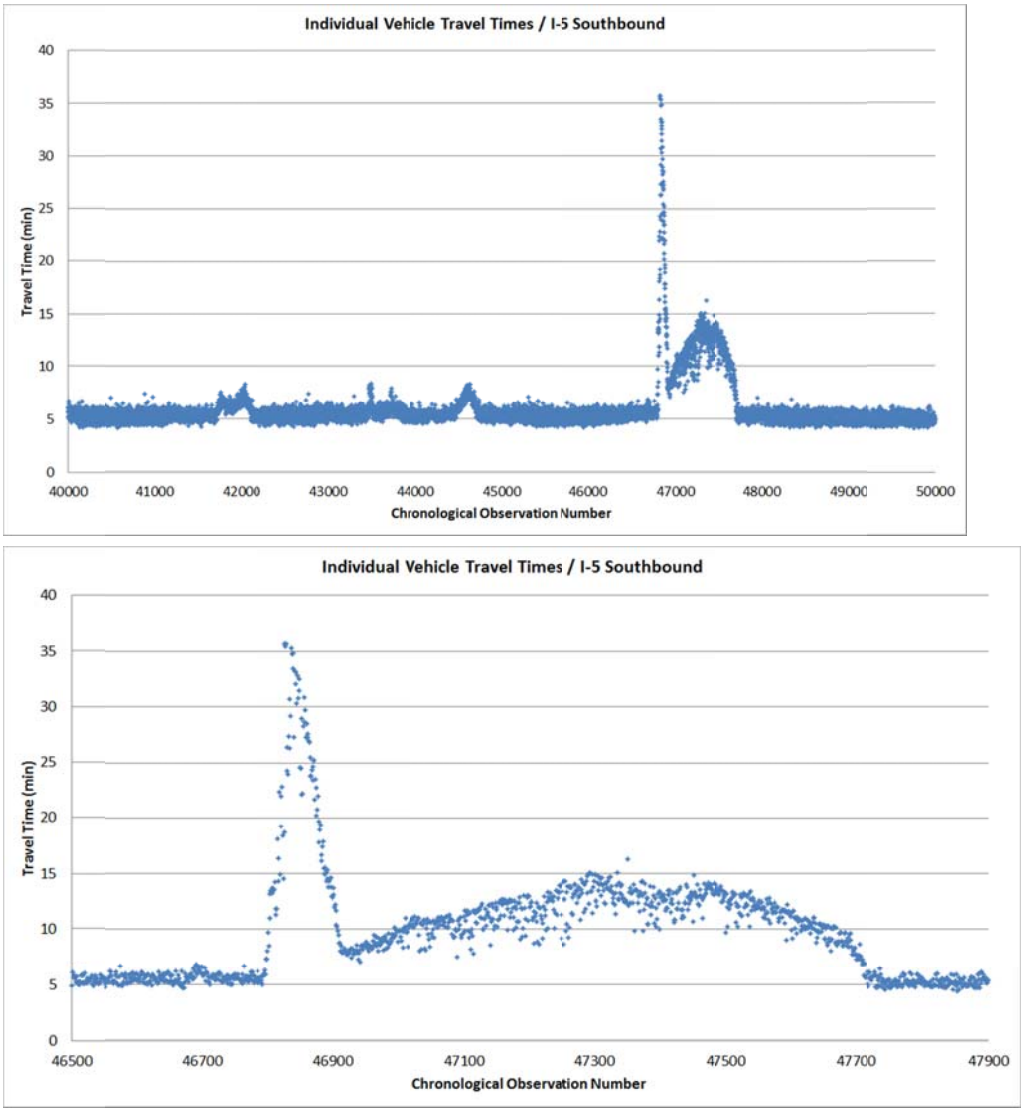
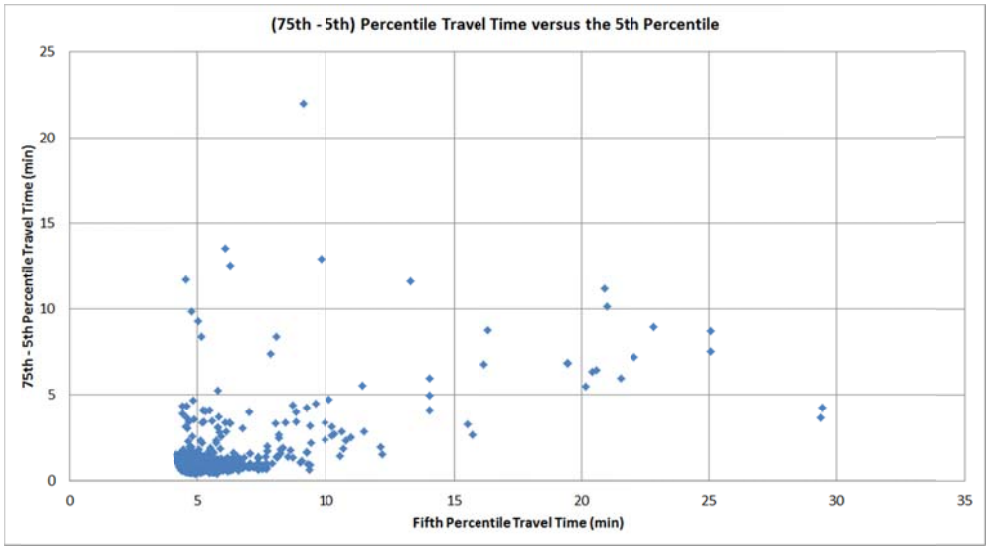


Exhibit D-29: Daily Trends in Individual Vehicle Travel Times – I-5 Southbound

Returning to the high-level perspective, one can ask whether this narrow banding in the travel times is always present. **Error! Reference source not found.** provides some insight. Plotted in the top half is the difference between the 5th and 75th percentile travel times versus the 5th percentile travel time for half-overlapping sequences of 50 Bluetooth observations across the three months. While the over-plotting makes it difficult to see how many data points there are for each combination, one can see that the spread between the 75th and the 5th percentile travel times is much larger when the 5th percentile travel time is low; said another way when the freeway is congested, the spread in the travel times is much smaller.



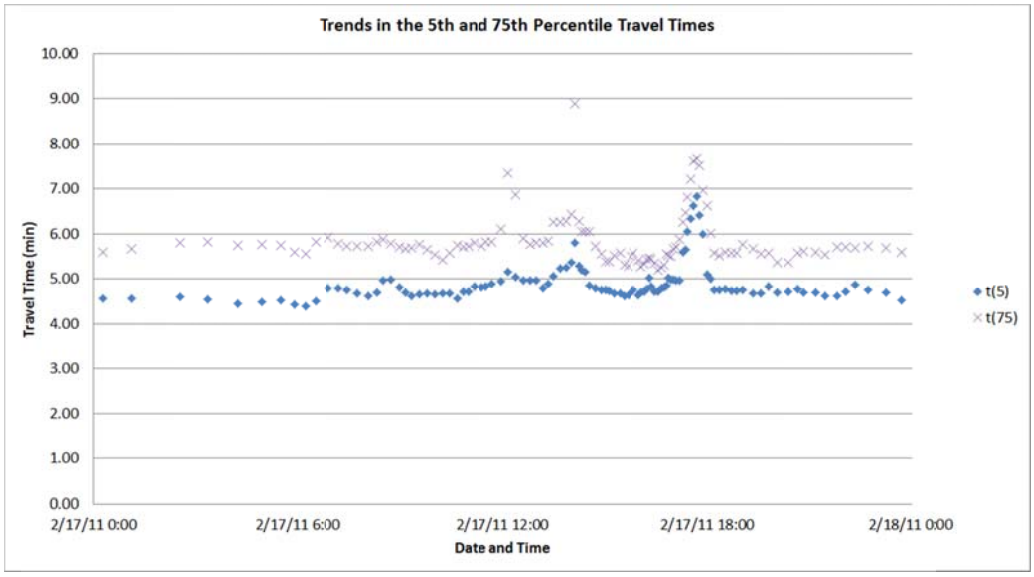


Exhibit D-30: Spreads in the Individual Vehicle Travel Times

Error! Reference source not found. provides an example of how the 5th and 75th percentile values vary. There is some evidence that the spread between the 5th and 75th percentile travel times does get smaller as the 5th percentile increases.

The implication of **Error! Reference source not found.** is that as the facility becomes more congested and the travel times increase, the *variation* in the travel times *decreases*. That is, the congestion makes it difficult for the vehicles to travel at widely varying speeds. Hence, when the travel time is larger, the consistency is *greater*.

This means that the issues in travel time reliability are more complex than just the system detector data might suggest. While the system is clearly *unreliable* during high congestion because it cannot provide the same travel time day-to-day for the same flow (congestion) condition, the travel time it does provide in each situation is very similar for all the vehicles involved—it is difficult for vehicles to have widely varying travel times—the consistency in the travel times is high.

Hence, what people may actually be complaining about when they focus on reliability is their inability to achieve desired travel times when the system is congested, i.e., from one day to another, or one peak load instance to another, or one situation to another. They cannot achieve the travel time they want; and the travel time they experience under those conditions is widely variable. It is *not* the inconsistency in travel times among drivers at a given point in time. Rather, it is the inability of the system to provide the same travel time under the same operating conditions. Or the same travel time when it is congested every time it is congested. Conversely, the users regard the system as being reliable when it is consistent in providing the same travel time from one trip to the next, as it can when it is uncongested. This occurs in spite of the fact that under that condition the variance in individual vehicle travel times is high, because the people can achieve the travel time they want.

Thus, the reliability of the system is perceived to be *high* when the variation in the individual vehicle travel times is also high. And reliability is perceived to be low when the variance in the individual vehicle travel times is low. **Error! Reference source not found.** helped show this. The message is this: people perceive reliability is high when the system lets them travel at their desired travel speeds (and achieve their desired travel times); but this is the condition when the variance in individual vehicle travel times is high. The reason is likely as follows: when the variance is high, such as when the system is lightly loaded, the system is able to deliver consistent performance from one condition realization to another and from one day to another, even though the variance is high and when non-recurring events arise.

That the travel time the system can deliver does vary from one realization to another can be seen in

Exhibit D-31. That is, in spite of the fact that **Error! Reference source not found.** shows that the individual vehicle travel times are very consistent within a given situation, across realizations the travel times are very different. Hence, in spite of the consistency for a given situation, the CDFs of the individual vehicle travel times, combined across situations, provide the same trend in travel times as those reported in

Exhibit D-26.

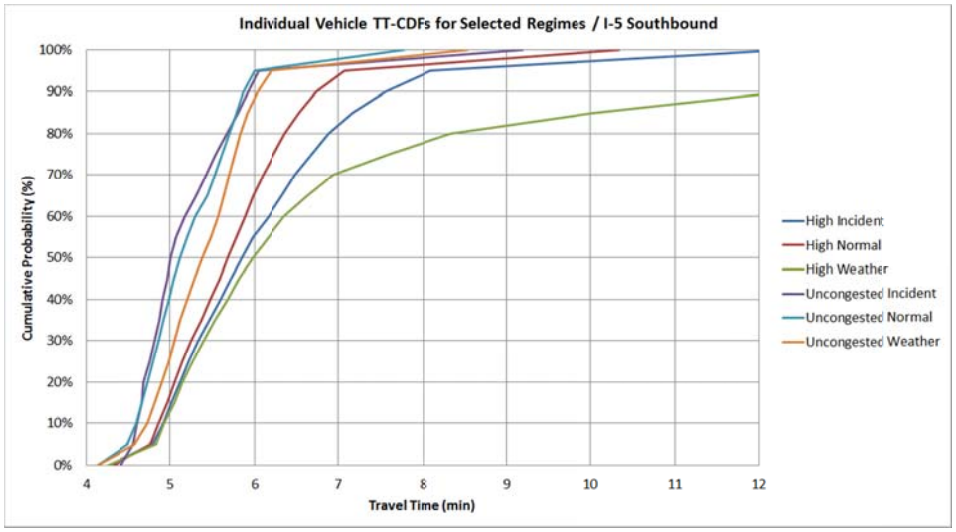


Exhibit D-31: CDFs for Individual Vehicle Travel Times in Several Regimes

In summary, from an individual vehicle travel time perspective, the answer to the original use case question is that the impact of adverse conditions (in this case rain) is: 1) under such conditions the system cannot deliver a reliable travel time; 2) the time it can deliver is different from the time the traveler wants; and 3) the travel time it does deliver is different from one realization of the condition to another.

Compare a Recent Adverse Condition with Prior Ones (MM2)

In this use case, the roadway manager wants to see if the agency did a better job of handling a recent adverse condition. The objective is to compare the reliability of the system in the recent event with similar events in the past. Perhaps the agency's response was different. This helps the agency decide whether the actions taken were sufficient, or if more could be done to reduce the traffic impacts. In rural areas, this information can help operators provide more accurate pre-trip information in inclement conditions.

Table D-18: Compare a Recent Adverse Condition with Prior Ones (MM2)

User	Roadway System Manager
Question	How do the reliability impacts from a recent adverse condition compare with prior, similar adverse conditions?
Steps	1. Select the network area of interest. 2. Identify the recent adverse condition of interest. 3. Assemble a database of historical normal and adverse conditions for segments in the study area that have been adversely affected. 4. Compare the impacts of the recent event with the impacts of prior occurrences.
Inputs	Historical TT-PDFs for the arterial segments in the study area for the recent condition and similar prior adverse conditions as well as normal ones.
Result	One or more figures comparing the TT-CDFs for the recent adverse condition with other similar events in the past and the normal conditions.

While data were not available for before-and-after situations in which agency actions were involved, it is still possible to address this use case by examining some of the Bluetooth data collected. Those data allow one to compare system performance under different realizations of the same or similar adverse conditions.

An interesting dataset to examine is the one for trips from South Lake Tahoe to Placerville, the same dataset that was used in use case AP6. As

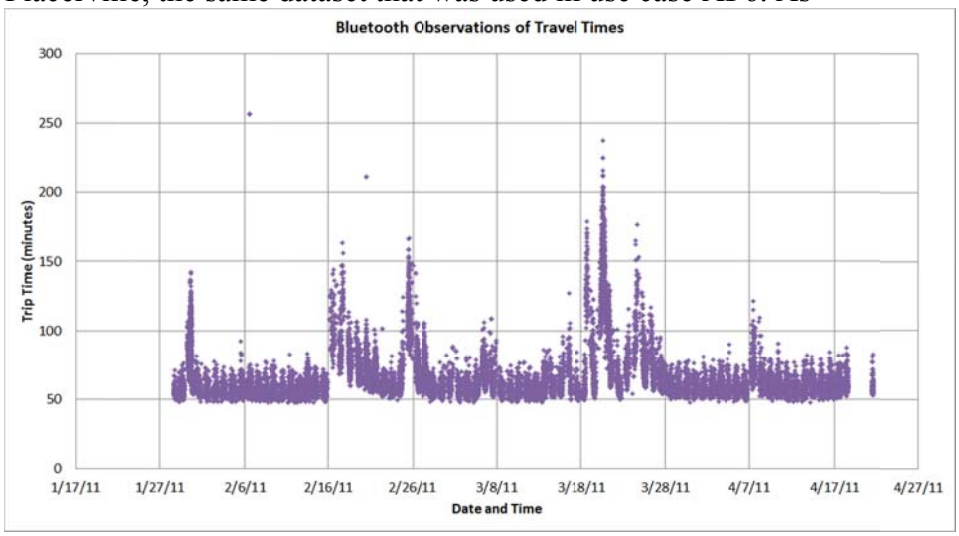


Exhibit D-22 indicated, there were several times when the route was subjected to bad weather conditions and the travel time increased. These conditions can be compared and contrasted to see similarities and differences.

As

Exhibit D-24 indicated, heavy snow is a condition that has a dramatic effect on the distribution of travel times. For the snows that occurred during the observation period, it raised the minimum travel time from 50 to 70 minutes, the median travel time from 55 to 140 minutes, and the 90th percentile travel time from 70 to 210 minutes.

There were six heavy snow storms during the period of observation: one on January 29; another on February 15, a third on February 24 and three more on March 18, 20 and 24. The impacts of these storms were felt across the following times:

- *1/29*: 1/29 at 21:30 to 1/30 at 21:00
- *2/15*: 2/15 at 18:00 to 2/18 at 18:00
- *2/24*: 2/24 at 12:00 to 2/27 at 0:00
- *3/18*: 3/18 at 12:00 to 3/19 at 15:00
- *3/19*: 3/19 at 15:00 to 3/22 at 18:00
- *3/24*: 3/24 at 0:00 to 3/25 at 15:00

Exhibit D-32 presents the TT-CDFs for the six storm events. As can be seen, the March 19th event produced the most significant effect on the travel times. The 90th percentile reached 160 minutes. By comparison, for the other heavy snows, the 90th percentile reached "only" 140 minutes on March 18 and between 110 and 120 minutes for the other four storms. These values are all in contrast with the 90th percentile value of 90 minutes for normal conditions.

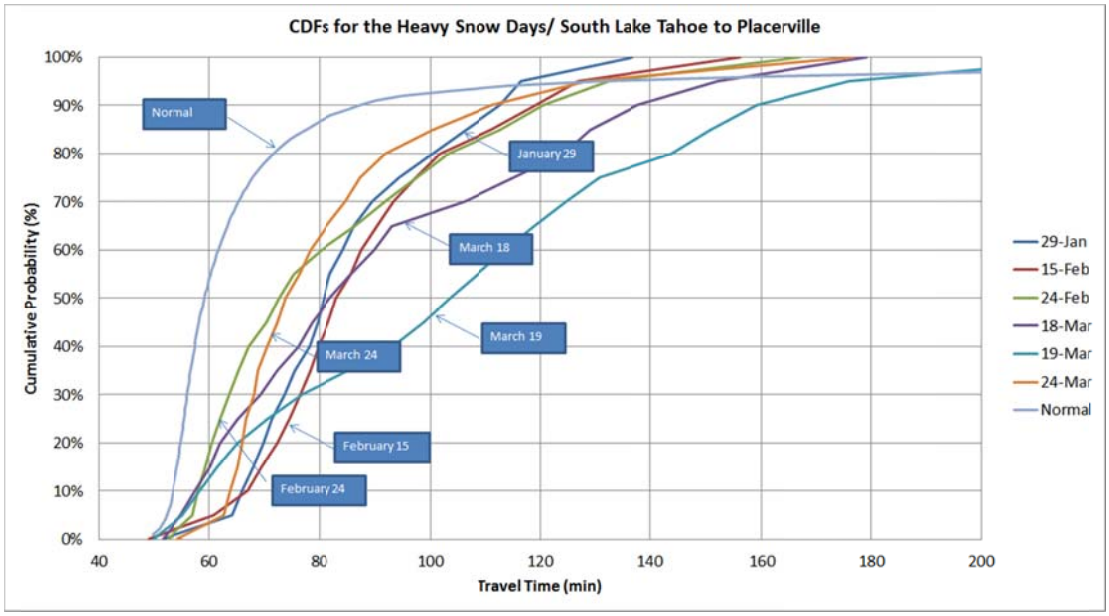


Exhibit D-32: CDFs for Individual Vehicle Travel Times in Several Regimes

A summary of these findings might be that: heavy snow adds up to 50 minutes for 90% of the trips and only 10% of the trips manage to complete the trip with an additional 20 minutes or less (50 versus 70 minutes).

Gauge the Impacts of New Arterial Management Strategies (MM3)

The user wants to gauge the effectiveness of new arterial management strategies in terms of travel times and travel time variability. The analysis compares before and after conditions. This supports the analysis of changes like signal timing updates, new access management policies, and geometric modifications.

Table D-19: Gauge the Impacts of New Arterial Management Strategies (MM3)

User	Roadway System Manager
Question	Has a new arterial management strategy improved travel time reliability?
Steps	1. Select the arterial segments of interest. 2. Identify the "before" and "after" conditions. 3. Assemble a database of segment and route TT-PDFs for the before and after conditions. 4. Analyze the differences in the TT-PDFs.
Inputs	Historical TT-PDFs for arterial segments and routes in the study area for the before and after conditions, minimizing the external factors like adverse conditions that might create differences due to other reasons.
Result	A figure comparing the TT-CDFs for the before and after conditions for the segments and routes of interest, with an overall assessment of the impact.

No data were collected during the case studies that could be used to address this use case. However, the analysis procedure is effectively identical to that used in use cases AE4 and/or AE5. The impacts of such changes could also be assessed using a simulation model.

Gauge the Impacts of New Freeway Management Strategies (MM4)

The user wants to gauge the effectiveness of new arterial management strategies in terms of travel times and travel time variability. The analysis compares before and after conditions. This supports the analysis, for example, of the impacts of ramp metering rate changes, geometric modifications, speed limit updates, or HOV lanes.

Table D-20: Gauge the Impacts of New Freeway Management Strategies (MM4)

User	Roadway System Manager
Question	Has a new freeway management strategy improved travel time reliability?
Steps	1. Select the freeway segments of interest. 2. Identify the "before" and "after" conditions. 3. Assemble a database of segment and route TT-PDFs for the before and after conditions. 4. Analyze the differences in the TT-PDFs.
Inputs	Historical TT-PDFs for freeway segments and routes in the study area for the before and after conditions, minimizing the external factors like adverse conditions that might create differences due to other reasons.
Result	A figure comparing the TT-CDFs for the before and after conditions for the segments and routes of interest, with an overall assessment of the impact.

No data were collected during the case studies that could be used to address this use case. However, the analysis procedure is effectively identical to that used in use cases AE4 and/or AE5. The impacts of such changes could also be assessed using a simulation model.

Be Alerted When the System has Become Unreliable (MM5)

The user wants to know when the travel times on a facility have become unreliable or are about to do so. Consistent with the discussions in MM1, this is an alert that tells the user the system is entering a condition where travelers cannot achieve the travel times they want because the congestion is too high (travel is constrained) and/or the system's ability to provide consistent travel times has become low. This is information that a roadway system manager might use as the basis for sending out alerts to variable message signs or route guidance devices.

Table D-21: Be Alerted When the System has Become Unreliable (MM5)

User	Roadway System Manager
Question	Has a route or system become unreliable?
Steps	1. Select the segments or routes being monitored. 2. Select the conditions for which notification is desired. 3. Design the test that will be used to identify the condition selected. 4. Monitor the TT-PDFs (or TR-PDFs) to see if an unreliable condition has arisen.
Inputs	Real-time information about the status of the segment or route plus historical TT-PDFs for the segments and routes under surveillance. In addition, real-time information about the network conditions as explanatory variables.
Result	An alert message that displays the facility and location where the travel time reliability is adverse plus TT-CDFs that compare the current segment or route travel time against the ones that would be expected.

This use case is akin to incident detection or identification of times when the system's behavior has become unstable. As has been seen in use case MM1 and elsewhere, under heavy congestion or under adverse non-recurring conditions (that is, when the system is under stress), individual vehicle travel times become less variant (i.e., more consistent) because the congestion keeps people from being able to travel at the speeds they want. Moreover, under these conditions, the system struggles to provide the same travel times each time it happens. It seems it cannot control the manner in which the vehicles interact or the effects on system capacity, etc. from the non-recurring event.

The steps in the use case are as follows. Step 1 is to select the segments or routes to be monitored. I-5 Southbound in Sacramento will be employed. Step 2 involves selecting the conditions for which notification is desired. The choice will be: any condition in which the facility has difficulty letting users travel at the speeds they want to choose. Step 3 involves designing the test that will be used. Step 4 is to monitor the TT-PDFs (or TR-PDFs) to see if reliability is suffering. The data collected will be used ex-post-facto to see when this did happen.

Based on data for individual vehicle travel times, it appears that the lower percentile travel times (the higher speeds) are affected earliest and the most (i.e., the higher percentile speeds decrease the most). Without question, the other percentile travel times change as well, but not as dramatically, at least initially. That is, it is the lower percentile travel times that provide the earliest sign that the system is entering an unreliable condition. In other words, as the system becomes more heavily loaded from either congestion or a non-recurring event, the system loses the ability to permit drivers to achieve the lowest travel times. It cannot let those vehicles thread their way through the traffic stream. Either the traffic density is too high or the non-recurring event has interfered with that ability (e.g., as a result of queuing).

The clearest evidence of this can be seen in time traces like Exhibit D-33. Shown are the percentiles of individual vehicle travel times for I-5 southbound in Sacramento on March 1, 2011. (Additional plots of the same data can be found in

Exhibit D-28, **Error! Reference source not found.**, and **Error! Reference source not found.**.) One can see that as incidents occur or the system becomes more heavily loaded the 5th percentile travel time increases.

The first event occurs at about 11:00 when the travel times abruptly rise and then return to normal. This was an incident. The second starts at about 15:00 when the travel times begin to increase in advance of the PM peak. In the first 11:00 instance, notice that all the percentile travel times increase – without any advance warning that they were going to; while in the 15:00 instance, the 5th percentile travel time begins to increase (and the standard deviation begins to decrease) well in advance of the changes in the other percentile travel times.

The message seems clear. In the case of recurring congestion, the low percentile travel times (e.g., 5th percentile) and the standard deviation both provide leading indications that a period of congested operation is approaching. The travel times (from day to day) are about to become unreliable in the sense that people will not be able to achieve their desired travel times, and the travel time they experience from one instance to the next will not be the same. However, when an unexpected non-recurring event, such as an incident, affects the system's operation, it does so abruptly, without leading indications (from the 5th percentile travel time or the standard deviation) that conditions are about to change. In addition, in the latter case, especially of incidents, when the event creates a bottleneck that affects all drivers, then the travel times not only all increase but become very consistent. However, when the event affects only some lanes, and thus only some drivers, the travel times increase but there remains a significant variation in the travel times achieved. People in the less affected lanes are able to achieve significantly shorter travel times than those in the more affected lanes. Finally, one thing remains true in all conditions: the lower percentile (e.g., 5th percentile) travel times are always affected, either in advance of the full-fledged condition (e.g., when congested operation occurs) or immediately upon its onset (e.g., with a non-recurring event during otherwise uncongested operation).

The implication of these observations is that a test that identifies these periods of unreliable operation can be predicated on the lower percentile travel times. There probably is not one test that fits all conditions. Most likely such tests need to be tuned to the facilities being observed, but a test based on the lower percentile travel times is likely to always work. (Tests based on reductions in the standard deviation will also work for the recurring event conditions; and such tests appear to provide an even earlier warning that conditions are in the process of changing.)

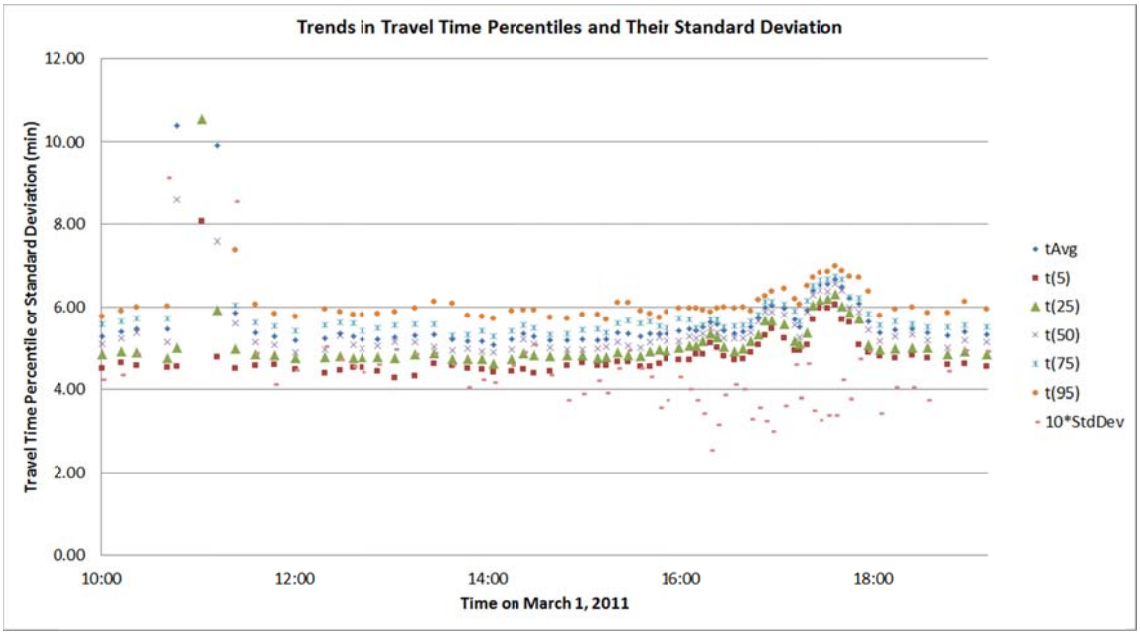


Exhibit D-33: Trends in Travel Time Percentiles and Their Standard Deviation

The results of applying one test are shown in Exhibit D-34. The setting employed was I-5 southbound in Sacramento, the same facility from which the data shown in Exhibit D-33**,** Exhibit D-28, and **Error! Reference source not found.** were obtained. The test involves checking three conditions: 1) the average of the 5th percentile travel time in four successive observations rises above 4.7, the 5th percentile rises above 5 in the current observation, or 3) the 75th percentile travel time rises above 6. The latter test seems to catch instances in which only some but not all of the lanes are affected by an incident.

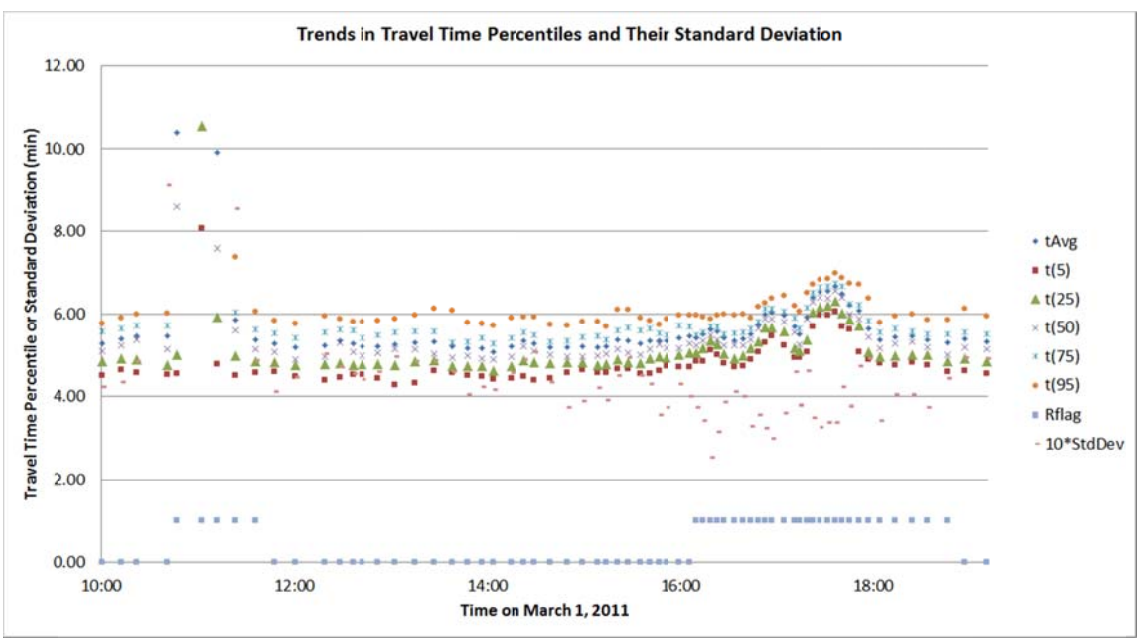


Exhibit D-34: Trends in Travel Time Percentiles and Their Standard Deviation

Determine Pricing Levels Using Reliability Data (MM6)

In this use case, the user wants to see what the pricing levels should be on some High Occupancy Toll (HOT) lanes. The notion is that better and more reliable travel times have value and people will pay for better service. The question is: how much?

Table D-22: Determine Pricing Levels Using Reliability Data (MM6)

User	Roadway System Manager
Question	What toll can be charged on the High Occupancy Toll (HOT) lanes given the comparative reliability of those lanes versus the mixed use lanes?
Steps	1. Identify the route and conditions under study. 2. Assemble the TT-PDFs for the HOT lanes and the mixed use lanes. 3. Compare the TT-PDFs and determine the fee that can be charged given the differential TT-PDFs that exist for the various conditions. 4. Implement the HOT lane fee structure.
Inputs	Historical TT-PDFs for the routes and conditions under study both in the HOT lanes and the mixed use lanes. Econometric information about the prices people are willing to pay for lower travel times and better travel time reliability (two separate thoughts).
Result	A pricing guide for different conditions on the routes studied.

Unfortunately, no data were obtained during the project that could be used to provide an example of this use case. However, the procedure would be akin to that used in use cases AE-4 and/or AE-5 where the focus was on changes in system performance over time. In this case, however, the emphasis would be on performance without and with the HOT lane instead of without and with the improvements made to the facility.

DRIVERS WITH CONSTRAINED TRIPS

The driver-related use cases fall into two categories: those that are constrained and those that are unconstrained. This section deals with the constrained trips. A trip is constrained if it has a specific time of arrival. Hence, early and late have meanings. Examples include trips for doctor's appointments, scheduled deliveries, and scheduled bus stops. Unconstrained trips have no particular arrival time.

Constrained trips have a specific, intended time of arrival. Late and early have definite meanings. Some of these trips are done frequently; others, infrequently. In the case of the frequent ones, the driver has a sense of how long the trip should take and how much the trip time should vary due to congestion and other factors. In the case of the infrequent ones, the user may not have a sense of the travel time, but needs to be on time nevertheless.

Understand Departure Times and Routes for a Trip (MC1)

In advance, a driver wants to understand the travel times and routing options for a trip that will be made frequently. This is something the driver might do if she or he has a new job or has selected a new day care center. The trip is not to be made right away, but it will be soon, and the driver wants to understanding how much time to allow and what route (or routes) to choose. The answer is obtained by analyzing historical data, including all conditions under which the trip might have been made, including inclement weather, incidents, etc. because the user wants to know what to do depending on the network conditions that exist.

Table D-23: Understand Departure Times and Routes for a Trip (MC1)

User	Driver
Question	What departure times are needed and what routes should be selected so as to arrive on time given past TT-PDFs for this trip?
Steps	1. Select the origin and destination. 2. Select the desired arrival time. 3. Decide what being on-time means (probability of being late). 4. Analyze the TT-PDFs to identify options for departure times and routes. 5. Create a table that shows what time to allow and what route to select depending on the network conditions that might exist.
Inputs	Historical TT-PDFs for the routes and departure times that are logical based on the conditions that might exist.
Result	Table of routes to select and departure times depending on the conditions that exist. The table is created by analyzing the TT-PDFs for the various routes and network conditions.

Step 1 involves the selecting the origin and destination. In this use case, the same origin and destination as A and B in Exhibit D-1 will be used which draws upon the three routes in San Diego.

Step 2 involves selecting the desired arrival time. In this specific case, most of the time, the trip is going to be made during the late afternoon, between 15:00-19:00. At this point, it is worth looking at some details on how individual travel times can be synthesized from 5-minute mean travel times; the subsequent paragraphs provide that description.

Most traffic management centers collect mean travel times every five-minutes from system detectors. These inputs provide insight into average operating conditions of the facility but not information sufficient for understanding variations in individual driver travel times. Two such data sources that are useful in answering questions pertaining to individual driver travel times are Advanced Vehicle Identification (AVI) and Advanced Vehicle Location (AVL). However, such data sources are not very common. Therefore, the question to be asked is the following "Is there a way to synthesize individual vehicle travel times from 5-minute mean travel times obtained from loop detector data?" The answer is yes, AVI data can be used. In this case it is Bluetooth data collected in Sacramento.

The data collection involved a 5-mile section on I-5 in Sacramento, CA. The location is depicted in

Exhibit D-26. Data were collected both in the northbound and southbound directions for approximately three months (January to April) in 2010. Bluetooth readers were stationed at four locations as shown in

Exhibit D-26. Every tag read in the dataset has following attributes: An encrypted MAC address, the tag reader-ID at both origin and destination, and time stamps associated with them. There are around 150,000 tag reads in each direction. About 110,000 tag-reads remain after removing outliers. Since non-recurring events like weather, incidents etc., have a significant impact on travel times experienced by individual drivers, it makes sense to further classify data based on non-recurring event type (Normal, Weather, and Incidents).

The origin-destination (OD) pair data were first sorted on the basis of chronological order on the basis of "O" time. In the first pass, based on fifty most recent trip rate observations, trip rates associated with each percentile, and mean trip rate associated with those set of observations were computed; then, the ratio of each percentile travel rate to that of mean travel rate was computed. The data were then stored in bins based on mean travel rates. Lastly, ratios to the mean were computed for each percentile travel rate.

These ratios are then used in conjunction with the average travel rates from the system detectors (in this case for the three routes in San Diego) to synthesize estimates of the travel rates (and then the travel times) for vehicles that would have represented each percentile (101 values) in the distribution for each 5-minute observation.

Step 3 involves deciding what being on-time means (probability of being late). In this specific use case the assumption is that the driver wants to know how wide the arrival time window is (in time) to encompass 90% of the arrivals. In other words, his/her on-time arrival window is 90%.

Step 4 involves assembling the data and creating TT-CDF's for each operating condition for each route. The analysis presented here is a two-step process. First, synthesized individual vehicle travel time data between 15:00-19:00 was used in generating TT-CDF's. Please note that these CDF's all percentile drivers. **Error! Reference source not found.** presents CDF plots for each route for each regime. These plots do provide some insights on the performance of each of those three routes. It seems like under Normal operating conditions both CA-163, and I-5 almost have identical 90% travel times (22 min), while I-15 performs marginally better with a travel time of about 19 minutes. However, under Incident, weather, and special events CA-163 performs consistently better than the other two routes. It seems like travel times grow significantly higher in the cases of weather events.

Exhibit D-36 summarizes these results.

Step 5 involves creating a table that shows what time to allow and what route to select depending on the network conditions that might exist.

Exhibit D-36 shows the 90th percentile travel times for various oprating conditions for these three routes. The highlighted cells represent the minimum travel times among the three routes for a given operating condition.

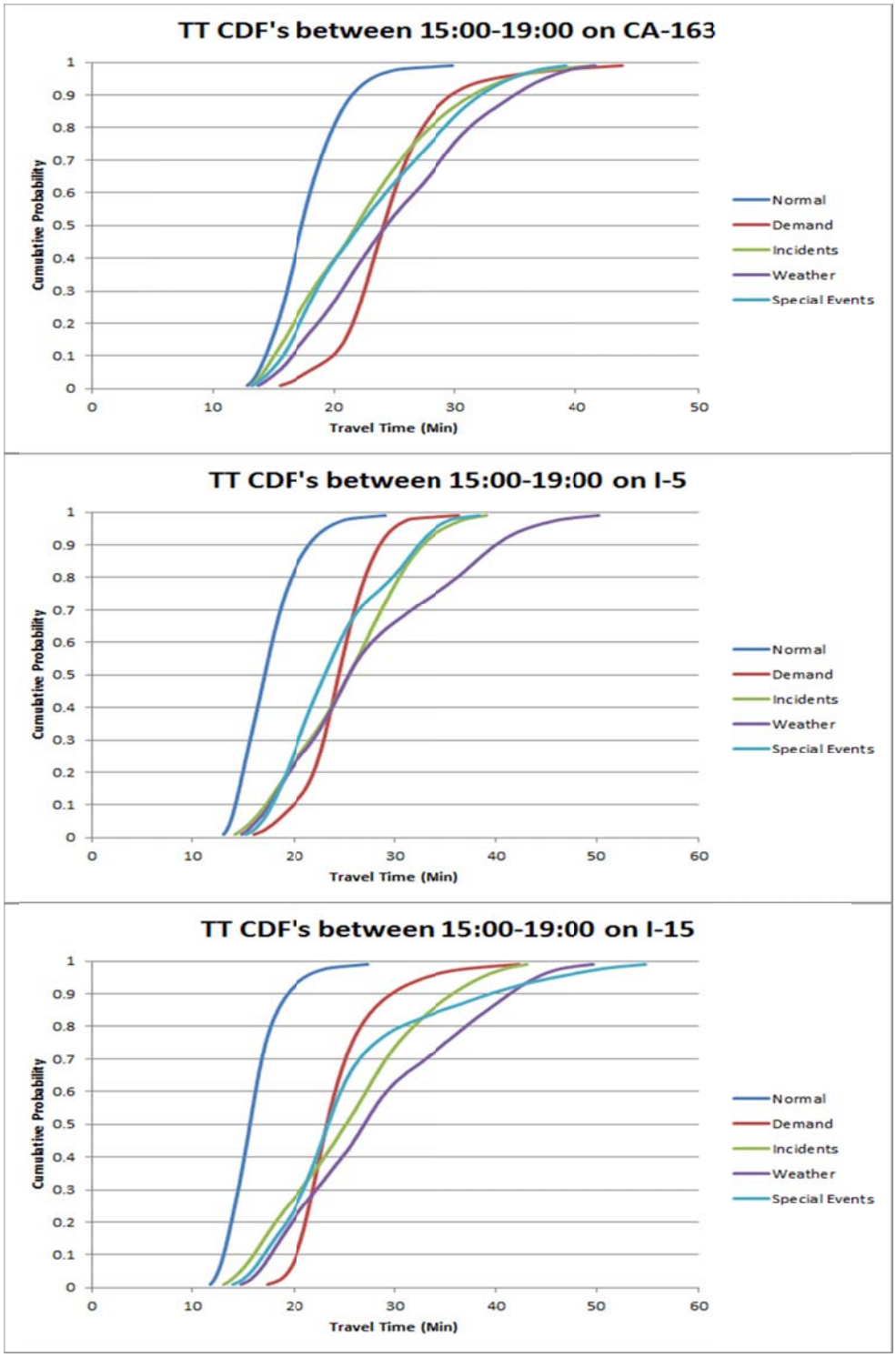


Exhibit D-35: Travel Time CDFs for Three Routes in San Diego

Route	90th Percentile Travel Time				
	Normal	Dem	Inci	Wea	SE
CA-163	21.48	29.65	31.42	34.82	32.07
I-5	21.55	28.48	32.68	39.98	32.28
I-15	19.38	29.62	35.73	41.35	39.42

Exhibit D-36: 90th Percentile Travel Time s for Each Route under Various Conditions

However, the analysis presented above does not take into account the risk-receptiveness of individual drivers: meaning, some drivers are more or less aggressive than others. For example, one can and should focus on specific classes of drivers (by aggressiveness, here) to provide guidance which is truly meaningful. In this case, three categories were employed: more aggressive drivers whose travel times are centered around 10th percentile travel times, median drivers whose travel times are centered around 50th percentile travel times, and conservative drivers whose travel times are centered around 90th percentile travel times.

This leads to a second analysis based on guidance by driver type. Without loss of generality, the discussion here is based on the aggressive drivers (those with travel times centered on 10th percentile travel times). It is further assumed that the distribution of travel times for any given driver type is normally distributed. For example, times for the aggressive driver class are normally distributed between the 5th and 15th percentiles with a mean equivalent to the 10th percentile travel time. Based on this frame work, travel times for one hundred drivers were synthesized for each 5-minute travel time observation from the system detectors.

Exhibit D-37 is a presentation of **Error! Reference source not found.** but for the 10th percentile drivers. Though, the choice of best routes hasn't changed for various non-recurring conditions, as expected the 90th percentile travel times are lower for these drivers. Under Normal operating conditions, aggressive drivers have travel times about 2 minutes shorter on all three routes. Under demand and incident conditions they are about 4 to 5 minutes shorter. Though there was not a significant drop in travel times on CA-163 and I-5 under weather and special event conditions, aggressive drivers have a travel time on I-15 about 7 minutes shorter when compared to the overall driver population. Exhibit D-38 summarizes these results.

Step 5 involves creating a table that shows what time to allow and what route to select depending on the network conditions that might exist. Exhibit D-38 shows the 90th percentile travel times for various oprating conditions for these three routes. The highlighted cells represent the minimum travel time among the three routes for a given operating condition.

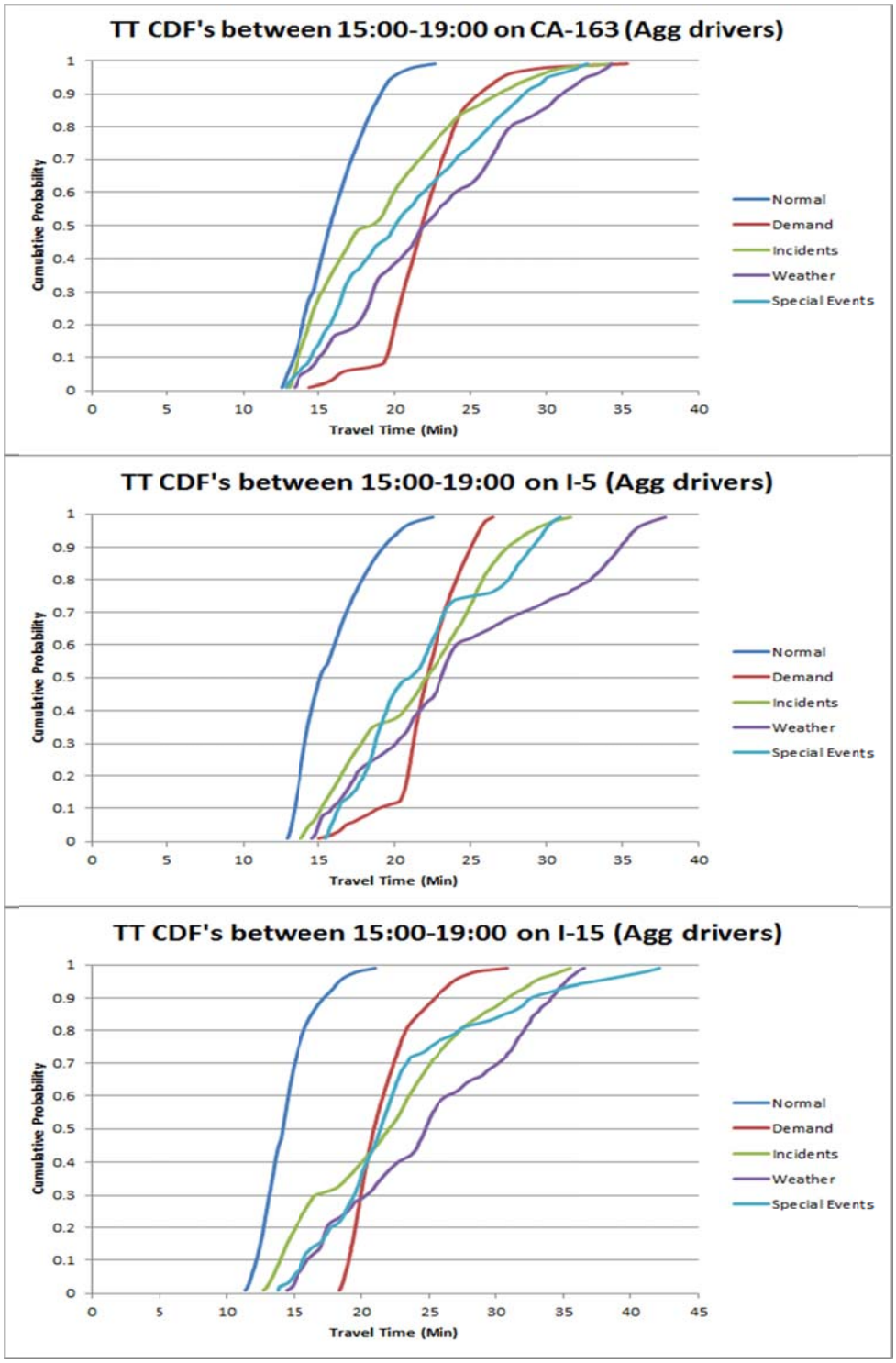


Exhibit D-37: Travel Time CDFs for Aggressive drivers

Route	90th Percentile Travel Time				
	Normal	Dem	Inci	Wea	SE
CA-163	19.05	25.57	26.83	31	28.52
I-5	19.23	25.03	27.43	34.9	29.05
I-15	17.25	25.4	30.85	34.05	32.57

Exhibit D-38: 90th Percentile Travel Time s for Each Route under Various Conditions

Determine a Departure Time and Route Just Before a Trip (MC2)

In this use case, the driver wants to know when to leave shortly before making a trip. He or she wants to know when to leave and what route to take so as to arrive on time. The driver needs to have predictions of what the travel times are likely to be on the routes he or she is most likely to select.

Table D-24: Determine a Departure Time and Route Just Before a Trip (MC2)

User	Driver
Question	Just before making a trip, when should the driver leave and what route should he or she take to arrive at a destination on time?
Steps	1. Select the origin and destination. 2. Decide what being on-time means (e.g., the probability of being late). 3. Obtain predictions of the TT-PDFs for routes that might be selected. 4. Determine the options for departure times and routes. 5. Select the departure time and route that minimizes the travel time but assures an on-time arrival.
Inputs	Forecasts of TT-PDFs by departure time for the routes that might be chosen given the current and anticipated network conditions
Result	Overlapping plots of the TT-CDFs for the various routes so that the distributions of their travel times can be compared and the one with the shortest travel time at a particular probability can be selected.

Step 1 involves the selecting the origin and destination. In this use case, locations A and B in Exhibit D-1 are again selected.

Step 2 involves selecting the desired arrival time. In this specific case, the driver wants to make the trip between 15:00 and 19:00, wants to know when to leave, and wants to know the likelihood of arriving at the destination on-time with 90% certainty (in other words, with a 90% probability of on-time arrival).

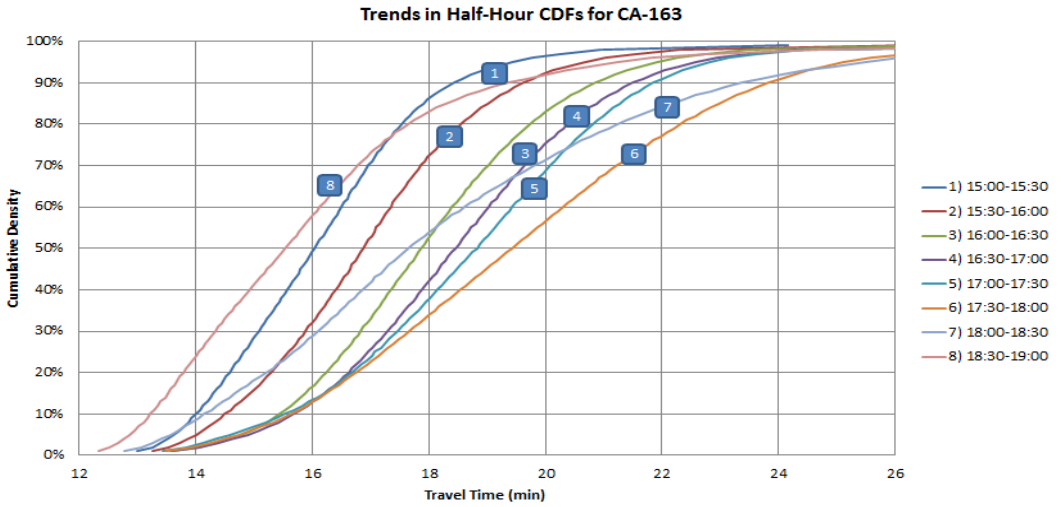
Step 3 involves assembling the data and creating TT-CDF's for Normal operating condition for each route. As mentioned earlier, driver wants to make the trip anytime between 15:00-19:00, and the driver wants to know what is the best route and best time to make the trip. The analysis presented here attempts to answer this question in the following way: the four hour time window of interest is further divided into eight half-hour time windows (15:00-15:30, 15:30-16:00, 16:00-16:30 etc.), and let us say for the purposes of illustration expected arrival

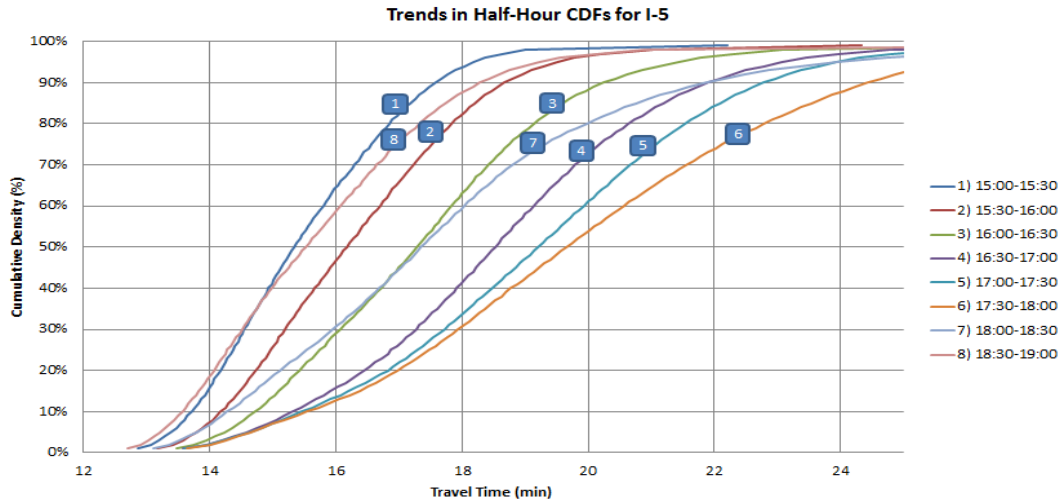
time of the driver are the end of each half-hour period (15:30, 16:00, etc.). Based on this frame work, the question can be reformulated as the following: which among the eight expected arrival times of interest will minimize the driver's travel time, and for what route.

There are two analyses presented for answering this question. The first makes use of synthesized individual vehicle travel time data between 15:00 and 19:00, and generates TT-CDFs for eight half-hours of interest. These CDFs provide guidance about when the driver has to leave in order arrive within a specific half-hour of interest. Note that these CDF's are for all percentile drivers. **Error! Reference source not found.** presents CDF plots for each route for Normal operating condition. These plots provide some insights on the performance of each of those three routes. Looking at CA-163 first, its TT-CDFs for first and eighth half-hour time windows are at left suggesting that those time widows have reliable travel times. Travel times from second to sixth half-hour windows got increasingly worse; operating conditions seem to get better in the seventh half-hour period, and the facility seem to resume to normal operating conditions during eight half-hour period. The story is similar in the case of both I-5 and I-15, with a parenthetical remark that TT-CDF for seventh half-hour period in the case of I-5 is significantly different.

Step 5 involves creating a table that shows what time to allow and what route to select depending on the network conditions that might exist.

Exhibit D-40 shows the 90th percentile travel times for various oprating conditions for these three routes. The 90th percentile travel time is minimum (18.43 minutes) for the first half-hour window of interest, which is 15:00-15:30; travel time for second to sixth half-hours of interest (15:30-16:00 to 17:30-18:00) has a positive slope, meaning it was constantly increasing from time window to the next. 90th percentile travel time was 19.62 minutes for second half-hour window, and it was 23.82 minutes for sixth half-hour window. Operating conditions seem to get better as travel time for the seventh half-hour window (18:00-18:30) was less than that of sixth. The story is similar in the cases of both I-5 and I-15. Based on that table, it seems like the best time window to leave is 15:00-15:30 and best route to choose is I-15.





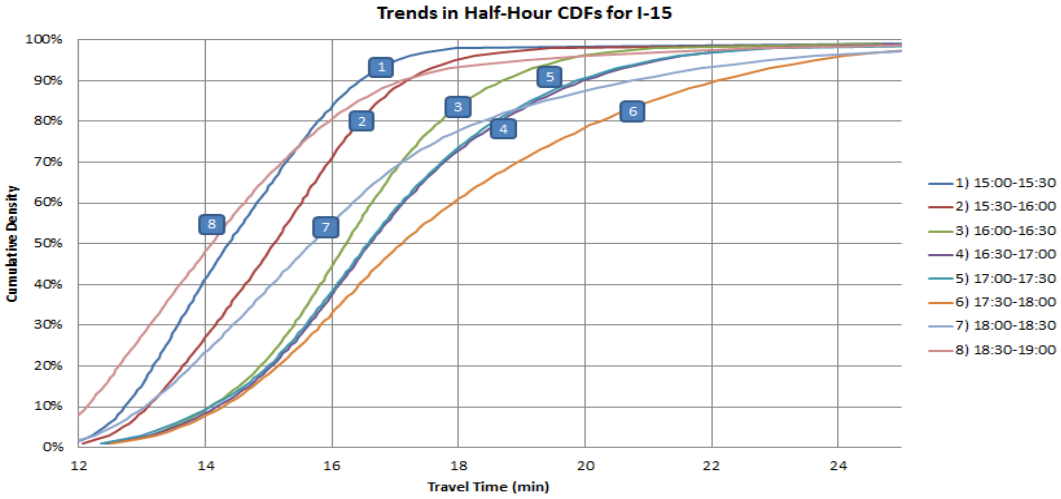


Exhibit D-39: Half-Hour TT-CDFs for Three Routes in San Diego under Normal Condition

Route	Expected Arrival Time (HH:MM)	15:30	16:00	16:30	17:00	17:30	18:00	18:30	19:00
CA-163	Travel Time(min)	18.43	19.62	20.85	21.5	21.85	23.82	23.37	19.35
	Departure Time(HH:MM)	15:11	15:40	16:09	16:38	17:08	17:36	18:06	18:40
I-5	Travel Time(min)	17.58	18.68	20.25	21.9	22.78	24.43	21.87	18.28
	Departure Time(HH:MM)	15:12	15:41	16:09	16:38	17:07	17:35	18:08	18:41
I-15	Travel Time(min)	16.45	17.18	18.7	19.98	19.88	22.1	20.75	17.1
	Departure Time(HH:MM)	15:13	15:42	16:11	16:40	17:10	17:37	18:09	18:42

Exhibit D-40: 90th Departure Times and Travel Times Correspondent to Different Arrival Times for Three Routes

As mentioned earlier, the analysis presented above takes into consideration all drivers. It would be interesting to see what the distribution of the travel times look like for various driver classes. The following analysis re-presents these results for aggressive driver class (centered on 10th percentile drivers). Exhibit D-41 presents CDF plots for each route for aggressive drivers for Normal operating condition. In the first glance, though trends in travel times in these plots seem similar to those presented in 4-23, they are different. In the case of aggressive driver population, one can expect shorter travel times. Looking at I-15 first, its TT-CDF's for most of half-hour time periods are at left, suggesting that most of the aggressive driver population have tight distribution of travel times; variation in travel times seems to be more in the case of I-5, and most in the case of CA-163. The 90th percentile travel time in any half-hour time period is about 2 to 3 minutes shorter than that for the overall driver population.

Exhibit D-42 summarizes values of 90th percentile travel times for these three routes.

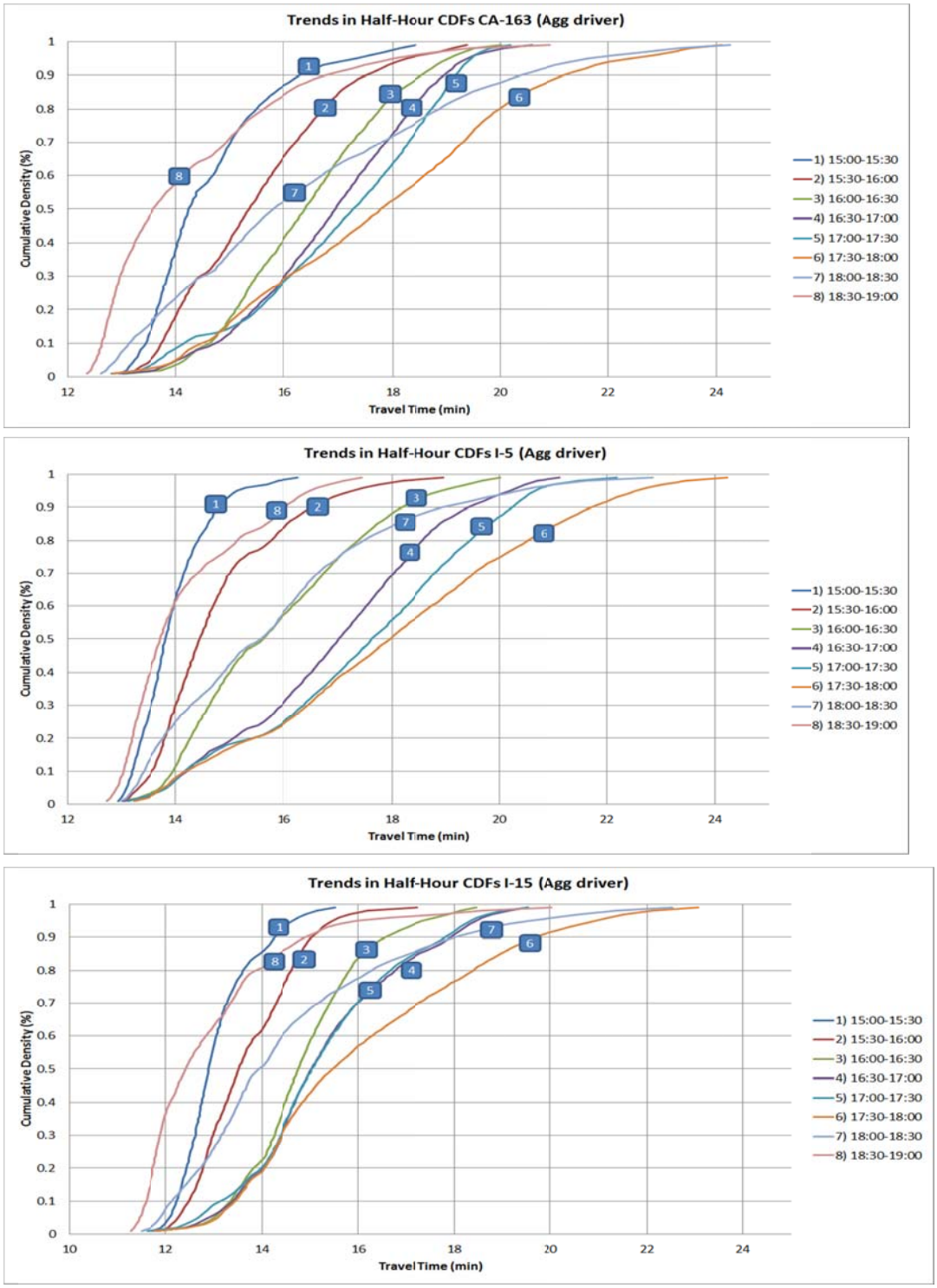


Exhibit D-41: Half-Hour TT-CDFs for Three Routes in San Diego under Normal Condition

Route	Expected Arrival Time (HH:MM)	15:30	16:00	16:30	17:00	17:30	18:00	18:30	19:00
CA-163	Travel Time(min)	16.3	17.52	18.55	18.97	19.18	21.18	20.38	16.77
	Departure Time(HH:MM)	15:13	15:42	16:11	16:41	17:10	17:38	18:09	18:43
I-5	Travel Time(min)	14.8	16.53	18.18	19.43	20.23	21.72	18.95	16.03
	Departure Time(HH:MM)	15:15	15:43	16:11	16:40	17:09	17:38	18:11	18:43
I-15	Travel Time(min)	14.25	15.05	16.55	17.92	17.82	19.67	18.02	14.92
	Departure Time(HH:MM)	15:15	15:44	16:13	16:42	17:12	17:40	18:11	18:45

Exhibit D-42: 90th Departure Times and Travel Times Correspondent to Different Arrival Times for Aggressive Drivers

Understand the Extra Time Needed for a Trip (MC3)

This is a variant on the prior two use cases. The question is: how much extra time is needed to make the arrival is on-time. Implicitly, it assumes that the driver has a sense of how long the trip should take. In the example presented here, it is assumed that the driver has queried a static path choice application that does not pay attention to time-of-day or real time conditions, and wants to know how much extra time is needed for the time of departure given the actual, current conditions.

Table D-25: Understand the Extra Time Needed for a Trip (MC3)

User	Driver
Question	How much extra time needs to be allowed for a trip so as to arrive on-time?
Steps	1. Select the origin and destination. 2. Identify when the trip will be made and the arrival time of interest. 3. Decide what being on-time means (probability of being late). 4. Determine the options for departure times and routes. 5. Develop the distribution of extra time needed for the trip.
Inputs	Historical, individual vehicle TT-PDFs for the routes and departure times that might be chosen based on the network conditions.
Result	Overlapping plots of the TT-CDFs for the various routes and departure times (including the distribution corresponding to the "assumed" travel time) so that the distributions of their travel times can be compared and the extra travel time needed for the various options can be understood.

Step 1 involves the selecting the origin and destination. In this use case, locations A and B in Exhibit D-1 are selected.

Step 2 involves selecting the desired arrival time. In this specific case, the driver wants to make the trip between 17:00-17:30, and he/she wants to know when to leave, and likelihood of arriving at destination by no later than 17:30

Step 3 involves deciding what being on-time means (probability of being late). In this specific use case the driver wants to know his/her likelihood of arriving at the destination on-time with 90% certainty, in other words 90% probability of on-time arrival.

Step 4 involves assembling the data and creating distribution of extra time for Normal operating conditions for each route. As described earlier, driver has a general sense of how long is the duration of the trip under normal conditions. However, the driver wants to have a sense of the extra time that might have to be added to the trip under other conditions. For the purposes of representing this scenario, two half-hour time periods (15:00-15:30 and 17:00-17:30) for Normal operating conditions were chosen. Travel time distribution in the first half-hour period i.e. 15:00-15:30 represents driver's perception of how long the trip would take under normal conditions; travel time distribution in the second half-hour period (17:00-17:30) represents actual travel times on that route under current conditions. Obviously both "normal" and "current" conditions have different TT-CDF's. Now the question, how to compute distribution of extra-time needed from these TT-CDF's. One way to compute this distribution is to sample TT-CDF's; calculate the algebraic difference in travel times; and look at the distribution of differences in travel times to answer the question. In this used case, TT-CDF's were sampled 10,000 times, and CDF was created based of these differences in travel times. Exhibit D-43 presents the distribution of extra time needed for these three routes. If the driver is making a trip on CA-163, he/she needs to add a cushion time of about 6.5 minutes to ensure on-time arrival 90 percent of times; that value is about 6 minutes in the case of I-15, and about 6 minutes in the case of I-5. Exhibit D-44 presents these plots again for the aggressive driver population.

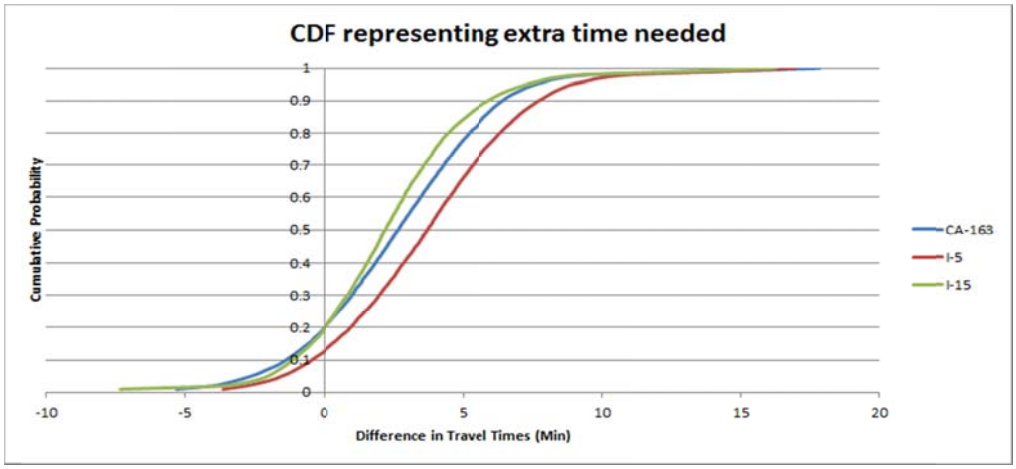


Exhibit D-43: Distribution of Extra time needed

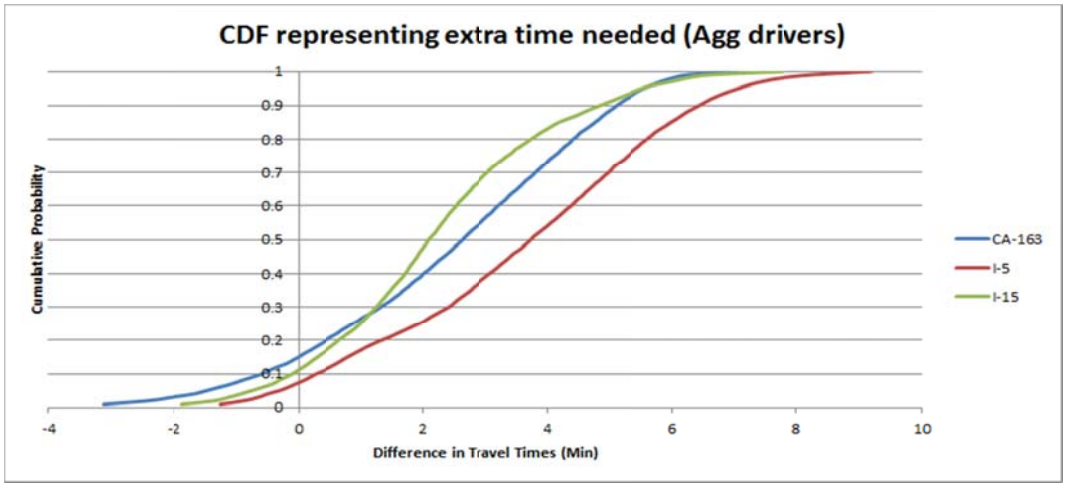


Exhibit D-44: Distribution of Extra time needed (Aggressive Drivers)

Decide How to Compensate for an Adverse Condition (MC4)

A driver wants to know how much extra time to allow so that he or she arrives at an event on-time given that the event will create congestion. The driver wants to be aware of the changes to the travel time because of an incident, bad weather, special event, or lane closure for a trip she or he plans to take. This information helps the driver plan for a non-recurrent scenario and determine how much extra time to allow when such an event occurs.

Table D-26: Decide How to Compensate for an Adverse Condition (MC4)

User	Driver
Question	For the route the driver plans to use, how much time should be allowed to compensate for the congestion that will be caused by an adverse condition?
Steps	1. Select the origin, destination, and route. 2. Decide what being on-time means (probability of being late). 3. Determine what travel time is expected. 4. Select the condition that will exist just before adverse condition occurs (e.g., peak congestion). 5. Select the adverse condition (e.g., incident, bad weather, special event). 6. Examine historical TT-PDFs for the adverse condition. 7. Compare these TT-PDFs with the one for the condition upon which the expected travel time is based. 8. Identify the distribution of extra travel time needed to compensate for the adverse condition.
Inputs	Historical TT-PDFs for the route and adverse condition as well as TT-PDFs for the condition upon which the expected travel time is predicated.
Result	A PDF for the extra time that should be allowed to ensure that the driver can arrive on-time given the adverse condition.

Step 1 involves the selecting the origin and destination. In this use case, locations A and B in Exhibit D-1 are selected.

Step 2 involves selecting the desired arrival time. In this specific case, the driver wants to make the trip between 17:00-17:30, and he/she wants to know when to leave, and the likelihood of arriving at the destination by no later than 17:30

Step 3 involves deciding what being on-time means (probability of being late). In this specific use case the driver wants to know his/her likelihood of arriving at destination on-time with 90% certainty, in other words 90% probability of on-time arrival.

Step 4 involves assembling the data and creating distribution of extra time for each operating condition for each route. The procedure used for generating extra time distribution is same as that of the one used in MC-3. Exhibit D-45 represents CDF plots for extra time needed for these three routes for each regime. As it can be seen, in the cases of CA-163, and I-5 Weather has worst effect on distribution of extra time needed. After weather: Incidents, special events, and demand (in that order) have significant impact in extra time distribution on those two routes. In the case of I-15, special events have worst effect on extra time distribution. After special events: Weather and Incidents (in that order) have significant impacts on the extra time distribution.

Route	90th Percentile Travel Time				
	Normal	Dem	Inci	Wea	SE
CA-163	6.421	10.321	10.921	17.49	15.72
I-5	7.72	10.8	16.15	24.29	12.5
I-15	5.9		17.7	20.54	23.321

Exhibit D-46 presents summary of these results for three routes. **Error! Reference source not found.** and

Exhibit D-48 re-present these results for aggressive drivers.

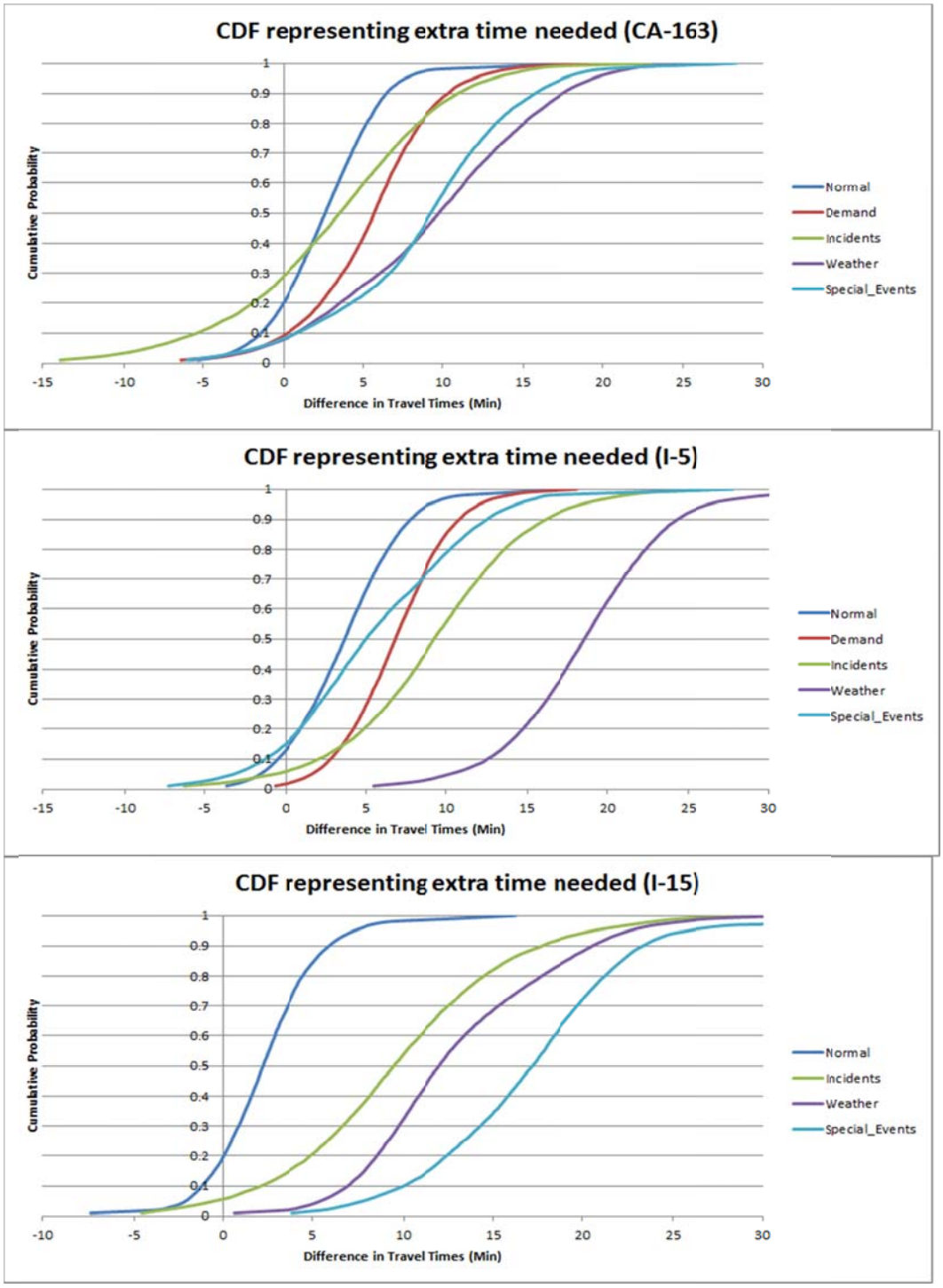
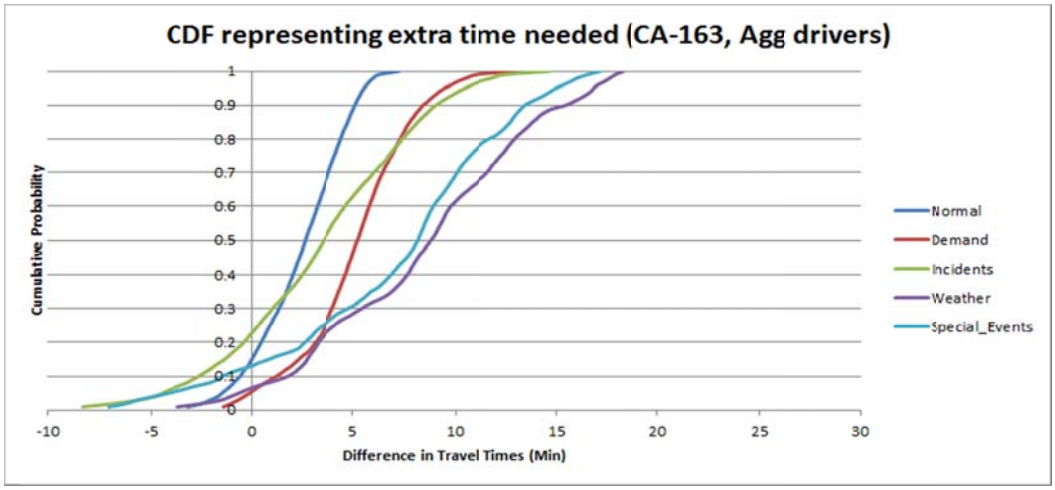
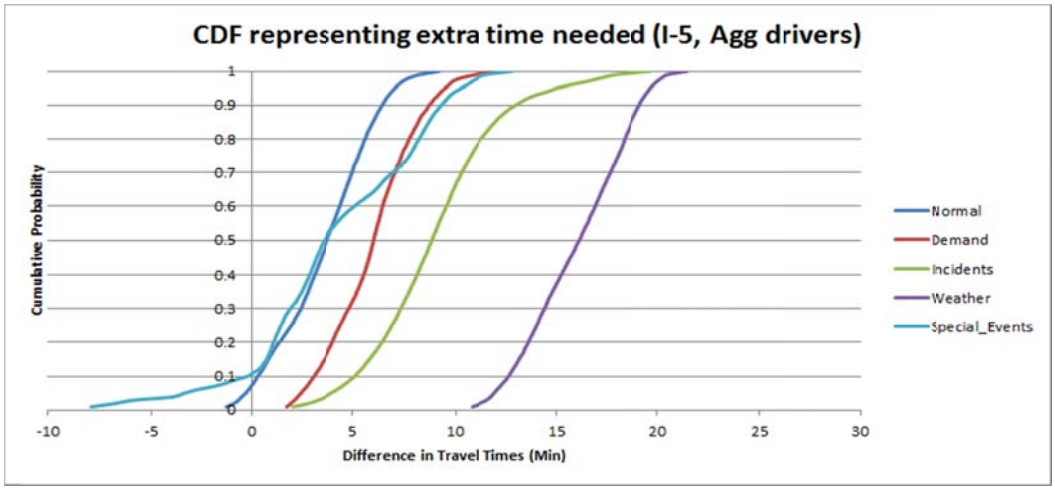


Exhibit D-45: CDF representing distribution of extra time needed for three routes

Route	90th Percentile Travel Time				
	Normal	Dem	Inci	Wea	SE
CA-163	6.421	10.321	10.921	17.49	15.72
I-5	7.72	10.8	16.15	24.29	12.5
I-15	5.9		17.7	20.54	23.321

Exhibit D-46: 90th percentile values of extra time needed for three routes





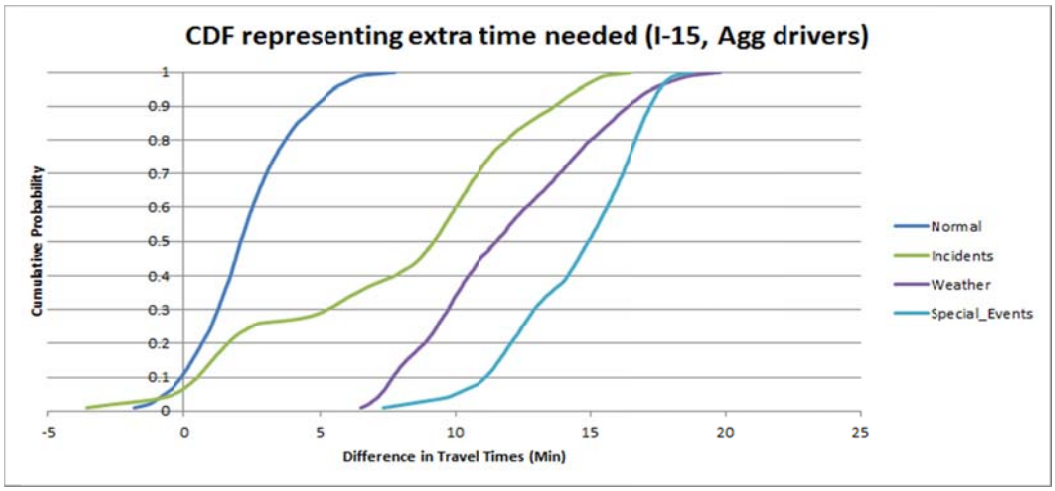


Exhibit D-47: CDF representing distribution of extra time needed for aggressive drivers for three routes

Route	90th Percentile Travel Time				
	Normal	Dem	Inci	Wea	SE
CA-163	5.10	8.40	9.03	15.44	13.46
I-5	6.43	8.71	13.00	19.12	9.30
I-15	4.83		13.67	16.40	17.23

Exhibit D-48: 90th percentile values of extra time needed for aggressive drivers for three routes

Decide En-Route Whether to Change Routes (MC5)

A driver en-route wants to determine whether an alternate route would increase the likelihood of an on-time arrival. At major splits in the roadway, travelers want information that will help them decide whether to stay on their planned route or detour to an alternate route. Travelers can receive this information from: (1) traditional data dissemination technologies, like variable message signs or (2) emergent in-vehicle technologies like route guidance systems. While this information is currently distributed in the form of average travel times, it could be improved if augmented with reliability information.

Table D-27: Decide En-Route Whether to Change Routes (MC5)

User	Driver
Question	Should an alternate route be chosen while en-route to increase the likelihood of being on-time?
Steps	1. Re-affirm the desired arrival time and definition of being on-time. 2. Examine TT-PDFs for routes that could be chosen based on the driver's current location. 3. See if the PDF for one of those routes would provide a better on-time arrival than the route currently being followed. 4. If so, change routes. If not, continue using the current route.
Inputs	Forecasts of TT-PDFs for alternate routes from the current location to the destination for the current time and the driver's current location.
Result	Travel Time CDFs for the current route and the alternate routes and a choice of the route that is best.

For the purposes of illustrating this use case, picture the following scenario. In Step 1 assume the driver is traveling on the freeway and at around 17:00, the driver reaches the junction where the three routes in San Diego (CA-163, I-5 and I-15) meet. The traveler has to make a route choice decision as the operational regime has changed. To further expand this thought, consider the following two scenarios. In scenario one, the driver started the trip on a day with "Normal" operating conditions, however, at around 17:00 there has been an incident, hence the operating conditions have changed. Now, he/she seeks the guidance of route guidance system for choosing the best alternate route. In scenario two, the traveler started the trip on a day with inclement weather conditions. So, obviously he/she would expect travel times to be longer than

what they would have been otherwise under Normal operating conditions. However, at around 17:00 (the time around which he/she reaches the junction) there is an incident, and therefore the expected travel time is different than when he/she originally started the trip. So, guidance is sought from the route guidance system for choosing the best alternate route.

Step 2 involves assembling the data and creating TT-CDF's for two scenarios presented above. In scenario one two possible non-recurring events types are "Normal" and "Incidents"; whereas in scenario two they are "Weather" and Incidents. If the driver started his trip on a Normal day, then the probability of a weather event is zero; on the contrary, if the driver started his/her trip on a day with inclement weather conditions, then the probability of "Normal" non-recurring event is zero. Furthermore, possible non-recurring event types in both scenarios are assumed to be independent: meaning, the occurrence/non-occurrence of one does not affect the occurrence/non-occurrence of the other. Since, the driver wants to make a path choice decision at around 17:00, historical data between 15:30-18:30 was used in generating these CDF's. Using this data, the probability of occurrence of these two events was computed. Also, mean travel rate CDF for each non-recurring type was generated. Monte Carlo simulation was used for sampling the CDF's. The number of Monte Carlo runs performed was computed in such way that it ensures five hundred data points for the least frequent event. Now, two random variables between zero and one are generated from a uniform distribution: The first one is used in determining the event type, and the second one is used to sample mean travel time for the corresponding non-recurring event. Hundred individual travel times were synthesized for each driver class (aggressive, median and conservative). Using this data, TT-CDF's were created for three routes.

Exhibit D-49 represents TT-CDF's for three driver classes for three routes, when operating conditions change from "Normal" to "Normal+Incidents". It can be inferred that I-15 is the best alternate route to choose regardless of what driver class one belongs to. The 90th percentile travel time for aggressive driver class on I-15 is about 18 minutes, whereas on both CA-163. And on I-5 it is about 20 minutes; for the median driver class it is about 20 minutes on I-15, and about 22 minutes on both CA-163, and I-5. Lastly, for the conservative driver class it is about 22 minutes on I-15, and about 24-25 minutes on both CA-163, and I-5. These results are summarized in Exhibit D-50.

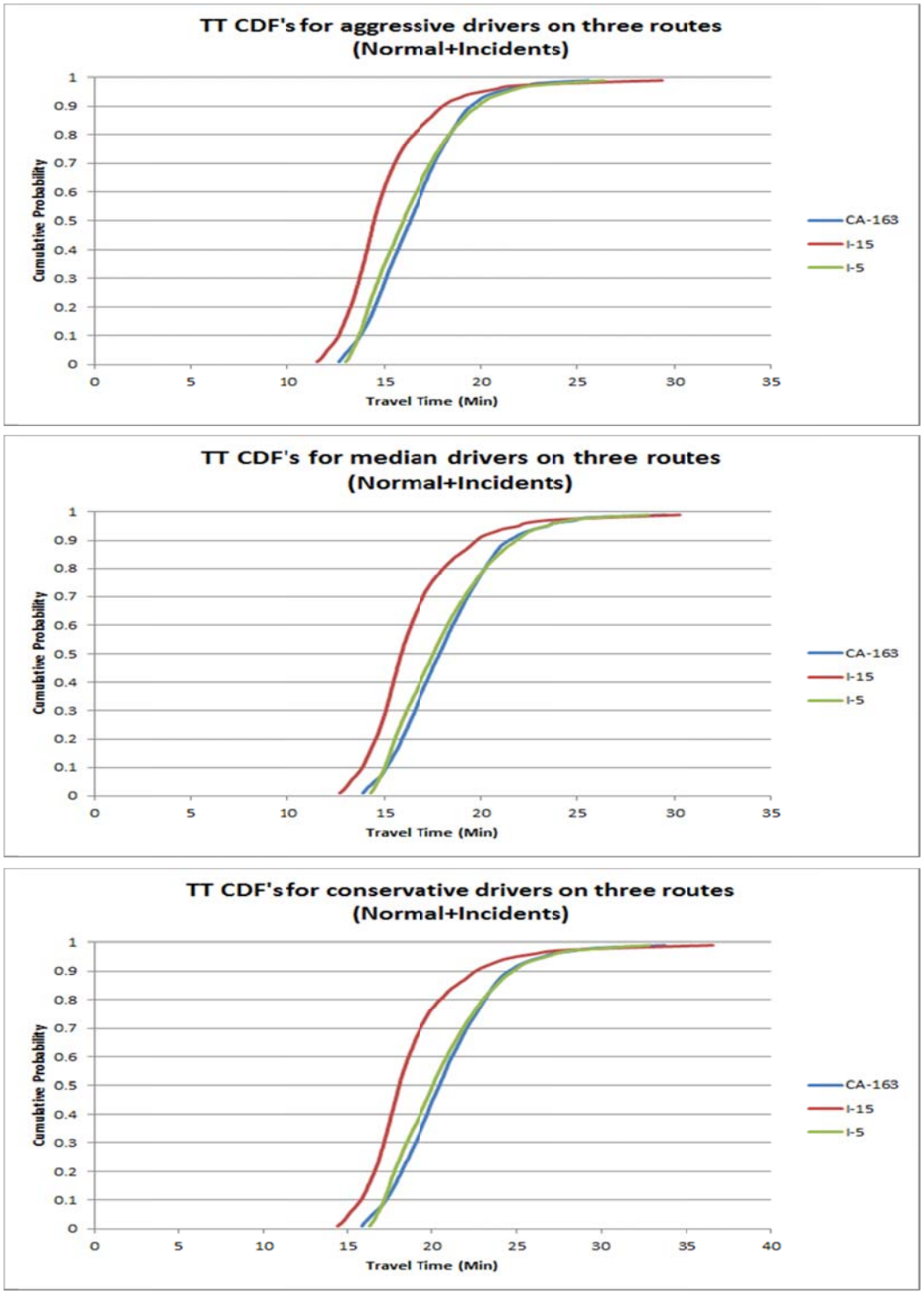


Exhibit D-49: CDF representing distribution of travel times when operating conditions change from Normal to Incident for various driver classes for three routes

Normal+Incidents			
Driver Type	**CA-163**	**I-5**	**I-15**
Aggressive	19.5	19.87	18.05
Median	21.45	21.83	19.8
Conservative	24.52	24.78	22.57

Exhibit D-50: 90th percentile travel time value when operating conditions change from Normal to Incidents for various driver classes for three routes

Error! Reference source not found. represents TT-CDF's for various driver classes for three routes, when operating conditions change from "Weather" to "Weather+Incidents". It can be inferred that CA-163 is the best alternate route to choose irrespective of what driver class one belongs to. 90th percentile travel time for aggressive driver class on CA-163 is about 31 minutes, whereas on both I-15. And for I-5 it is about 36-37 minutes; for the median driver class it is about 34 minutes on CA-163, and about 40 minutes on both I-15, and I-5; lastly, for the conservative driver class it is about 39 minutes on CA-163, and about 44-45 minutes on both I-15, and I-5. These results are summarized in Exhibit D-52.

It can be inferred from these TT-CDF's the impact of an incident on travel times is significantly higher in the case days with inclement weather than those with "Normal" days.

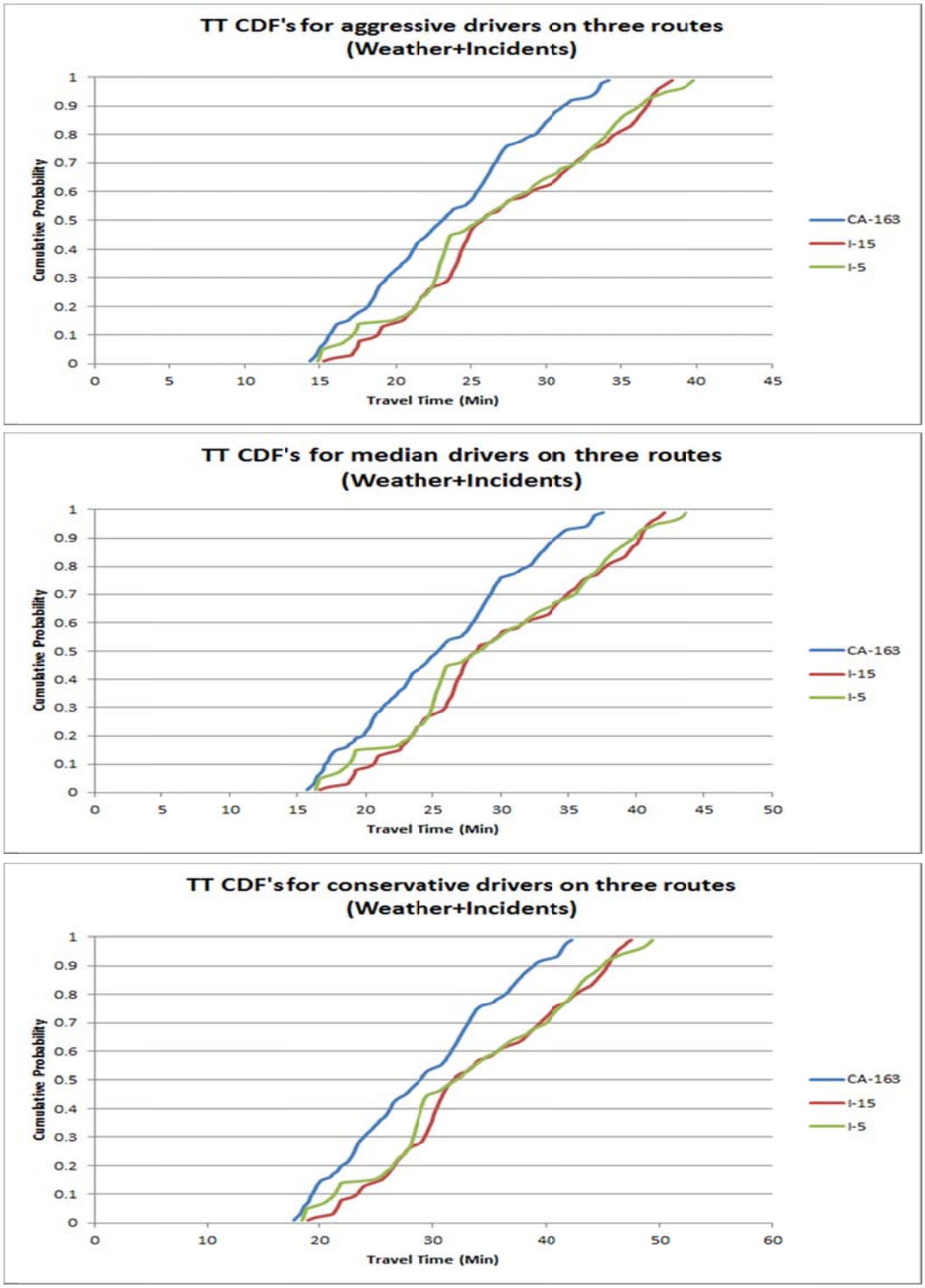


Exhibit D-51: CDF representing distribution of travel times when operating conditions change from weather to Incident for various driver classes for three routes

Weather+Incidents			
Driver Type	**CA-163**	**I-5**	**I-15**
Aggressive	31.18	36.18	36.68
Median	34.08	39.83	40.27
Conservative	38.88	44.98	45.45

Exhibit D-52: 90th percentile travel time value when operating conditions change from Normal to Incidents for various driver classes for three routes

DRIVERS WITH UNCONSTRAINED TRIPS

Unconstrained trips are ones that have no particular arrival time against which a measure of schedule delay can be calculated. Consistency becomes the focus. Examples include shopping trips and visits to zoos, museums, etc. The main question posed is: when to make the trip so that it does not take long.

Determine the Best Time of Day to Make a Trip (MU1)

In this use case, the driver has a range of times when the trip could be made and wants to know what time is best. That is: what departure time has the most reliable travel time.

Table D-28: Determine the Best Time of Day to Make Trip (MU1)

User	Driver
Question	When should a trip be made so that it has the most reliable travel time?
Steps	1. Select the origin and destination 2. Decide what is meant by a reliable trip time (e.g., probability of being late) 3. Assemble TT-PDFs for the times and conditions when the trip might be made (e.g., during the mid-day on days without adverse conditions). 4. Find the departure time and route that provides the most reliable travel time.
Inputs	Historical TT-PDFs for the departure times that might be selected and plausible routes given those departure times.
Result	A set of TT-CDFs for the various departure times and routes that could be chosen and a diagram that identifies the best of these, i.e., the best time to make the trip and the best route to use.

Step 1 involves the selecting the origin and destination. In this use case, locations A and B in Exhibit D-1 are selected.

Step 2 involves selecting the desired arrival time. In this specific case, the driver wants to make the trip between 15:00-19:00, and he/she wants to know when to leave, and the likelihood of arriving at the destination on-time with 90% certainty, i.e., a 90% probability of an on-time arrival.

Step 3 involves assembling the data and creating TT-CDF's for a given operating condition for each route. In this use case two non-recurring event conditions were considered: Normal, and Weather. It was further assumed that the driver falls into the category of aggressive driver class. As mentioned earlier, driver wants to make the trip anytime between 15:00 and 19:00, and he/she wants to know what is the best route and best time to make the trip. The methodology used in developing TT-CDF's here is similar to the one used in use case MC2, and therefore details of the methodology are left out.

Error! Reference source not found. presents TT-CDF plots for each route for the Normal operating condition. These plots do provide some insights on the performance of each of those three routes. Looking at I-15 first, its TT-CDF's for most of the half-hour time periods are at left, suggesting a tight distribution of travel times; variation in travel times seems to be more in the case of I-5, and most in the case of CA-163. Furthermore, TT-CDF's for first and eighth half-hour time windows are at left suggesting that those time widows have reliable travel times. Travel times from second to sixth half-hour windows get increasingly worse; operating conditions seem to get better in the seventh half-hour period, and the facility seem to resume to normal operating conditions during eight half-hour period. It seems like under Normal operating conditions the best time for making the trip is between 15:00-15:30, and the best route chose is I-15. Exhibit D-54 summarizes values of the 90th percentile travel times for these three routes.

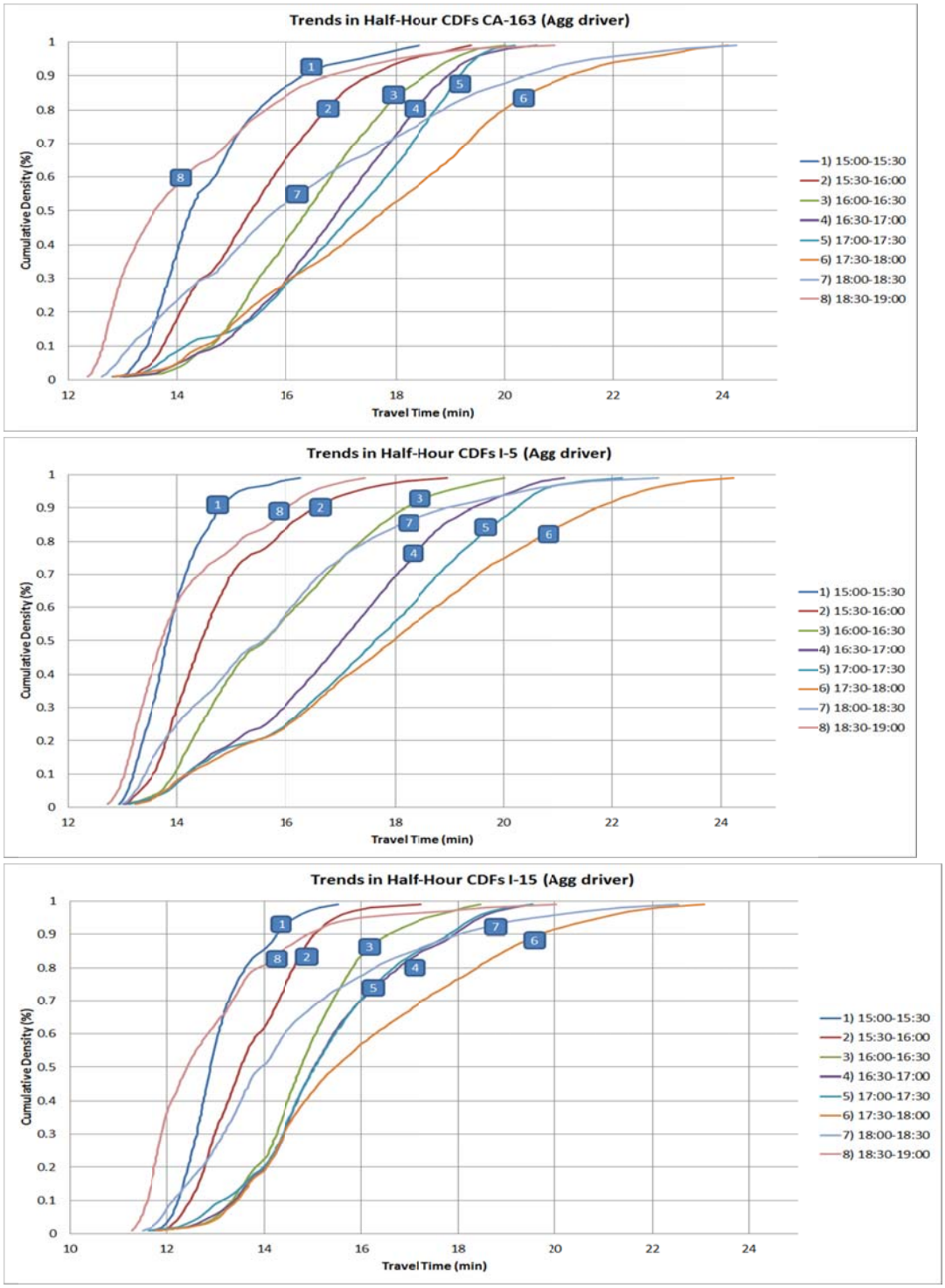


Exhibit D-53: Half-Hour TT-CDFs for Three Routes in San Diego under Normal Condition

Route	Expected Arrival Time (HH:MM)	15:30	16:00	16:30	17:00	17:30	18:00	18:30	19:00
CA-163	Travel Time(min)	16.3	17.52	18.55	18.97	19.18	21.18	20.38	16.77
	Departure Time(HH:MM)	15:13	15:42	16:11	16:41	17:10	17:38	18:09	18:43
I-5	Travel Time(min)	14.8	16.53	18.18	19.43	20.23	21.72	18.95	16.03
	Departure Time(HH:MM)	15:15	15:43	16:11	16:40	17:09	17:38	18:11	18:43
I-15	Travel Time(min)	14.25	15.05	16.55	17.92	17.82	19.67	18.02	14.92
	Departure Time(HH:MM)	15:15	15:44	16:13	16:42	17:12	17:40	18:11	18:45

Exhibit D-54: 90th Departure Times and Travel Times Correspondent to Different Arrival Times under Normal conditions for three routes

Exhibit D-55 re-presents TT-CDF plots for each route under inclement weather conditions. These plots do provide some insights on the performance of each of those three routes. Starting with CA-163, it can be inferred that travel times on this route are highly unreliable under bad weather; therefore it is best to avoid this route under these conditions. As noted earlier, 90th percentile travel times under Normal operating conditions got increasingly worse between second and sixth half-hour periods, the story is different under weather conditions: 90th percentile travel time was increasingly longer between second and fifth half-hour periods, and it's value reduced for sixth half-hour period, and it was worst for seventh half-hour period (about 34 minutes). It can further be inferred that TT-CDF trends in the case of both I-5, and I-15 are highly unreliable as well, with an exception of first half-hour period (15:00-15:30) on I-15. It seems like under inclement weather conditions the best time for making the trip is between 15:00-15:30, and the best route chose is I-15. Exhibit D-56 summarizes values of 90th percentile travel times for these three routes.

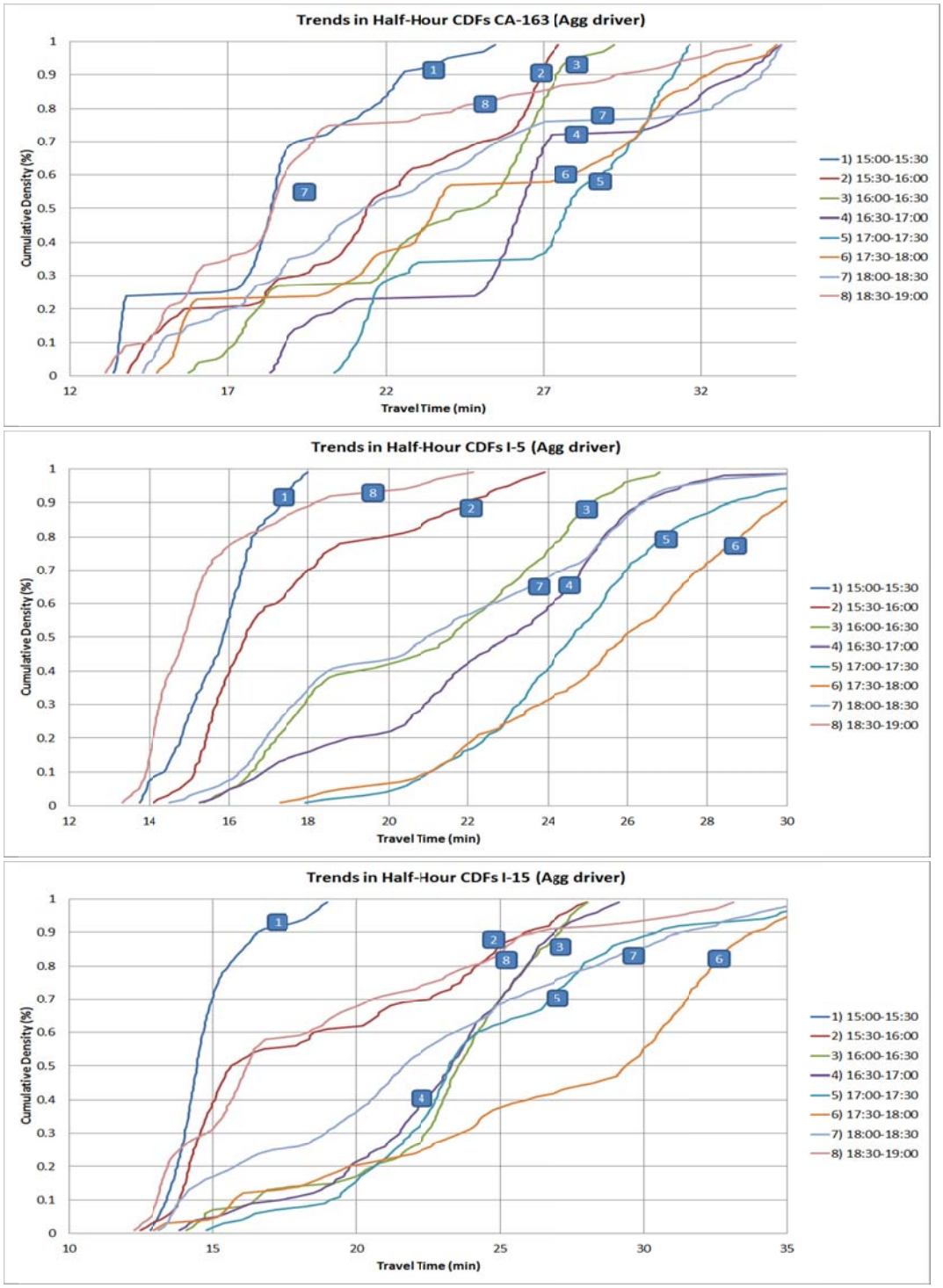


Exhibit D-55: Half-Hour TT-CDFs for Three Routes in San Diego under Weather Condition

Route	Expected Arrival Time (HH:MM)	15:30	16:00	16:30	17:00	17:30	18:00	18:30	19:00
CA-163	Travel Time(min)	22.5	26.9	27.42	33.32	31.1	32.22	33.9	29.3
	Departure Time(HH:MM)	15:07	15:33	16:02	16:26	16:58	17:27	17:56	18:30
I-5	Travel Time(min)	17.33	21.98	25.12	26.32	28.57	29.9	26.42	18.17
	Departure Time(HH:MM)	15:12	15:38	16:04	16:33	17:01	17:30	18:03	18:41
I-15	Travel Time(min)	16.55	25.87	27.12	26.9	30.45	33.8	31.27	26.23
	Departure Time(HH:MM)	15:13	15:34	16:02	16:33	16:59	17:26	17:58	18:33

Exhibit D-56: 90th Departure Times and Travel Times Correspondent to Different Arrival Times under Weather conditions for three routes

Determine How Much Extra Time is Needed (MU2)

A user wants to know how much extra time to allow so that he or she can arrive on time for a special event (e.g., a baseball game). It assumes that the user has some idea how long the trip ought to take.

Table D-29: Determine How Much Extra Time is Needed (MU2)

User	Driver
Question	How much extra time is needed for a common trip to generally arrive on time?
Steps	1. Select the origin and destination. 2. Select the condition(s) under which the trip is to be made. 3. Decide what is meant by arriving on time (e.g., the probability of being late). 4. Assemble TT-PDFs for the time at which the trip is to be made, the routes that might be chosen, and the network conditions that would exist. 5. Develop a PDF of the extra time that might be needed given the TT-PDFs from step 4 and the probabilities that the trip might be made under the conditions indicated.
Inputs	Historical TT-PDFs for the departure times that might be selected and the routes that might be used given the network conditions that might exist for those times.
Result	A PDF of the extra time that should be allowed to arrive on time.

Step 1 involves the selecting the origin and destination. In this use case, locations A and B in Exhibit D-1 are again selected.

Step 2 involves selecting the conditions under which he is making the trip. In this specific case, the driver is going to a special event and the events starts by 19:00, and hence wants to make the trip between 18:30-19:00.

Step 3 involves deciding what being on-time means (probability of being late). In this specific use case the driver wants to know his/her likelihood of arriving at destination on-time with 90% certainty, in other words 90% probability of on-time arrival.

Step 4 involves assembling the data and creating TT-CDF's for these given operating condition for each route. Since it's a special event, the likelihood of an incident taking place is

high, therefore, in order to accommodate for any delay that might be caused in case of an incident, two non-recurring event conditions were considered: Special Events, and Incidents. It was further assumed that the driver falls into the category of aggressive driver class. The methodology used in developing TT-CDF's here is similar to the one used in use case MC5, and therefore details of the methodology are left out.

Exhibit 4-46 presents TT-CDF plots for each route for "special event + incidents" operating conditions. It is evident from these plots travel time distributions for CA-163 and I-5 are far more reliable than those of I-15. 90th percentile travel time on I-5 is about 16 minutes, it is around 20 minutes in the case of CA-163, and about 30 minutes in the case of I-15. Therefore, the best route that minimizes travel is I-5, and if he leaves about 16 minutes before the start of the event, he/she should reach there around 19:00.

Exhibit D-46:

TRANSIT USE CASES

These use cases focus on operators and users of transit services. On the supply (service provider) side, three main emphases exist: *service planning* (developing bus routes, identifying required bus headways, and considering ways to improve ridership), *scheduling* (assigning buses and drivers as efficiently as possible to meet planning, operational, and customer needs), and *operations* (using real-time and archived information to better manage day-to-day service issues).

For these use case examples, the San Diego bus system is used, and more specifically vehicles equipped with an AVL-based tracking system. Buses on nine of the routes were so equipped:

- Route 6: Fashion Valley – North Park
- Route 7: Downtown – Balboa Park/Zoo – La Mesa
- Route 10: Old Town – University & College
- Route 15: Downtown – San Diego State University
- Route 20: Downtown – Del Lago Transit Station
- Route 41: Fashion Valley – USCD/VA Medical Center
- Route 88: Old Town – Fashion Valley
- Route 150: Downtown – UTC/VA Express

In some instances, many of the buses had the AVL equipment installed, so there was lots of data; other routes had less. The routes chosen for analysis here had the most data and served origin-destination pairs that were interesting to analyze.

The equipped buses generate the following information for every stop:

- The Route-ID
- The Trip-ID (based on the time of departure, etc.)
- The latitude and longitude of the bus when it stops

- The Stop-ID of the location where the bus stops (based on the latitude and longitude of the location where it stops)
- The distance of the bus from the pre-defined location of the Stop-ID
- The time when the doors open and when they close
- The time when the bus was supposed to stop at the Stop-ID given the trip it was on
- Many other data items not used in this analysis including the number of people who get on and off the bus and how many are on-board the bus when it leaves the stop

This is a rich set of data that can be used extensively and effectively to study the quality of the transit services provided.

Transit Planners

The following use cases demonstrate system functionalities that are helpful for transit system planners. These people have responsibility for determining where major improvements are needed, where the buses should go, and how much service should be provided.

Identify Routes with the Poorest Reliability (TP1)

A service planner wants to determine which routes have the poorest reliability – the most variability in on-time performance at the stops. This information is helpful as a supplement to passenger demand analysis when designing express bus routes, as it allows the planner to analyze which routings minimize the average travel time and/or the travel time variability.

Table D-30: Identify Routes with the Poorest Reliability (TP1)

User	Transit Planner
Question	Which routes have the poorest reliability?
Steps	1. Select the routes and conditions of interest. 2. Assemble PDFs for the deviations from scheduled stop times. 3. Rank the routes based on greatest deviations from the scheduled stop times.
Inputs	A database of deviations from scheduled stop times by route for the conditions of interest (could be all conditions).
Result	A rank ordering of the routes based on their deviations from scheduled stop times, from poorest to best performance.

Step 1 involves selecting the routes and conditions of interest. In this case the routes are the nine equipped with AVL buses; the time frame is August, 2011, the month for which data were collected.

Step 2 involves assembling PDFs for the deviations from the scheduled stop times. **Error! Reference source not found.** presents these PDFs for the nine routes that had AVL equipped buses. As can be seen, in the worst cases the departures can be as much as (or in one case more than) 6 minutes early and as much as 16 minutes late.

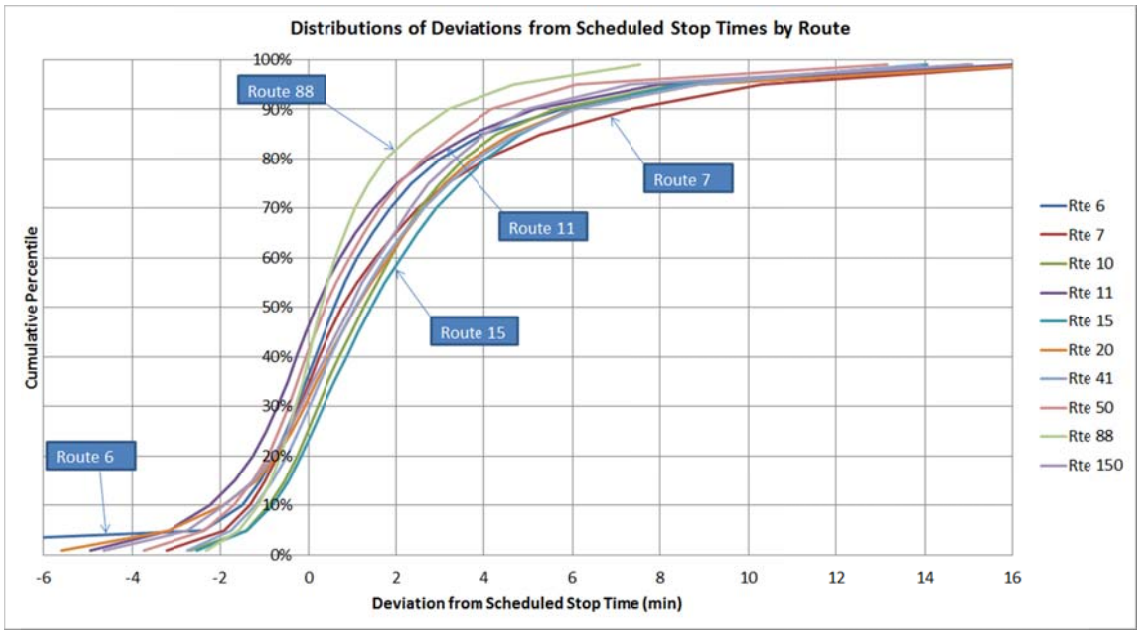


Exhibit D-57: Deviations from Scheduled Stop Times by Route

The bus route with the best performance is Route 88. This can be observed in **Error! Reference source not found.** by comparing the CDFs and seen numerically in

Exhibit D-58. The standard deviation for that route is only 2.0 while all the other routes have higher values. Route 11 has the largest standard deviation. It appears to be buried in the cluster of CDFs in **Error! Reference source not found.**, but in fact it has a significant tail in terms of early departures (negative values) reaching down to 5 minutes early.

Route	StDev (min)
Rte 6	4.49
Rte 7	4.02
Rte 10	4.63
Rte 11	9.37
Rte 15	3.24
Rte 20	4.07
Rte 41	3.49
Rte 50	3.01
Rte 88	2.00
Rte 150	3.62

Exhibit D-58: Standard Deviations for the Differences from Scheduled Stop Times by Route

Step 3 involves ranking the routes based on the reliability of their services. For the nine routes shown in **Error! Reference source not found.**, this means creating a list going from the most to the least reliable route, effectively from the CDF with the narrowest range of values to the one with the largest. This is in essence reflected in the standard deviations shown in

Exhibit D-58, so a reasonable ranking can be based on the values displayed; from most reliable to least: 88, 50, 15, 41, 150, 7, 6, 10, and finally 11.

Interestingly, and compared with the standard deviation rankings, the routes that seem to stand out in **Error! Reference source not found.** are different: Route 88, the one with the narrowest range of values and the smallest deviations at the higher percentiles; Route 15, the one that seems to be latest the most often; Route 11, which apparently has the worst reliability according to

Exhibit D-58; Route 7, which has the greatest deviations for the percentile values above 80%; and Route 6, which seems to have a significant percentage of early departures. These other metrics simply provide additional ways to extract information from the CDFs about the relative performance of the routes.

Compare Exclusive Bus Lanes with Mixed Traffic Operations (TP2)

A planner wants to the reliability of buses traveling in mixed traffic with those operating on exclusive bus lanes. This is useful when studying the possibility of moving an existing service onto a dedicated lane, such as might happen during the development of a Bus Rapid Transit route.

Table D-31: Compare Exclusive Bus Lanes with Mixed Traffic Operations (TP2)

User	Transit Planner
Question	How much would an exclusive bus lane help with reliability?
Steps	1. Select the routes and conditions of interest. 2. Assemble PDFs for the deviations from scheduled stop times for routes that do and do not have exclusive bus lanes. If there are no routes with exclusive bus lanes presently, assemble data for those routes that operate in the least congested conditions, or create a simulation model. 3. Assess the reduction in deviations from scheduled stop times that can be achieved by having the buses operate in their own lane.
Inputs	A database of deviations from scheduled stop times for routes with and without exclusive bus lanes. If none exist, use data for routes that operate in the least congested conditions.
Result	An assessment of the extent to which on-time performance is improved by exclusive bus lanes.

The bus system in San Diego does not technically have a route that operates on an exclusive bus lane, so this use case cannot be addressed directly. However, a hypothetical analysis can be performed based on, say, the contrast between the performance of Route 88 and Route 7.

The steps in the analysis process are as follows. Step 1 is to select the routes and conditions of interest. In this instance the nine AVL-equipped bus routes will be used, based on the August data. Step 2 is to assemble PDFs for the deviations from scheduled stop times for

routes that do and do not have exclusive bus lanes. If there are no routes with exclusive bus lanes presently, assemble data for those routes that operate in the least congested conditions, or create a simulation model. In this instance the best performing bus route will be used as the basis for comparison. Step 3 involves assessing the reduction in deviations from scheduled stop times that can be achieved by having the buses operate in their own lane.

As can be seen in

Exhibit D-59, Route 88 performs much better than Route 7. At the 90th percentile, the buses on Route 7 are as much as 8 minutes late leaving their stops whereas the buses on Route 88 are only 3 minutes late. In addition the buses on Route 7 are on rare occasions more than 3 minutes early leaving their stops while the buses on Route 88 are never more than slightly more than 2 minutes early.

If the Route 88 buses were operating on a busway and the Route 7 buses were in mixed traffic, there would be evidence that the busway was helping to improve on-time performance.

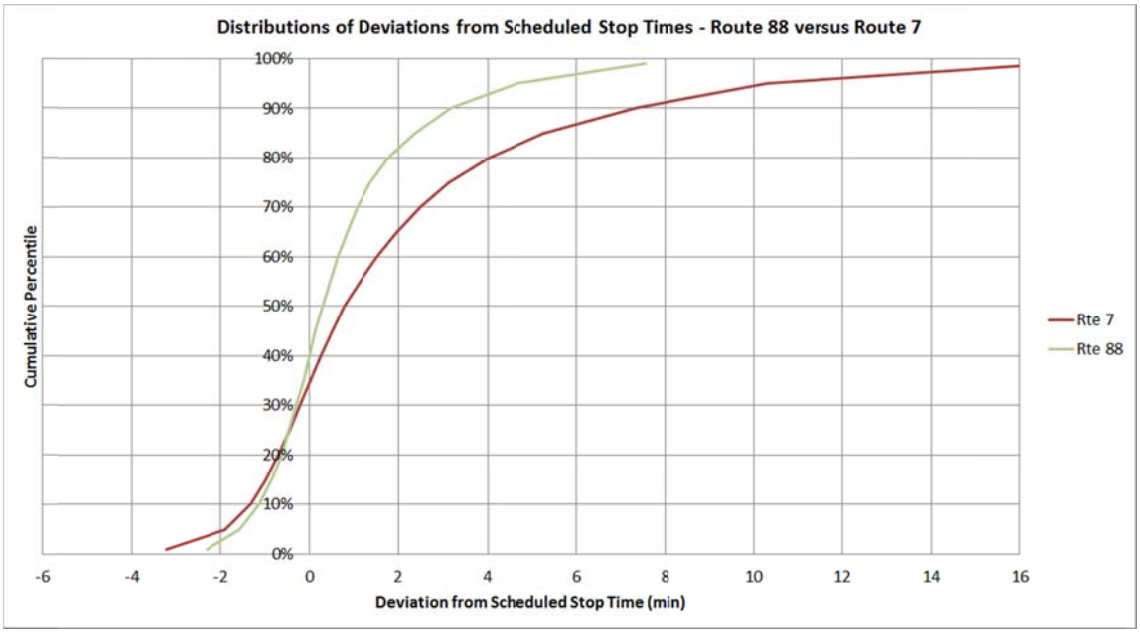


Exhibit D-59: Distributions of the Deviation from Scheduled Stop Times – Route 88 versus Route 7

Transit Schedulers

The next few use cases illustrate how the monitoring system can help transit schedulers. These people want to know what schedules are feasible, what reliability they can have and whether existing schedules need to be adjusted so that the advertised stop times can be achieved.

Acquire Reliability Data for Building Schedules (TS1)

A scheduler wants to determine the amount of recovery time to include in an existing bus route's schedule to ensure that most late-arriving buses will be able to depart for their next trip on time. This is a basic scheduling activity. The total round-trip time on a bus route (or *cycle time*) typically is based on four elements (*2)*):

- The average round-trip running time for the route;
- The minimum break time (*layover time*) for drivers required by policy or contract;
- Any additional *recovery time* required (the greater of zero or the round-trip buffer time minus the layover time); ideally zero; and
- Any additional time required to achieve a desired headway; ideally zero.

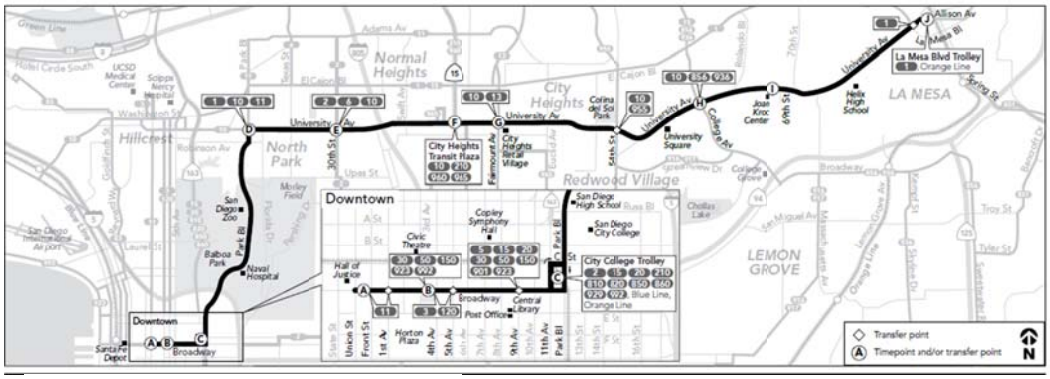
This use case helps schedulers to build timetables that are based on the variability associated with roadway and environmental conditions as well as passenger demand or any other variability specifically associated with the provision of transit service.

Table D-32: Acquire Reliability Data for Building Schedules (TS1)

User	Transit Scheduler
Question	What schedule can be achieved given the variability in the travel times along the route?
Steps	1. Select the route of interest. 2. Assemble PDFs for the deviations from advertised stop times by trip for the typical and adverse conditions of interest. 3. Define what is meant by being on-time (the limits of being either early or late and the probability of being within that window). 4. Assess the extent to which adjustments in the schedule would improve the on-time performance.
Inputs	A database of deviations from scheduled stop times by trip for the route of interest (and the conditions of interest).
Result	An assessment of the extent to which adjustments in the schedule would improve the on-time performance of the route.

This use case addresses an issue that lies at the heart of building good route schedules. As with the highway (auto) focused use cases, in transit scheduling it is not so much the travel time that matters, but the reliability of the travel time. The objective is to build schedules that can actually be followed. Otherwise, the bus drivers get frustrated – no matter how hard they try, they cannot make the stops at the scheduled times. Riders too are frustrated because they cannot get to their destinations at the times listed in the schedule and they miss their transfers. The schedule has no value.

A little background about Route 7 is helpful before addressing the use case directly. Route 7 runs between downtown and La Mesa along Broadway, Park Boulevard and University Avenue as shown Exhibit D-60, part a). The length of the route is about 17.6 miles and it requires a little more than an hour to traverse, end-to-end. The timetable shows varying stop patterns as can be seen in Exhibit D-60, part b). In fact, there are some even shorter stop patterns, not shown, that seem to be used only when the public schools are in session. The database contains eight different stopping patterns ranging from 32 stops up to 66.



Route 7 — Monday through Friday / *lunes a viernes*

Downtown ➡ North Park ➡ City Heights ➡ La Mesa

Ⓐ Broadway & Front St. DEPART	Ⓑ Broadway & 3rd Av.	Ⓒ City College Trolley Sta. (11th Ave.)	Ⓓ Park Blvd. & University	Ⓔ University & 30th St.	Ⓖ University & Fairmount	Ⓗ University & College Av.	Ⓘ University & 69th St.	Ⓙ La Mesa Blvd. Trolley ARRIVE
4:40a	4:43a	4:48a	4:56a	5:01a	5:10a	5:18a	5:21a	5:28a
5:00	5:04	5:10	5:19	5:24	5:34	5:43	5:46	—
5:20	5:24	5:30	5:39	5:44	5:54	6:03	6:06	6:13
5:35	5:39	5:45	5:54	5:59	6:09	6:18	6:21	—
5:50	5:54	6:00	6:09	6:14	6:24	6:33	6:36	6:43
6:03	6:07	6:13	6:23	6:29	6:39	6:49	6:52	—
6:15	6:19	6:25	6:35	6:41	6:51	7:01	7:04	7:12
6:27	6:31	6:37	6:47	6:53	7:03	7:13	7:16	—
6:37	6:41	6:48	6:59	7:05	7:16	7:27	7:31	7:39
6:48	6:53	7:00	7:11	7:17	7:28	7:39	7:43	—
7:00	7:05	7:12	7:23	7:29	7:40	7:51	7:55	8:03
7:12	7:17	7:24	7:35	7:41	7:52	8:03	8:07	—
7:24	7:29	7:36	7:47	7:53	8:04	8:15	8:19	8:27
7:36	7:41	7:48	7:59	8:05	8:16	8:27	8:31	—
7:48	7:53	8:00	8:11	8:17	8:28	8:39	8:43	8:51
8:00	8:05	8:12	8:23	8:30	8:42	8:53	8:57	—
8:12	8:17	8:24	8:35	8:42	8:54	9:05	9:09	9:18
8:24	8:29	8:36	8:47	8:54	9:06	9:17	9:21	—
8:36	8:41	8:48	8:59	9:06	9:18	9:29	9:33	9:42
8:48	8:53	9:00	9:11	9:18	9:30	9:41	9:45	—
9:00	9:05	9:12	9:23	9:30	9:42	9:53	9:57	10:06
9:12	9:17	9:24	9:35	9:42	9:54	10:05	10:09	—
9:24	9:29	9:36	9:47	9:54	10:06	10:17	10:21	10:30
9:36	9:41	9:48	9:59	10:06	10:18	10:29	10:33	—
9:48	9:53	10:00	10:11	10:18	10:30	10:41	10:45	10:54
10:00	10:05	10:12	10:23	10:30	10:42	10:53	10:57	—
10:12	10:17	10:24	10:35	10:42	10:54	11:05	11:09	11:18
10:24	10:29	10:36	10:47	10:54	11:06	11:17	11:21	—
10:36	10:41	10:48	10:59	11:06	11:18	11:29	11:33	11:42
10:48	10:53	11:00	11:11	11:18	11:30	11:41	11:45	—

La Mesa ➡ City Heights ➡ North Park ➡ Downtown

Ⓙ La Mesa Blvd. Trolley DEPART	Ⓘ University & 69th St.	Ⓗ University & College Av.	Ⓖ University & Fairmount	Ⓕ City Heights Transit Plaza & I-15	Ⓔ University & 30th St.	Ⓓ Park Blvd. & University	Ⓒ City College Trolley Sta. (Park Blvd.)	Ⓑ Broadway & 4th Av.	Ⓐ Broadway & Union St. ARRIVE
—	—	—	—	4:30a	4:36a	4:40a	4:48a	4:51a	4:54a
—	4:33a	4:36a	4:45a	4:48	4:55	5:00	5:08	5:12	5:15
—	4:48	4:51	5:00	5:03	5:10	5:15	5:23	5:27	5:30
—	5:00	5:03	5:12	5:15	5:22	5:27	5:35	5:39	5:42
—	5:12	5:15	5:24	5:27	5:34	5:39	5:47	5:51	5:54
—	5:24	5:27	5:36	5:39	5:46	5:52	6:00	6:04	6:07
—	5:36	5:39	5:48	5:51	5:58	6:04	6:12	6:16	6:20
—	—	—	—	6:03	6:10	6:16	6:24	6:28	6:32
5:47a	5:54	5:57	6:06	6:09	6:16	6:22	6:30	6:34	6:38
—	—	—	—	6:15	6:23	6:29	6:37	6:41	6:45
—	6:02	6:06	6:17	6:21	6:29	6:35	6:43	6:47	6:52
—	—	—	—	6:27	6:35	6:41	6:49	6:53	6:58
6:07	6:14	6:18	6:29	6:33	6:41	6:47	6:55	6:59	7:04
—	—	—	—	6:39	6:47	6:53	7:01	7:05	7:10
—	6:26	6:30	6:41	6:45	6:53	6:59	7:07	7:11	7:16
—	—	—	—	6:51	6:59	7:05	7:13	7:17	7:22
6:31	6:38	6:42	6:53	6:57	7:05	7:11	7:19	7:23	7:28
—	—	—	—	7:03	7:11	7:17	7:26	7:30	7:35
—	6:49	6:53	7:05	7:09	7:17	7:23	7:32	7:36	7:42
—	—	—	—	7:15	7:23	7:29	7:38	7:42	7:48
6:53	7:01	7:05	7:17	7:21	7:29	7:35	7:44	7:48	7:54
—	—	—	—	7:27	7:35	7:41	7:50	7:54	8:00
—	7:13	7:17	7:29	7:33	7:41	7:47	7:56	8:00	8:06
—	—	—	—	7:39	7:47	7:53	8:03	8:07	8:13
7:15	7:24	7:28	7:40	7:45	7:53	7:59	8:09	8:14	8:20
—	—	—	—	7:51	7:59	8:05	8:15	8:20	8:26
—	7:36	7:40	7:52	7:57	8:05	8:11	8:21	8:26	8:32
—	—	—	—	8:03	8:11	8:17	8:27	8:32	8:38
7:39	7:48	7:52	8:04	8:09	8:17	8:23	8:33	8:38	8:44
—	—	—	—	8:15	8:23	8:29	8:39	8:44	8:50

Exhibit D-60: Route 7 in San Diego

The steps in the process for this use case are as follows. Step 1 is to select the route of interest. Route 7 will be employed (as shown above). Step 2 is to assemble PDFs for the deviations from advertised stop times by trip for the typical and adverse conditions of interest. This is illustrated in **Error! Reference source not found.** and

Exhibit D-59, but will be expanded in the analysis below. Step 3 is to define what is meant by being on-time (the limits of being either early or late and the probability of being within that window). Step 4 involves assessing the extent to which adjustments in the schedule would improve the on-time performance.

That there are challenges with schedule reliability is evident from Exhibit D-61. Shown are all the differences from scheduled stop times for all equipped buses and all routes for the data received. Bear in mind that the *n*th stop is not always referring to the same location in this particular plot because the stop sequences are different, but even with this caveat, it is clear that the bus drivers find it challenging to keep the buses on time. They sometimes start the run early, by as much as 20 minutes, and leave intermediate stops early so they can hopefully be on-time for the stop whose times are printed in the timetable (the stop times for all stops are not included in the published timetable). Unfortunately, even with their efforts, some of the buses are as much

as 10 to 20 minutes late by the time they reach the end of the route; that is, they slip to about the times published for the bus that left ahead of them.

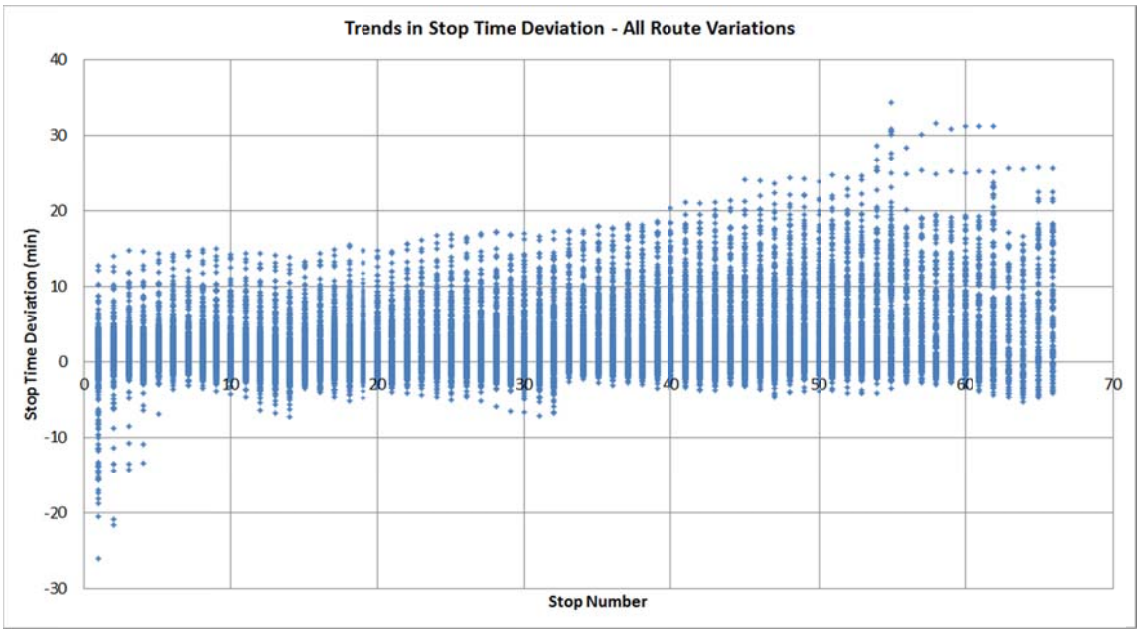


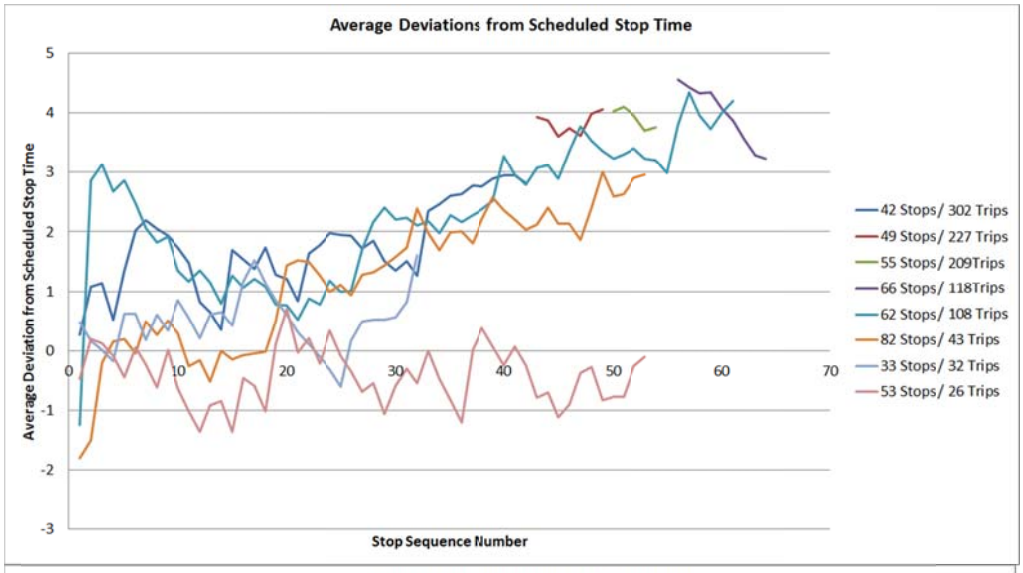
Exhibit D-61: Schedule Deviations for Route 7 in San Diego

Exhibit D-62 is more precise in that it shows the growth in *average* lateness for the stop sequence that involves 66 stops: the maximum number. If the average lateness remained close to zero, then the buses would, on average, be on-time. But it is clear they are not. The average lateness continues to increase along the route. This means the schedule is too aggressive; the buses cannot keep up, and more slack is needed. The one exception is the stopping pattern involving 53 stops. The buses following that stop schedule seem to stay on time.

The standard deviation of the lateness shows similar trends. The standard deviation could easily be constant across the route, meaning buses are likely to be both early and late and the extent to which they deviate from the scheduled stop times is constant across the route. This is in fact true for the stopping pattern involving 53 stops. But for the others, the standard deviation grows, which says that the deviations from the average lateness are growing as one progresses along the route. This re-emphasizes the fact that more schedule slack is needed.

As qualitative affirmation that the route has schedule challenges, the on-time performance of several buses can be examined. Plotted in

Exhibit D-63 are the schedule deviations by stop for five buses. It is clear that Bus #2 encountered problems. Between about the 4th and 6th stop it got delayed and it never recovered. It was late for the rest of the stops. Its pattern closely resembles that of Bus #5 that also struggled to stay on time as it progressed along the route. In fact, all of the buses except Bus #3 get further behind the further they progress along the route.



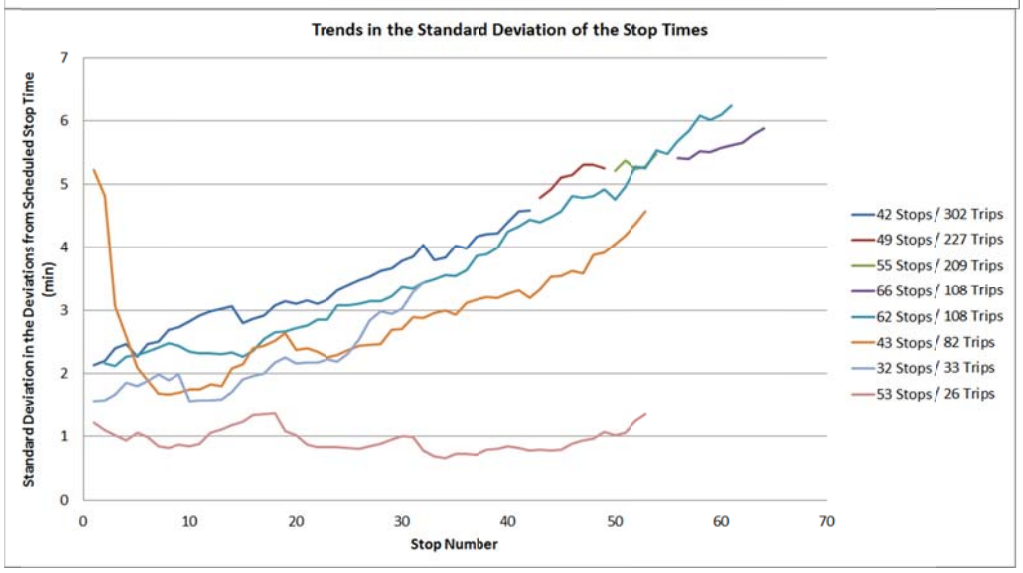


Exhibit D-62: Schedule Deviations for Route 7 in San Diego

The message seems clear. The schedule needs to be lengthened. Perhaps the existing schedule dates from an earlier year when the streets were not as congested as they were when the data were collected. Perhaps uncongested travel times were used instead of the conditions that pertain when the buses are operating.

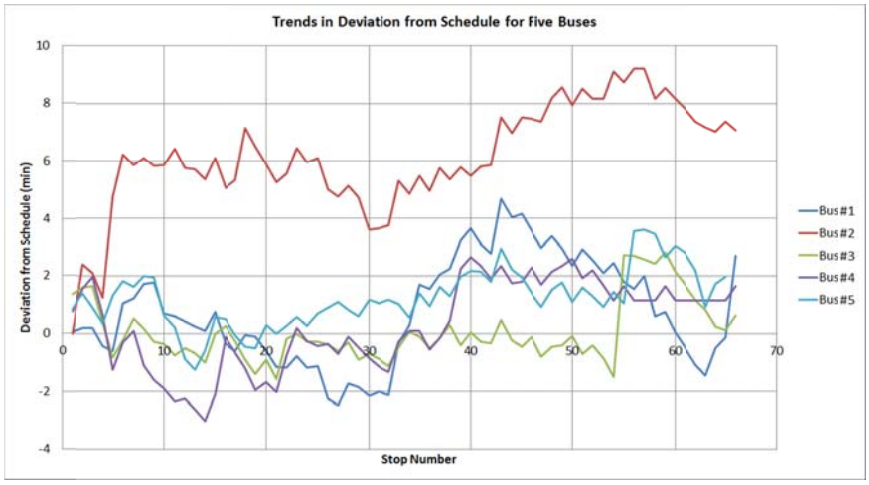


Exhibit D-63: Schedule Deviations for Five Buses

A good sense of how much time to add can be obtained by examining Exhibit D-64. Shown is the CDF for the lateness of buses at Stop #60, almost at the end of the route. (Two stop ID's pertain to this stop; the CDFs for both are shown.) The actual end of the route is not used because it is the depot; and lateness at the depot is not of concern from a schedule standpoint. As can be seen, 90% of the buses are late by 12 minutes or less. There is not a "right" answer for how much time to add, but adding 12 minutes so that 90% of the buses can complete the route on-time seems reasonable. Only one in 10 will be late. And the tail begins to extend significantly beyond that point, probably reflecting delays over which the bus drivers have little or no control. Exhibit D-61, Exhibit D-62, and Exhibit D-63 all suggest that the place to add this time is after about the 25th stop, so that is the strategy suggested here.

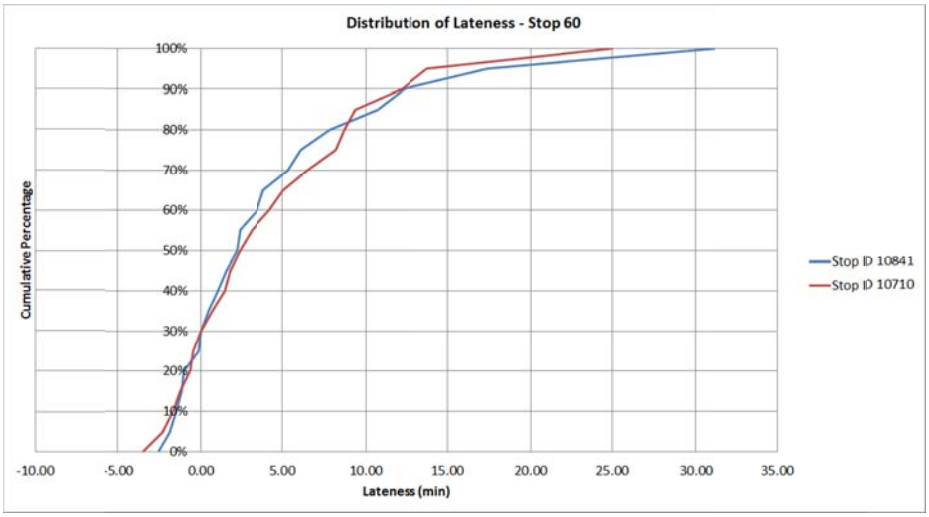


Exhibit D-64: Schedule Deviations at Stop #60 (out of 66)

Choose Departure Times to Minimize Arrival Uncertainty (TS2)

A scheduler wants to choose departure time for a route that will minimize the likelihood that the stops are not on-time. This analysis is useful when planning the schedule for a specific route. The scheduled departure and arrival times may be flexible, but the transit vehicle needs to arrive when scheduled. This analysis helps a user schedule a route to minimize travel time variability.

Table D-33: Choose Departure Time to Minimize Arrival Uncertainty (TS2)

User	Transit Scheduler
Question	When should a specific trip start to minimize the likelihood that the stops will not be on-time?
Steps	1. Select the route and trip of interest. 2. Assemble PDFs for the deviations from advertised stop times for the typical and adverse conditions of interest. 3. Define what is meant by being on-time (probabilities of being late and early). 4. Assess the extent to which an adjustment in the departure time will improve the on-time performance at the stops.
Inputs	A database of stop times by trip for the route and trip of interest (and the conditions of interest).
Result	An assessment of the extent to which an adjustment in the departure time will improve the on-time performance of the route.

This use case is very much like TS1 except the focus is on the departure time for the route rather than the intermediate stop times. It is as though an earlier stop time helps ensure the stops are made on time. To some degree, this is a reasonable thought, especially if the first stop is some distance from the depot.

For purposes of discussion, it is reasonable to re-use the analysis of Route 7 conducted in TS1 to illustrate the application of the use case. Assume the objective was to reach Stop #60 on time based on the current timetable. Then two things would need to be done. First, the buses would need to start their routes about 12 minutes earlier than they presently do (based on

Exhibit D-64) and second, the intermediate stop times would need to be adjusted to earlier times so that the timetable reflected a schedule that got the bus to Stop #60 on-time.

Transit Operators

Transit Operators care about travel time reliability because it is strongly linked with:

- *Costs:* Less reliable services have higher costs. Extra buses and drivers are needed to fill in for buses that are late. Bus bunching occurs. The bus loadings are uneven. The amount of time required for a bus to make a round trip ultimately determines how many buses and drivers are required to provide a given service frequency. Simply put, the need for more buses equates to higher operations and capital costs.

- *Ridership:* More people use the service when it is more reliable. The bus loadings also become highly variable when the service is unreliable. Bus bunching occurs. Passengers have to wait longer than expected for a bus and experience overcrowded conditions. More reliable service makes transit more competitive with other travel options.
- *Revenue:* Reliable service is more attractive to passengers, which generates more ridership and, in turn, more revenue.

Many factors influence transit service reliability. *TCRP Report 100: Transit Capacity and Quality of Service Manual, 2nd Edition* (1)) gives the following examples: traffic conditions and road construction, vehicle and maintenance quality, vehicle and driver availability, existence of transit preferential treatments, schedule achievability, evenness of passenger demand, variations in bus operator experience, wheelchair lift and ramp usage, route length and the number of stops, and operations control strategies.

A reliability monitoring system needs to give transit system service providers two types of reliability information. First, reliability metrics for general traffic along bus routes that operate in mixed traffic (more than 99% of all route miles in the U.S.); this requires access to the same data described in the previous use cases. Second, transit-specific travel time information measured relative to a schedule or designated headway; this requires collecting data from transit vehicles equipped with tracking devices, typically a GPS-based Automatic Vehicle Location system.

To support transit-specific reliability monitoring, these use cases introduce specialized metrics such as schedule adherence and headway regularity. Note that transit providers may use a travel time slightly faster than the average travel time (e.g., a 40th-percentile travel time) for scheduling purposes (to reduce the possibility that buses will need to sit and wait at a timepoint) and that the buffer time used in scheduling may be based on something other than a 95th-percentile travel time (e.g., a 90th-percentile travel time).The following use cases demonstrate system functionalities that are helpful for a transit provider's bus operations department.

Identify Routes with the Poorest Reliability (TO1)

A transit operator wants to determine which routes have the poorest reliability. This information helps prioritize routes for further analysis to find the sources of the unreliability.

Table D-34: Identify Routes with the Poorest Reliability (TO1)

User	Transit Operator
Question	What routes have the poorest reliability performance?
Steps	1. Select the routes of interest (could be all) 2. Select the operating conditions of interest (could be all conditions). 3. Assemble a database of variations from scheduled stop times for all the stops on the routes, classified by operating condition. 4. Identify the routes with the worst PDFs for the variations from scheduled stop times.
Inputs	An historical database of stop times by stop for the routes of interest (and the conditions of interest) plus the scheduled stopping times.
Result	A rank ordered list of the routes based on the extent to which the actual stopping times for the stops on the routes differ from the intended stopping times.

This use case is effectively the same as TP1. The objective is to identify routes that have the poorest reliability.

Exhibit D-58 helps answer that question in the context of the routes equipped with the AVL system. At a standard deviation of 9.37 minutes, Route 11 has the poorest reliability. The second worst is route 10 with a standard deviation of 4.63 minutes.

It is also important to note that the ranking of the routes, based on

Exhibit D-58, is slightly different from the impression conveyed by **Error! Reference source not found.**. In viewing the CDFs it appears that Routes 7 and 15 are the ones whose performance is "the poorest" because Route 7 has the greatest deviations from the scheduled stop times from the 80th percentile onward and Route 15 has the greatest deviations from the 20th percentile to the 80th. This helps illustrate the fact that there is not just one "right" answer to the question of "the poorest." It depends on the perspective one has on how "poorest" should be measured.

Review Reliability for a Route (TO2)

A user wants to review the reliability performance of a single route. This helps identify the possible cause(s) of the problem and, ultimately, a potential solution. It also aids the transit operator in diagnosing possible reasons for the unreliability: insufficient running time in the schedule (trips arriving consistently late at the end of the route), insufficient recovery time (trips consistently starting later than scheduled), spot issues along a route (reliability issues consistently starting within a particular segment of a route), driver performance (trips operated by a particular driver being consistently late), or bus bunching.

Table D-35: Review Reliability for a Route (TO2)

User	Transit Operator
Question	How does the on-time performance vary for a specific route?
Steps	1. Select the route of interest. 2. Select the operating conditions of interest (could be all conditions). 3. Assemble a database of variations from scheduled stop times for all the trips on the route, classified by operating condition. 4. Investigate why the worst deviations arise. This could be due to a variety of reasons.
Inputs	An historical database of stop times for the route of interest (and the conditions of interest) relative to the scheduled stop times.
Result	PDFs for the deviations of specific stop times from their intended stop times, a ranking of the stops based on this deviation, and ideas about why the deviations arise.

This use case is very similar to use case TS1. The question is: how does the on-time performance vary. The answer in the context of Route 7 is that it varies a lot, with buses being as late as 20 minutes for a one-hour run as can be seen in Exhibit D-61. Exhibit D-62showed that the buses tend to be late, on average, and that the deviation in that lateness increases along the route. Exhibit D-62 and

Exhibit D-63 tend to show that the problems with the route are more related to the later rather than the earlier stops. The biggest delays arise after the 20th stop. And it appears that adding 12 minutes to the timetable would resolve the on-time problems.

Examine the Potential Impacts of Bus Priority on a Route (TO3)

This use case explores the merits of introducing bus priority on a route. Bus priority is one way to enhance reliability. The buses can control the green times and extend the green so they are not delayed or delay the green so they can get going without having to merge with conflicting traffic. Data on the amount of signal delay experienced by buses would help support the case for transit signal priority and justify its potential impacts to other traffic.

Table D-36: Examine the Potential Impacts of Bus Priority on a Route (TO3)

User	Transit Operator
Question	By how much would bus priority (e.g., at signals) improve the reliability of a transit route?
Steps	1. Select the route of interest. 2. Select the operating conditions of interest (could be all conditions). 3. Identify other routes where bus priority has been introduced or where the impacts of signal delay are less significant. If none exist, then build a simulation model that can be used to do the assessment. 4. Compare the TR-PDFs (rates) for the route of interest with TR-PDFs for the routes where bus priority has been introduced or where the impacts are less significant. Do this using simulation if necessary. 6. See how much impact bus priority has.
Inputs	A database of trip times for the route of interest (and the conditions of interest) and for routes where bus priority has already been introduced.
Result	Differential TT-PDFs that show how the route's reliability could be improved if bus priority were introduced.

This use case is much like TP2. Here the question is whether bus priority would help. In TP2 the question was whether an exclusive bus would add value. In both cases, the question is whether some special treatment for buses would help improve reliability, either removing them from the mixed traffic stream or giving them the ability to be served by priority traffic signal operations. The method of analysis is the same in both cases. As illustrated in TP2, CDFs should be assembled for the on-time performance based on the deviations from planned stop times, and if the bus priority improves this performance, as was the case in comparing Route 7 with Route 88, then the treatment has merit.

Assess a Mitigating Action for an Adverse Condition (TO4)

In this use case, a transit operator wants to plan operational changes for future adverse conditions (e.g., incidents, severe weather, construction, or special events) and prepare riders for what the service will be like during these conditions.

Table D-37: Assess a Mitigating Action for an Adverse Condition (TO4)

User	Transit Operator
Question	What benefit would be obtained by taking an action intended to mitigate the impacts of an adverse condition?
Steps	1. Select the route of interest. 2. Select the adverse condition of interest. 3. Select the mitigating action to be tested. (One or more could be assessed.) 4. Assemble a database of TR-PDFs (rates) for routes under typical conditions and under conditions where the mitigating action has been implemented. If none exist, then build a simulation model that can be used to conduct that assessment. 4. Compare the TR-PDFs (rates) for typical and adverse conditions with and without the mitigating action. 6. See if the mitigating action has a significant impact.
Inputs	A database of trip times for the route of interest (and the conditions of interest) and for routes where bus priority has already been introduced. Use simulation if necessary.
Result	Differential TR-PDFs that show how the route's reliability would be improved if the mitigating actions were used.

This use case is focused on seeing if a mitigating action improves the reliability of a bus route under adverse conditions. Unfortunately during August 2011, the time period during which the data were collected, no significant adverse conditions arose nor were actions taken to mitigate those adverse conditions. Hence, this use case cannot be addressed directly by the data available.

However, the use case analysis is again comparable to either TP2 or TO3. The objective is to see if the on-time performance is enhanced during the adverse condition by the action taken. For example, if heavy rains or snow was an issue—obviously not the latter in San Diego—then the question would be whether a mitigating action like adding extra buses helps mitigate the negative impacts. The analysis technique would be the same as that used in either of those two use cases.

Transit Passengers

This section focuses on transit riders. These people benefit from reliability information when planning specific trips, either pre-trip or en-route. As with motorists, transit passengers are primarily concerned with trips: when should they start their trip, what route(s) they should take, and how much extra time they should allow for on-time arrivals. Unlike motorists, however, their options are constrained by the transit service network and schedule.

Determine the On-Time Performance of a Trip (TC1)

A user wants to know the on-time performance of a specific trip on a bus route. The trip has an origin, destination, and departure time. The user wants to know, in general, how long the trip will take.

Table D-38: Determine the On-Time Performance of a Trip (TC1)

User	Transit Passenger
Question	How often does a specific bus trip arrive at a specific stop on time?
Steps	1. Select the bus route, departure stop, and arrival stop. 2. Assemble a database of TT-PDFs for this bus route and stop pair of interest (if available) for the arrival time and condition(s) of interest. 3. Develop a PDF for the deviation from scheduled arrival time at the stop of interest.
Inputs	Historical database of TT-PDFs for the bus route and trip of interest (if available) for the conditions of interest.
Result	A PDF for the deviation from scheduled arrival time at the stop of interest.

This use case is the fundamental building block of the analysis procedures related to transit riders. It focuses on determining the on-time performance for a specific trip – from an origin stop to a destination stop on the same bus route.

The steps involved are: 1) select the bus route, departure stop and arrival stop. In this instance Route 7 will be used with boarding stop 99343 (Broadway & 11th Street) and alighting stop 10314 (University Avenue and Maple Street); 2) assemble a database of TT-PDFs for the route and stop pair of interest; and 3) develop a PDF for the deviation from scheduled arrival time at the stop of interest.

The TT-PDF between 99343 and 10314 is shown in Exhibit D-65. The CDF is based on 115 observations of trip times between these two stops during the month of August. It seems the trip can take anywhere from 35 minutes to nearly 80 minutes. Even the 90th percentile travel time is 58 minutes, nearly double the shortest time observed.

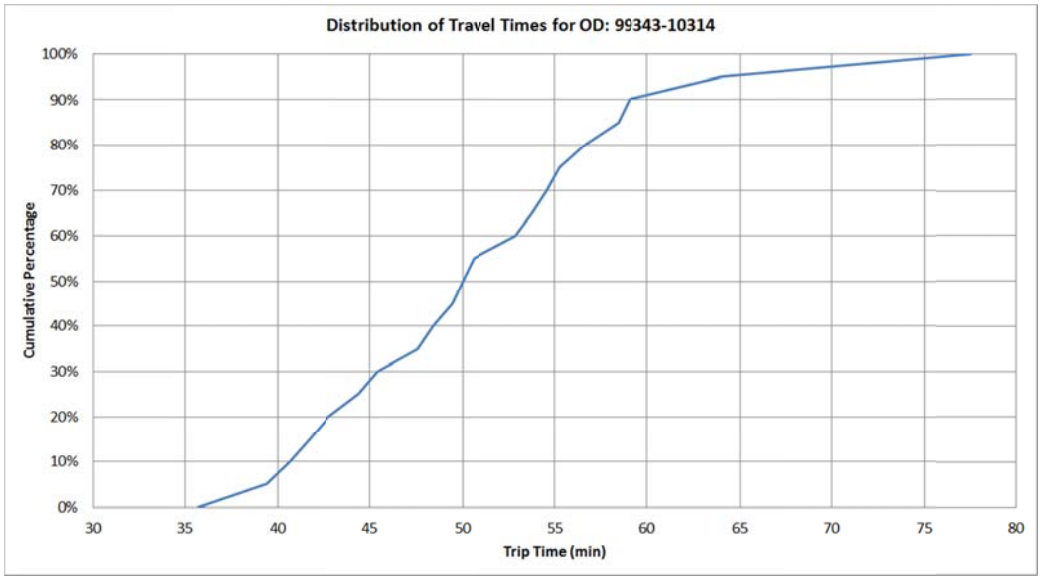


Exhibit D-65: Travel Times on Route 7 from Broadway & 11th Street (99343) to University Avenue & Maple (10314)

Exhibit D-66 shows the distribution of trips based on whether the departure from the origin was early, on-time, or late; and whether the arrival at the destination was early, on-time, or late. On-time was defined as being a half minute early to two minutes late.

Origin	Destination		
	Early	On-Time	Late
Early	11	9	3
	43.05	48.33	53.01
	4.93	5.41	4.88
On-Time	24	11	25
	44.73	50.89	55.14
	5.59	6.40	7.72
Late	2	2	27
	44.55	47.88	55.15
	12.49	3.72	6.57

Exhibit D-66: On-Time Assessment for Route 7 from Broadway & 11th Street (99343) to University Avenue & Maple (10314)

Most often, 27 times out of the 115 observed the buses are late departing from the origin stop and late arriving at the destination. The average travel time in this condition is 55.15 minutes and the standard deviation is 6.57 minutes. This is strikingly different from the best performance which occurred 11 times, and for which the average travel time was 43.05 minutes with a standard deviation of 4.93 minutes. About 48% of the time (3 + 25 + 27) the bus is late arriving at the destination; while about 30% of the time (2 + 2 + 27) it is late leaving.

Exhibit D-67 shows the CDF for deviation from the scheduled stop time at the destination. Although about 35% of the time the bus will arrive at or before the scheduled stop time, 65% of the time it is late; and at the 90th percentile, it is about 12 minutes late.

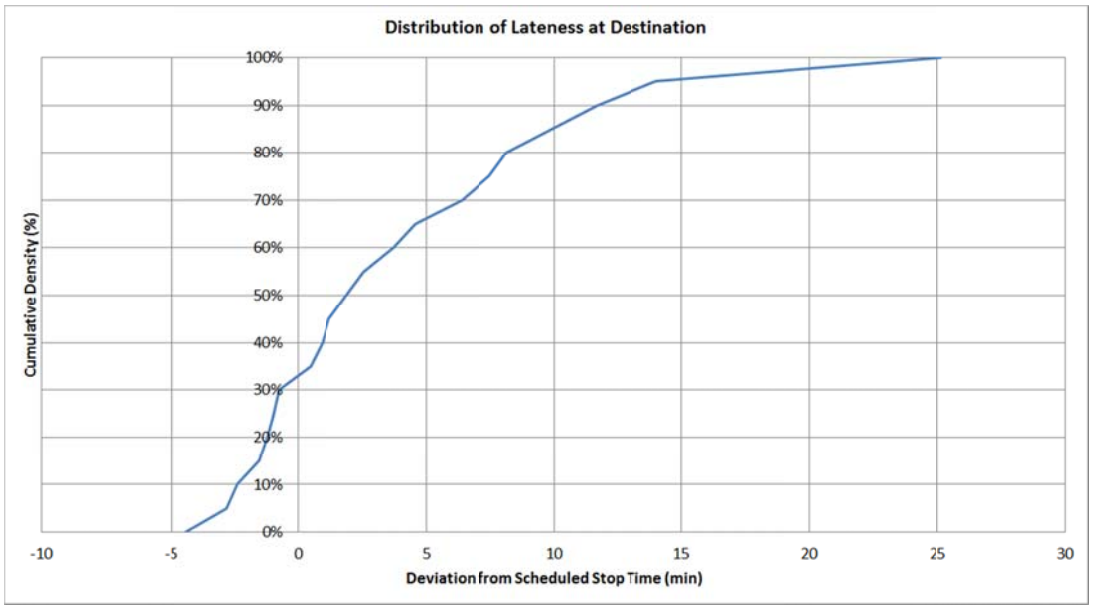


Exhibit D-67: CDF for Lateness (Deviation from Scheduled Stop Time) at the Destination

Determine an Arrival Time Just Before a Trip (TC2)

A rider wants to determine, just before a trip, when he or she might arrive. This is similar to TC1, but it uses data about current conditions. In addition, since the inquiry is occurring just before a trip, the departure time is relatively fixed and the arrival time becomes the focus.

Table D-39: Determine Route and Arrival Time Just Before a Trip (TC2)

User	Transit Rider
Question	Just before making a trip, when does the rider have to leave to arrive at a destination on time?
Steps	1. Select the origin and destination. 2. Decide what being on-time means (probability of being late). 3. Determine the options for departure times. 4. Select the departure time that ensures an acceptable arrival.
Inputs	Forecasts of passenger TT-PDFs by departure time for the routes that might be chosen given the current and anticipated network conditions
Result	Plots of the TT-CDFs for the various departure times so the most appropriate departure time can be selected.

Step 1 in the analysis involves selecting an origin and destination. The same two stops employed in TC1 will be used. Step 2 involves determining what on-time means (the probability

of being late). Step 3 involves determining the options for departure times. Step 4 is to select the departure time that ensures an acceptable arrival.

At the heart of this analysis is a plot like the one in

Exhibit D-68. Shown are the travel times from the origin stop to the destination by time of day (by bus departure time, which means the same run). It is clear that the time required to make the trip varies widely and is heavily dependent on the time of day.

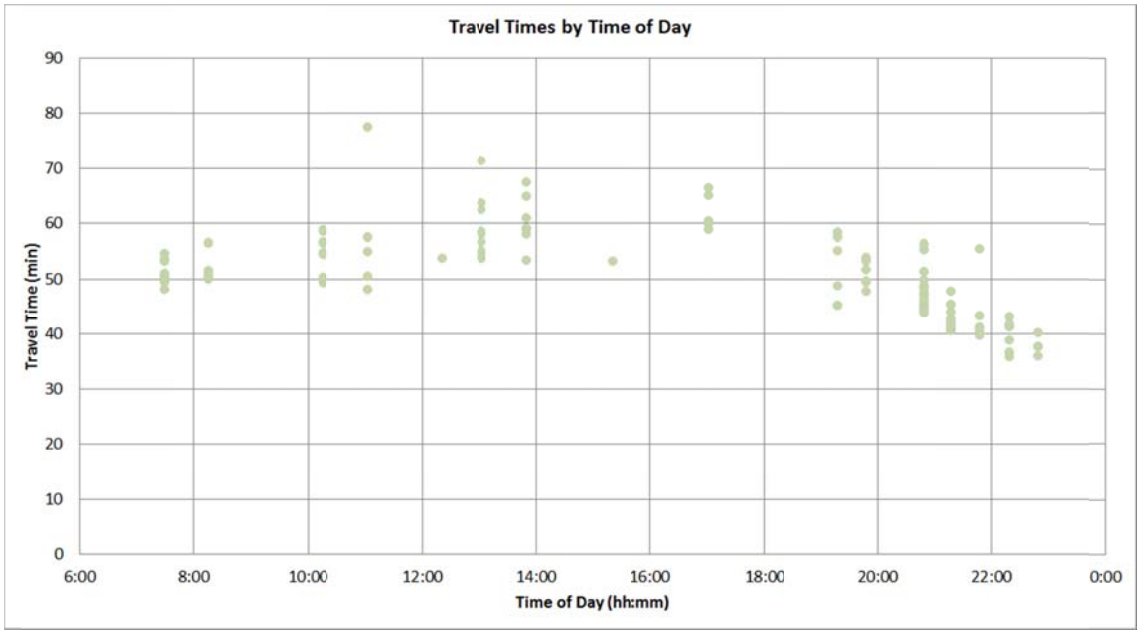


Exhibit D-68: CDF for Lateness (Deviation from Scheduled Stop Time) at the Destination

Not enough data are available for any given departure time to create a complete CDF but the spread in the data for August can certainly be observed.

A logical answer to the question is something like this. Early in the morning, say before 10:00am, an hour needs to be allowed. The bus might actually arrive in 50 minutes, but allowing for 60 minutes is safe. Across the middle of the day 70 minutes needs to be allowed, although (unfortunately) there are times when only 50 minutes will be needed. Toward evening, the time needed drops back to 60 minutes and then to less than 50 and by about 11:00pm, only 40 minutes needs to be allowed. Moreover, the travel times are very consistent. The value in having real information about the trip times – in this case by time of day – is strikingly apparent.

Determine a Friend's Arrival Time (TC3)

In this use case, the TTRMS user wants to know when his or her friend will arrive. The use case is similar to TC2 because it focuses on the arrival time and depends on information about current conditions. However, in this case, the route is already known, so the question is: when will the friend arrive.

Table D-40: Determine a Friend's Arrival Time (TC3)

User	Friend of a Transit Rider
Question	When will the friend arrive?
Steps	1. Select the origin, destination, route, and bus being ridden. 2. Assemble current information for this bus run (if available) and historical TT-PDFs for this bus route and this specific run (if available). 3. Develop an arrival time PDF for this bus trip at the stop of interest.
Inputs	Information about this bus run (if available) and historical TT-PDFs for this bus route and this specific run (if available). Adjust for the current conditions.
Result	Arrival time PDF for this bus trip at the stop of interest.

In state-of-the-art bus systems, the progress of individual buses can be tracked via a web page or cell phone app. Such systems make it easy to answer this question. But most systems today are not state-of-the-art, so historical information needs to be used instead.

Step 1 is to select the origin, destination, route, and bus being ridden. Without loss of generality, Route 7 will again be selected, origin 99343, destination 10314, and—to make it interesting—departure time 13:00. As can be seen in

Exhibit D-68, the trip for this departure time can take anywhere from 55 to 72 minutes, a spread of 17 minutes.

The conclusion might be: plan on being ready to the friend as early as 55 minutes after he or she leaves, do not plan on doing something until at least 72 minutes after he or she departs, and have his or her cell phone number. There is enough variation that making a call to find out where the bus is would be valuable.

In contrast, late at night, say with the (about) 11:00 departure, there is less need for contingency planning. The shortest travel time is about 35 minutes and the longest is about 40. Hence, it would be fine to show up at the bus stop about 35 minutes after the friend leaves the origin and expect to wait no more than about 5 minutes for the bus to arrive.

Understand a Trip with a Transfer (TC4)

A rider wants to find out, in advance, what time to leave and what route(s) to take to reach a destination on-time where a transfer is involved. Missing the bus at the origin is of concern as well as missing transfers, and being late or early at the destination. The use case is based on historical data, rather than current conditions, and as such is suitable for travelers who want to plan a trip in advance rather than immediately before they leave.

Table D-41: Understand a Trip with a Transfer (TC4)

User	Transit Rider
Question	What departure times are needed when a transfer is involved?
Steps	1. Select the origin, destination, desired arrival time, and route. 2. Decide what being on-time means (probability of being late). 3. Analyze the TT-PDFs to identify options for departure times. 4. Create a CDF of the travel times so that an acceptable departure bus can be selected.
Inputs	Historical, passenger TT-PDFs for the departure times that are logical based on conditions.
Result	Table of departure times depending on the conditions. The table is created by analyzing the TT-PDFs for the routes involved and network conditions.

This use case focuses on understanding departure times and routes for a trip that involves a transfer. Without loss of generality, a bus trip from the Gaslight district to the San Diego zoo can be used to illustrate. In August 2010 when the bus data were collected, the San Diego Zoo was open from 9:00 AM to 9:00 PM on weekdays. Hence, arrival at the zoo will be targeted within this window.

One feature of this trip which is important is that a transfer is involved. The San Diego transit's trip planner suggests several possible paths, one of which uses bus Routes 11 and 7. For about a 1:00 PM trip on a weekday, the trip planner suggests the following path:

1) Walk 0.4 mile north from the Gaslamp Trolley Station to Market Street at 6th Avenue
2) At 12:50 PM take the MTS BUS route 11 SDSU via Downtown / Adams Ave
3) Get off the stop on Park Boulevard & University Avenue at approximately 01:19 PM.
4) Walk 0.1 mile south from Park Boulevard & University Avenue to Park Boulevard at University Avenue
5) At 01:25 PM take the MTS BUS route 7 Downtown via University Ave
6) Get off the bus at the stop on Park Boulevard at Zoo Place at approximately 01:29 PM.
7) Walk 0.2 mile west to the ZOO

It was hoped that all the buses on Routes 11 and 7 would be equipped with monitoring devices, but such was not the case. Only about half of them were. If they all had been equipped, it would have been possible to construct trip travel times by: selecting a "boarding a bus", "riding it to the transfer point", "transferring from it to the next transfer bus" and then "riding to the destination". But this proved infeasible because all the buses were not instrumented. A different strategy was needed.

The analysis involved two steps: 1) pre-processing the bus trip data to develop information needed to conduct the analysis and 2) generating a synthesized set of hypothetical, representative trips through Monte Carlo simulation.

Exhibit D-69 shows the process used to synthesize the trip times. The flow chart at the top of the exhibit provides an overview. The bottom flow chart provides more detail. The whole exhibit is annotated with letters from A to J to provide reference markers for the description that follows.

The overview starts with Marker "A", focused on the initial bus boarding process. The passenger arrives; as does a bus on Route 11. Depending on when they arrive, the passenger either gets on the 1st Route 11 bus or the next (2nd) one. If he/she gets on the 2nd one, a delay of one- headway is incurred. (Later text will describe what this means in more detail.) In either event, as shown by the blocks near marker "B", the passenger travels to and arrives at the transfer point, as shown near Marker "C". Arriving separately is the 1st Route 7 bus. An analysis of when that bus arrives relative to when the passenger arrives on the Route 11 bus determines whether the passenger gets on the 1st Route 7 bus or has to wait for the next (2nd) one. If he/she gets on the second Route 7 bus, an additional delay is incurred. (Later text will describe this in more detail.) In either event, as shown by the blocks near marker "D", the passenger then arrives at the destination.

The detailed description starts with Marker "E". Near it are shown the PDFs for the arrival of the passenger (Px) and the 1st Route 11 bus. Consistent with Bowman and Turnquist (1981)[3], the passenger PDF (Δt_0) tends to favor early arrivals with a small probability of being late. Separately, consistent with the San Diego data, the Route 11 bus (Δt_1) follows a second PDF[4]. The distribution for the bus indicates a small probability of departing early (earlier than the scheduled departure time) and a much larger probability of departing late. If the passenger arrives before the Route 11 bus departs, then the passenger boards the 1st Route 11 bus. If that happens, the descending dashed line toward marker "F" indicates that the passenger incurs a travel time (Δt_2) to reach the transfer stop and the passenger (on the Route 11 bus) arrives at the transfer stop at t_1, which is at some point in time relative to the scheduled departure time (Δt_3). (Departure times have been used as the reference because they are "worst case" times – we know for sure that the passenger has arrived when the bus departs.) If the passenger misses the 1st Route 11 bus, because he/she arrives after the 1st Route 11 bus departs, then a schedule delay (Δt_4) is incurred until the next Route 11 bus arrives (to the right of marker "E"). A 2nd Route 11 bus arrives (Δt_5), the passenger boards, and Route 11 bus travels to the transfer location (Δt_6), shown by marker "G", and the passenger arrives at the transfer stop at t_2, which is at some time relative to its scheduled departure (Δt_7).

Whichever arrival time governs (t_1 or t_2) becomes the start of the second part of the trip (Marker "H"). Moreover, the corresponding relative arrival time (Δt_4 or Δt_7) becomes the basis (Δt_8) for determining which transfer bus is caught. If the passenger's relative arrival time on the Route 11 bus (Δt_8) is less than the sum of the scheduled connection time (Δt_9) and the relative departure time for the Route 7 bus (Δt_{10}), then the 1st Route 7 bus is caught. This leads to a travel time to the destination (Δt_{11}), an arrival time (t_3) and a relative arrival time compared to the schedule (Δt_{12}) (Marker "I"). On the other hand, if the Route 11 bus arrives late (Δt_8) or the Route 7 bus departs early ($\Delta t_9 + \Delta t_{10}$), then the passenger may miss the 1st Route 7 bus, incur a delay (Δt_{13}), until the next Route 7 bus arrives (Δt_{14}), then incur a travel time (Δt_{15}) to the destination and arrive at t_4 with a relative arrival time (Δt_{16}) (Marker "J").

[3] Bowman, L.A., and M.A. Turnquist, "Service Frequency, Schedule Reliability and Passenger Wait Times at Transit Stops," *Transportation Research,* 15A:6, pp.465-471, 1981.

[4] All the PDFs for the buses are derived from the San Diego data

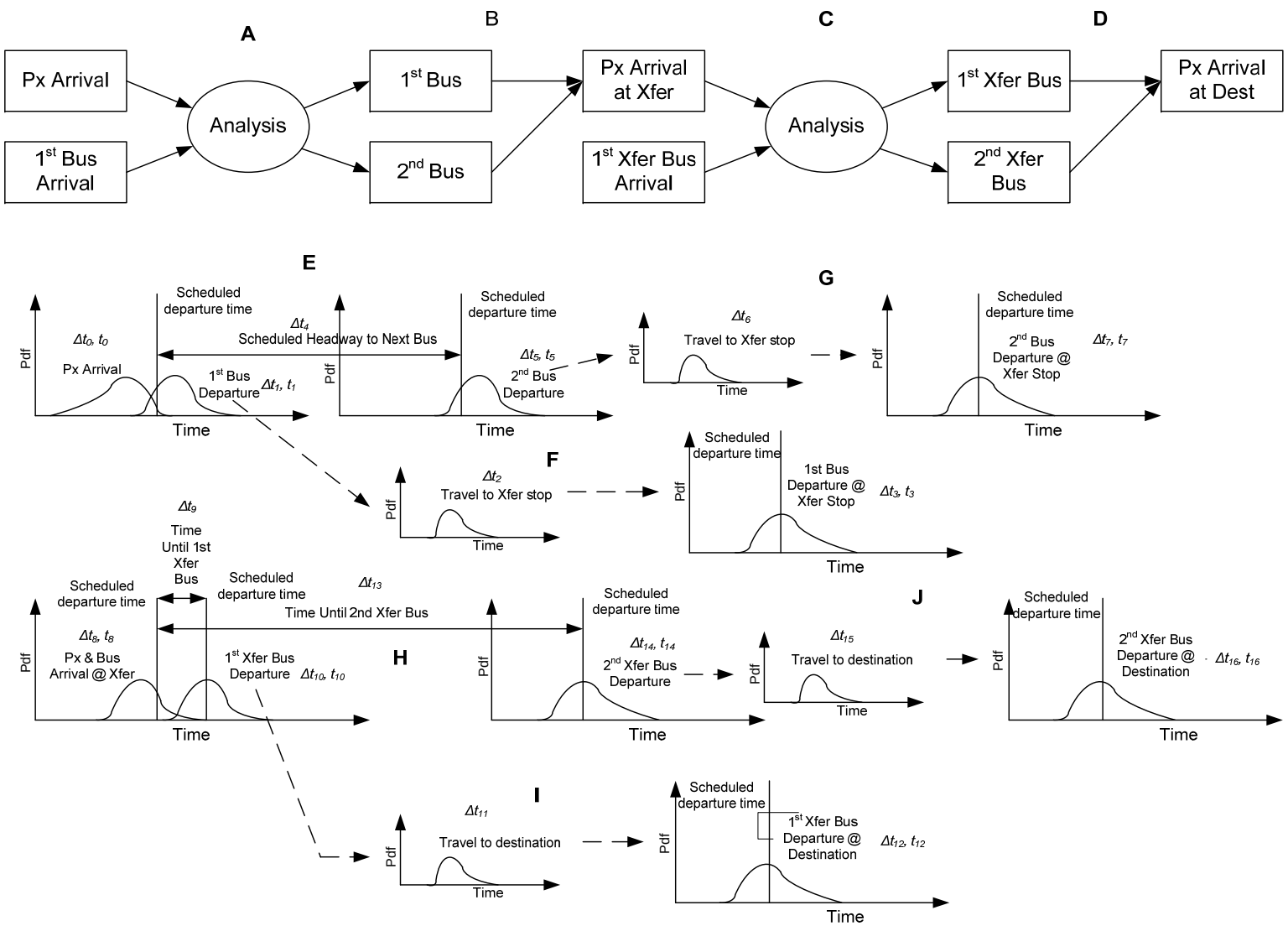


Exhibit D-69: Transit Trip Time Analysis Method

A couple of numerical examples will help illustrate the analysis. Exhibit D-70 presents four of them. In the first, no bus is missed. In the second, the connection bus is missed. In the third, the first Route 11 bus is missed but the subsequent connection is made. In the fourth, both the first Route 11 bus is missed and the first Route 7 transfer bus is missed. In all cases the reference time when $t = 0$ is the scheduled departure time of the first Route 11 bus. All the values are in seconds.

Metric	No Miss	Miss 2	Miss 1	Miss Both
Δt_0	-120	-90	-30	50
Δt_1	30	15	-50	-100
Δt_2	1570	1730	-	-
Δt_3	20	350	-	-
Δt_4	-	-	900	900
Δt_5	-	-	-30	40
Δt_6	-	-	1400	1800
Δt_7	-	-	-100	400
Δt_8	20	350	-100	400
Δt_9	240	240	240	240
Δt_{10}	50	-100	70	-100
Δt_{11}	190	-	210	-
Δt_{12}	-10	-	20	-
Δt_{13}	-	720	-	720
Δt_{14}	-	10	-	-30
Δt_{15}	-	180	-	190
Δt_{16}	-	-10	-	30
t_0	-120	-90	-30	50
t_1	30	15	-	-
t_3	1600	1745	-	-
t_5	-	-	870	940
t_7	-	-	2270	2740
t_8	1600	1745	2270	2740
t_{10}	1870	-	2680	-
t_{12}	2060	-	2890	-
t_{14}	-	2365	-	3270
t_{16}	-	2545	-	3460
tt	2180	2635	2920	3410

Exhibit D-70: Example Trip Times

The first example starts with $\Delta t_0 \leq \Delta t_1$ ($-120 \leq 30$), which means the passenger gets to catch the first Route 11 bus. The starting time for the trip (t_0) becomes -120 seconds (i.e., the passenger arrived 2 minutes before the scheduled departure time, which is the reference point for $t = 0$). The travel time to the transfer point is $\Delta t_2 = 1570$, the arrival

time is $t_3 = t_8 = 1600$, and the relative arrival time at the transfer point (relative to the scheduled departure at that location) is $\Delta t_3 = \Delta t_8 = 20$.

The next thing to do is to analyze the connection. The relative arrival time is $\Delta t_8 = 20$, the transfer time is $\Delta t_9 = 240$ and the 1st Route 7 bus is late $\Delta t_{10} = 50$, so the passenger has no problem catching the first transfer bus ($\Delta t_8 \leq \Delta t_9 + \Delta t_{10}$). The passenger then departs the transfer stop at $t_{10} = t_8 - \Delta t_8 + \Delta t_9 + \Delta t_{10} = 1600 – 20 + 240 + 50 = 1870$, travels to the destination $\Delta t_{11} = 190$, arrives at the destination at $\Delta t_{12} = t_{10} + \Delta t_{11} = 1870 + 190 = 2060$, with an arrival relative to the scheduled arrival time of $\Delta t_{12} = -10$ (10 seconds early) and an overall travel time of $tt = t_{12} – t_0 = 2060 – (-120) = 2180$ seconds (36.3 minutes).

In the second example, the first Route 11 bus is caught, but the first Route 7 transfer bus is missed. The example starts with $\Delta t_0 \leq \Delta t_1$ ($-90 \leq 15$), which means the passenger catches the first Route 11 bus. The starting time for the trip (t_0) becomes -90. The travel time to the transfer point is $\Delta t_2 = 1730$, the arrival time is $t_3 = t_8 = 1745$, and the relative arrival time at the transfer point (relative to the scheduled departure time) is $\Delta t_3 = \Delta t_8 = 350$. The transfer time is $\Delta t_9 = 240$ and the 1st Route 7 bus leaves early $\Delta t_{10} = -100$, so the passenger misses the first transfer bus ($\Delta t_8 \geq \Delta t_9 + \Delta t_{10}$, or $350 \geq 240 + (-100)$). Hence, the passenger has to wait for the second transfer bus which has a scheduled time $\Delta t_{13} = 720$ which is 12 minutes later than the 1st transfer bus, and it arrives a little late $\Delta t_{14} = 10$. This means it leaves at $t_{14} = t_8 - \Delta t_8 + \Delta t_9 + \Delta t_{13} + \Delta t_{14} = 1745 – 350 + 240 + 720 + 10 = 2365$. The Route 7 bus then travels to the destination $\Delta t_{15} = 180$ and arrives a little early $\Delta t_{16} = -10$ at $t_{16} = 2545$. The overall trip time is $tt = t_{16} – t_0 = 2645$ (43.9 minutes).

In the third example, the first Route 11 bus is missed and the first Route 7 transfer bus is caught. The example starts with $\Delta t_0 > \Delta t_1$ ($-30 > -50$), so the passenger misses the first Route 11 bus. (The starting time for the trip (t_0) becomes -30.) The passenger has to wait for the next bus $\Delta t_4 = 900$ which is a little early $\Delta t_5 = -30$. The travel time to the transfer point is $\Delta t_6 = 1400$, the arrival time is $t_7 = t_8 = 2270$, and the arrival time at the transfer point relative to the scheduled departure time is $\Delta t_7 = \Delta t_8 = -100$. The transfer time is $\Delta t_9 = 240$ and the 1st Route 7 bus leaves late $\Delta t_{10} = 70$, so the passenger catches the first transfer bus ($\Delta t_8 \leq \Delta t_9 + \Delta t_{10}$, or $-100 \leq 240 + 70$). The passenger departs the transfer stop at $t_{10} = t_8 - \Delta t_8 + \Delta t_9 + \Delta t_{10} = 2270 – (-100) + 240 + 70 = 2680$, travels to the destination $\Delta t_{11} = 210$, arrives at the destination at $t_{12} = t_{10} + \Delta t_{11} = 2680 + 210 = 2890$, with an arrival relative to the scheduled arrival time of $\Delta t_{12} = 20$ (20 seconds late) and an overall travel time of $tt = t_{12} – t_0 = 2890 – (-30) = 2920$ seconds (48.7 minutes).

In the fourth example, both the first Route 11 bus and the first Route 7 transfer bus are missed. The example starts with $\Delta t_0 > \Delta t_1$ ($50 > -100$), so the passenger misses the first Route 11 bus. (The starting time for the trip (t_0) becomes 50.) The passenger has to wait for the next bus $\Delta t_4 = 900$ which is a little late $\Delta t_5 = 40$. The travel time to the transfer point is $\Delta t_6 = 1800$, the arrival time is $t_7 = t_8 = 2740$, and the arrival time at the transfer point relative to the scheduled departure time is $\Delta t_7 = \Delta t_8 = 400$. The transfer time is $\Delta t_9 = 240$ and the 1st Route 7 bus leaves early $\Delta t_{10} = -100$, so the passenger misses this bus ($\Delta t_8 \geq \Delta t_9 + \Delta t_{10}$, or $400 \leq 240 + (-100)$) and has to catch the second one. The added wait for the next bus is $\Delta t_{13} = 720$ which is 12 minutes later than the 1st transfer bus, and that bus arrives a little early $\Delta t_{14} = -30$. This means the departure time from the transfer stop is $t_{14} = t_8 - \Delta t_8 + \Delta t_9 + \Delta t_{13} + \Delta t_{14} = 2740 – 400 + 240 + 720 + (-30) = 3270$. The Route 7 bus then travels to the destination $\Delta t_{15} = 190$ and arrives a little late $\Delta t_{16} = 30$ at $t_{16} = 3460$. The overall trip time is $tt = t_{16} – t_0 = 3460 – 50 = 3410$ (56.8 minutes).

To conduct these analyses with the San Diego data, a somewhat lengthy, but straightforward process is involved. Nine major steps were involved:

1) For each route separately, combine the data for the individual weekdays into a combined dataset for all the weekdays in August.
2) Extract the records for which the latitude and longitude fields are not blank. (This happens to be the case for about 50% of the records.)
3) Compute average latitude and longitude values for every Stop-ID based on the non-blank records.
4) Backfill the lat/lon fields with average values computed above for all the records that are blank so that every record has these fields filled.
5) If any records remained with no lat/lon data, use the lat/lon values for the stops on either side to determine what the lat/lon most likely was for the stops with no lat/lon data. (This situation arose for one Route 7 stop.)
6) Create a set of unique "stop names" (cross-street descriptors) for every Stop-ID based on the lat/lon for the stop.
7) Add the stop names to every record in the database.
8) Extract from the dataset the stops of interest for the trip time analysis (Sixth and Market and University Avenue and Park Boulevard for Route 11; University Avenue and Park Boulevard and Park Boulevard and Zoo Place for Route 7).
9) Extract the records for these stops into two new datasets, one for each route.

To provide a sense of the result, the Route 7 database for the two stops of interest in the direction of interest includes 484 records. The Route 11 database contains 1,415 records.

Some analysis results taken directly from these datasets provides an indication of the way in which these two routes operate for the stops involved in the trip being studied. Exhibit D-71 shows the distribution of relative departure times for the two stops on Route 11 and the two stops on Route 7. Notice that the buses do sometimes leave early, but most of the time they leave late, by as much as five or more minutes. Exhibit D-71 also shows the distribution of travel times between the two stops of interest. For Route 11, the travel times are much longer and they are skewed toward longer values. For Route 7 the distribution is almost uniform between 120 and 300 seconds (2-5 minutes).

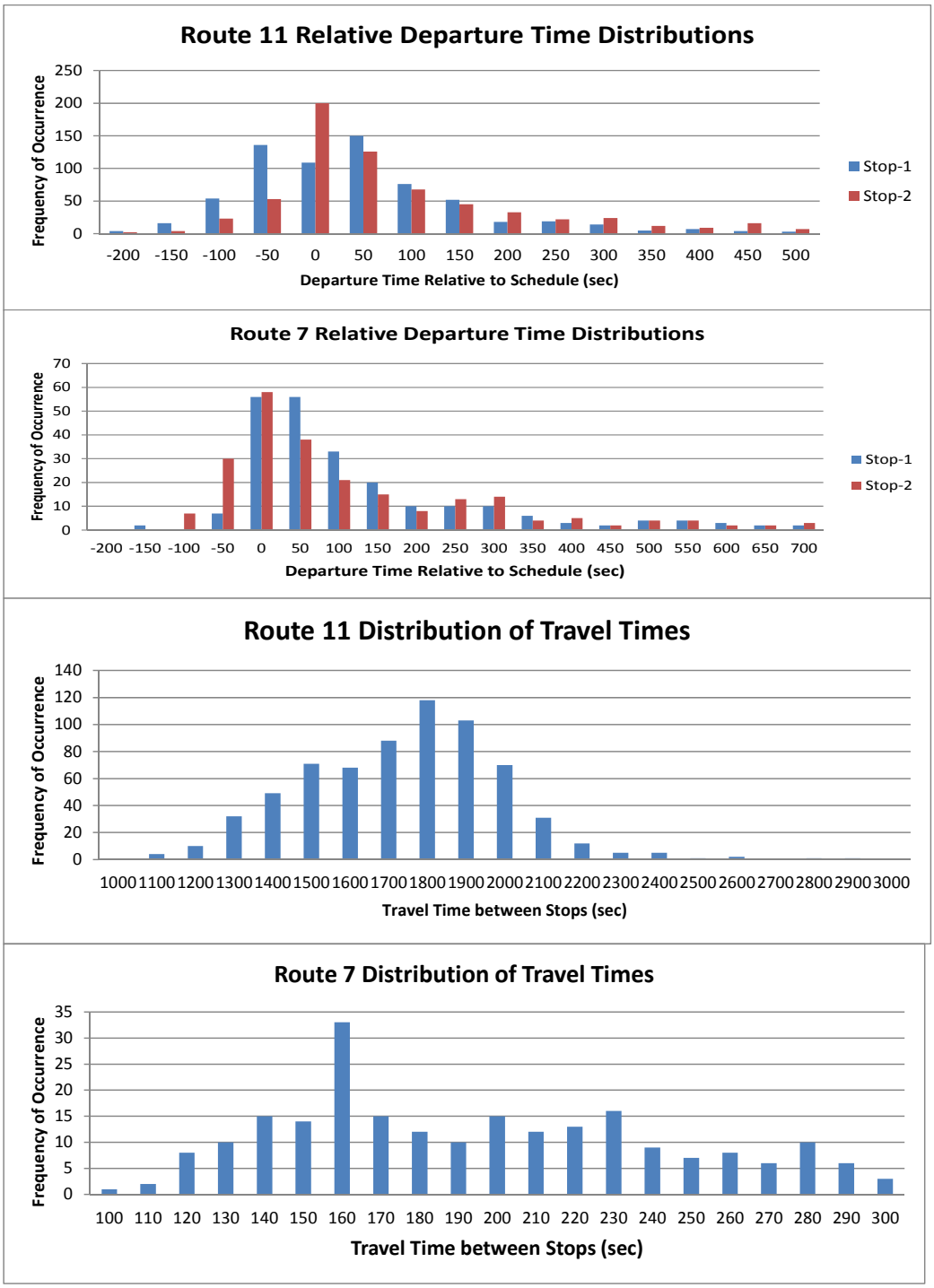


Exhibit D-71: Distributions of Relative Departure Times and Travel Times between Stops

Exhibit D-72 displays the correlations among these various times. The top two plots show the correlations between the differential stop time at the first and second stops. Clearly there is a correlation; one that is very pronounced in the case of Route 7; probably because the stops are close to one another. The bottom two plots show the absence of

correlation between the differential stop time at the first stop and the travel time to the transfer (or destination) stop.

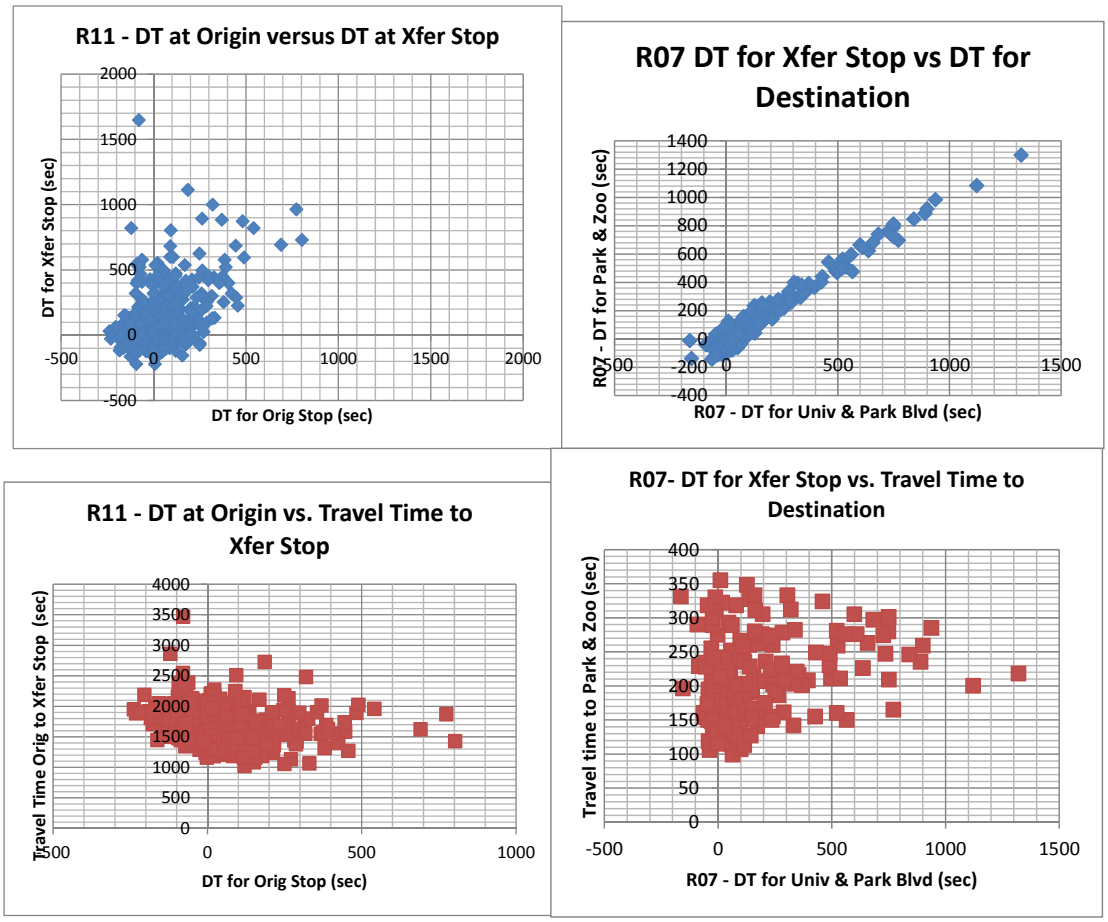


Exhibit D-72: Correlations among the Differential Stop and Travel Times

The correlations between the differential stop times motivated a change in the strategy for conducting the Monte Carlo simulations. Instead of fitting probability density functions to the data, which is what we expected to do, instead we decided to directly sample the observed datasets. That is, during simulation, to obtain values for Δt_1, Δt_2, and Δt_3 for the first Route 11 bus (or Δt_5, Δt_6, and Δt_7 for the 2nd one), we directly sample values from the 484 Route 11 values developed by the data analysis. In the case of Δt_{10}, Δt_{11}, and Δt_{12} for the first Route 7 bus (or Δt_{14}, Δt_{15}, and Δt_{16} for the 2nd one), we do exactly the same thing; sample values from the 1,415 records developed by the data analysis. This means a large-scale simulation is needed to sample all of the records in the two datasets; but, by sampling the datasets directly, we can ensure that the combinations of values is used in the simulation are combinations that were observed in the field, not ones created through a synthesizing process.

Finally, for the passenger arrival times at the initial stop, the distribution observed by Bowman and Turnquist (1981)[5] was used. Consistent with the guidance they provided, the original observations for buses with a 20-minute headway service were scaled to reflect values for a 15-minute headway service. The resulting distribution is shown in

Exhibit D-73. Again, for purposes of simulation, the distribution shown was directly sampled to obtain arrival times for the passengers relative to the scheduled arrival time of the bus.

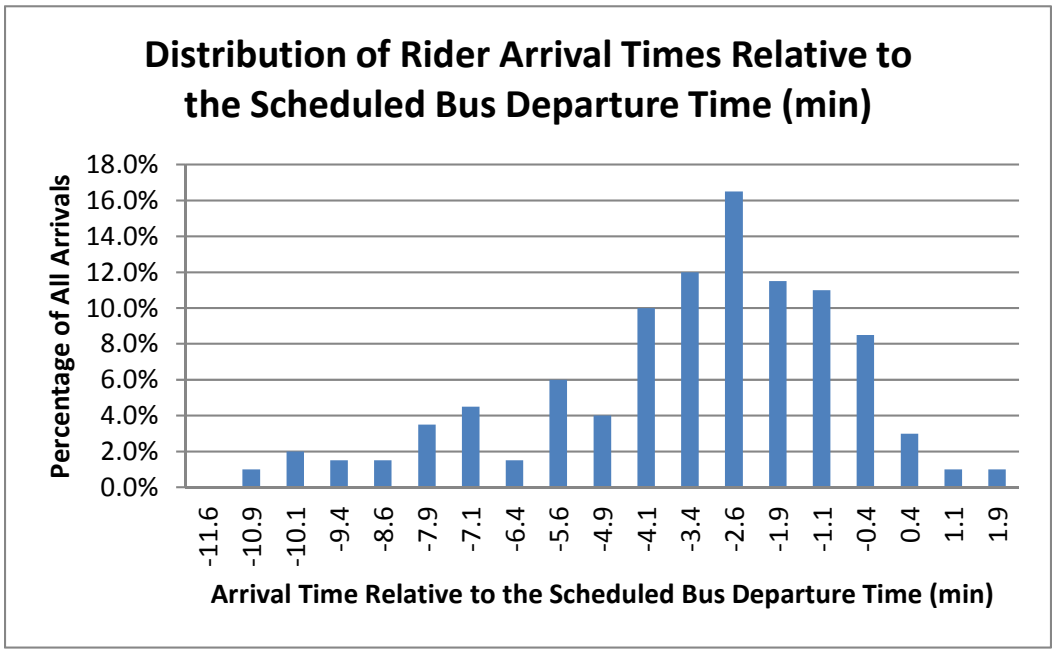


Exhibit D-73: Arrival Times for the Transit Passengers Relative to the Scheduled Arrival time of the Bus

A simulation of 1,000 trips produces the cumulative density function shown in Exhibit D-74. The shortest travel time is 30 minutes, the longest is 72. The 50th percentile is reached at 44 minutes and the 95th percentile is reached at 58 minutes. The average is 44 minutes. Thus, the longest travel time is 32% longer than the mean and twice as long as the shortest time. Guidance to potential passengers might be that they should expect the trip to take 44 minutes but in one out of every 20 trips it takes longer than 58 minutes.

[5] Bowman, L.A., and M.A. Turnquist, "Service Frequency, Schedule Reliability and Passenger Wait Times at Transit Stops," *Transportation Research,* 15A:6, pp.465-471, 1981.

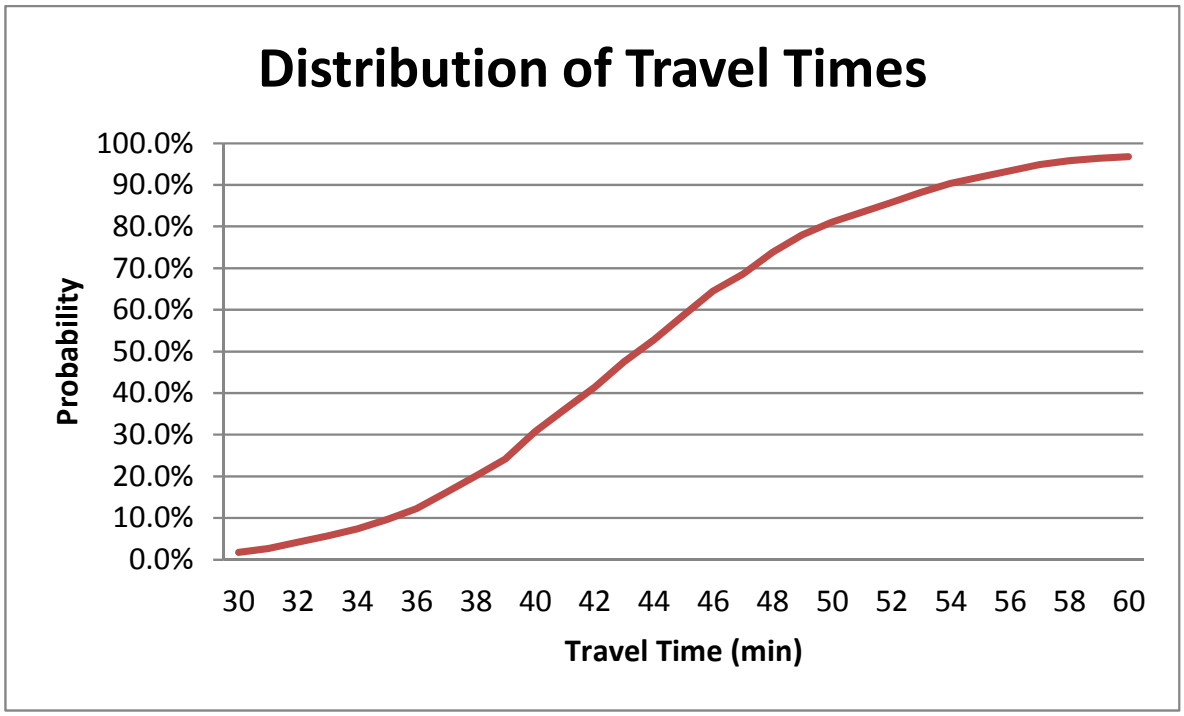


Exhibit D-74: Distribution of 1,000 Simulated Trips

FREIGHT USE CASES

This section presents use cases for freight service providers and customers. The vehicles involved are assumed to be trucks and vans, but the methodologies pertain to other freight modes as well, such as rail, water, and air freight. The use cases are clustered into two groups, those that pertain to the customers (e.g., shippers and receivers) and those that pertain to the service providers (e.g., trucking companies).

Within the service providers, there is a further clustering into three groups insofar as the motivations for the use cases are concerned:

- *Truckload (TL) Carriers*, where entire truckloads of freight are picked up at one location and delivered to another. Chemical Leaman is an example.
- *Less-than-Truckload (LTL) Carriers,* where shipments (e.g., pallets, not packages) are transported from shippers to receivers. Yellow Freight is an example. Local trucks make pick-ups and bring the shipments to a terminal. The shipments are then transported by one or more line haul trucks to a terminal that services the area where the receiver is located. A local delivery truck then carries the shipment to the receiver (along with other shipments going to other receivers).
- *Parcel Carriers,* where shipments (predominantly packages) are carried from shippers to receivers. United Parcel Service is an example. The logistics are much the same as the LTL carriers in that the trucks make a series of pick-ups and drop-offs of relatively small packages along a route that may vary from day to day.

Travel time reliability matters to all these carriers, especially the ones that have promised delivery times, like FedEx. Shippers and receivers often specify pick-up and delivery windows because they are shipping or receiving multiple items per day. The shippers and receivers want the shipments to be picked up and delivered within those windows and the carriers strive to ensure that they do the pick-ups and deliveries during those windows. In fact, as illustrated by FedEx or UPS, people are willing to pay more for the service to either have the shipment delivered faster or to ensure that it is delivered on-time. Most freight drivers accumulate information about travel times and reliability through experience and know how to avoid spots in the network where the travel times are unreliable. Carriers also use route guidance devices to direct their trucks around problem spots and to make sure that deliveries are made on-time.

Freight Service Providers (Trucking Companies)

The next set of use cases show how the monitoring system can be helpful to trucking companies that are trying to ensure that their deliveries will occur on-time.

Identify the Most Reliable Delivery Time (FP1)

A trucking company wants to find the best time of day and route for a specific delivery. The probability of being on time is important as well as the travel time. This analysis is useful for carriers that have flexibility in when their departure and arrival times can be scheduled, but need to arrive as scheduled.

Table D-42: Identify the Most Reliable Delivery Time (FP1)

User	Trucking Company
Question	When should a delivery be made if the most reliable delivery time is desired?
Steps	1. Select the origin and destination. 2. Assemble TT-PDFs by route and time-of-day and perhaps network condition. 3. Define on-time delivery (e.g., percentage within an on-time window). 3. Identify the time of day (and route) that minimizes the duration of the on-time window.
Inputs	A database of TT-PDFs for truck travel times by route and time of day from the origin to the destination under the network operating conditions that pertain.
Result	A rank ordering of the departure times (and routes) based on the duration of the on-time window (narrowest to widest).

In this use case, Step 1 involves the selecting the origin and destination. For purposes of the example presented here the same origin and destination used in Exhibit D-1 was employed, involving the three routes in San Diego.

Step 2 is to assemble the TT-PDFs by route and time-of-day and perhaps network condition. In this case, only the normal condition is examined – reflecting decision making under "normal" conditions. The same Monte-Carlo simulation technique used in the traveler use cases was employed to generate individual vehicle travel times for the I-5, I-15, and CA163 routes. For each normal 5 minute time period during the weekdays in 2009, 100 truck trips were simulated, one for each percentile based on the average travel time observed.

Step 3 is to define what is meant by the on-time delivery window. In this use case, it was decided that attention would be focused on the narrowest window in which 80% of the arrivals occurred. That meant that the analysis would seek the ith and j^{th} percentile arrival times such that 1) the total arrivals between the two percentiles was 80% (e.g., between the 5th and the 85th percentiles) and 2) the difference in the arrival times between these two percentiles was the smallest (e.g., that the difference in arrival times between the 7th and the 87th arrival travel time was the smallest of all possible percentile travel times encompassing 80% of the arrivals).

Step 4 involves identifying the time of day (and route) that minimizes the duration of the on-time window. In this case, we calculated each percentile delivery time for every 5 minutes time period and got the minimum on time window that satisfy the 80 percentage requirement. Then we compared all of the minimums for every 5 minute for each route. Finally, we created a table showing the routes and on-time window for each 5 minute within 8:00 AM and 5:00 PM.

Exhibit D-75 shows the result of routes correspondent to the time window. The x-axis stands for departure times and y-axis stands for the correspondent on-time windows. The two vertical lines stand for the boundary from 8:00 – 17:00. The Minimum_Window stands for the smallest on-time window of each 5-miniute departure times among the three routes. The exhibit shows that I-15 performs better during peak hours while I-5 performs better during off-peak hours. The minimum on-time window is between 2 min and 3 min during off-peak hours while it varies from 3 min to 6 min during PM peak. After comparing the three routes and each 5-minute time period, we know that when departure time is 8:00 AM on I-15, the on-time window is 2.02 min which is the smallest one.

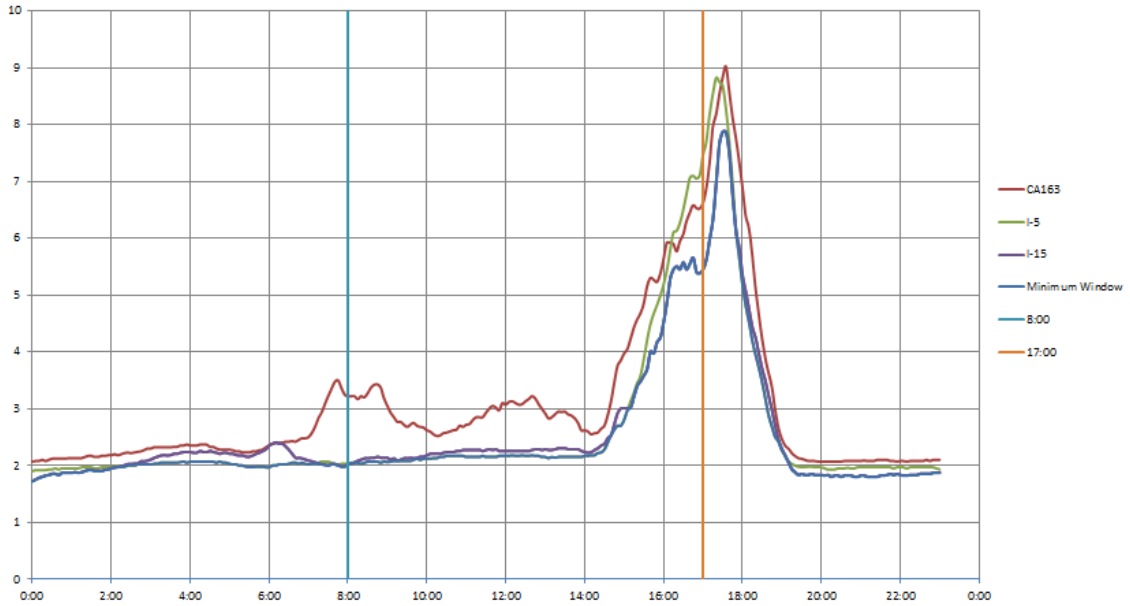


Exhibit D-75: Route Selection

Estimate a Delivery Window (FP2)

A user wants to see what the delivery window is for a departure time and route. This helps the trucking company find a window that minimizes the impact of traffic. It also helps with deliveries in rural areas a limited number of routes exist for an origin and destination.

Table D-43: Estimate a Delivery Window (FP2)

User	Trucking Company
Question	What delivery window should be promised?
Steps	1. Select the origin, destination, departure time, and route. 2. Decide what the on-time percentage is to be (i.e., probability of being neither late nor early). 3. Assemble TT-PDFs by time-of-day (and perhaps network operating condition) for the route. 3. Determine when the delivery window begins and ends given the on-time percentage.
Inputs	A database of TT-PDFs for truck travel times by time of day for the selected route under the network operating conditions of interest.
Result	The delivery window (begin to end) for the on-time percentage.

Step 1 involves the selecting the origin and destination. In this instance, the same origin and destination are used as those in Exhibit D-1 which shows the three routes in San

Diego. For departure times, 8:00 AM to 5: 00 PM are used without loss of generality inasmuch as these are typical working hours. For the route, CA 163 is selected.

Step 2 involves deciding what the on-time percentage is to be. In this use case, the 80% on-time window was selected consistent with the previous use case.

Step 4 involves determining when the delivery window begins and ends given the on-time percentage. Exhibit D-76 shows the travel times to the beginning and end of the on-time window for departures between 8:00 AM and 5:00 PM – marked with vertical lines. The exhibit indicates, for example, that if the truck were to leave at 8:00 AM, the smallest on-time window begins about 13 minutes later (at 8:13 AM) and ends about 16 minutes later (a little after 8:16 AM). The x-axis is the departure time and the y-axis shows the travel time.

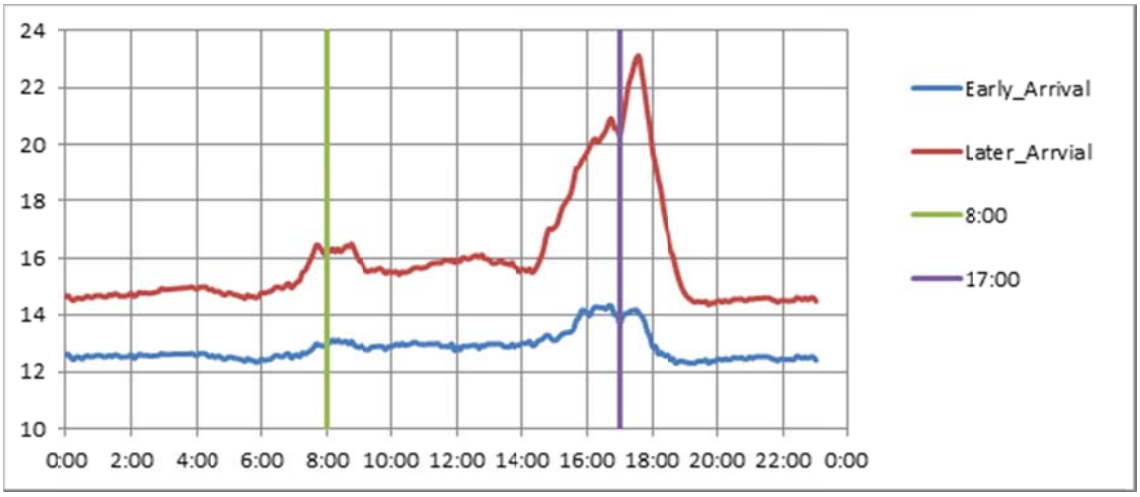


Exhibit D-76: Travel Times to the Beginning and End of the On-Time Window

As can be seen, the arrival times do not vary much and the travel time grows to above 20 minutes late in the afternoon. As can be seen, the departure times with the smallest on-time windows (the ones with the smallest difference between the starting and ending times) occur between 10:00 and 10:30.

It is helpful next to plot the length of the on-time window as a function of the departure time during the day – the difference between the red and blue lines in Exhibit D-76. This trend is presented in Exhibit D-77.

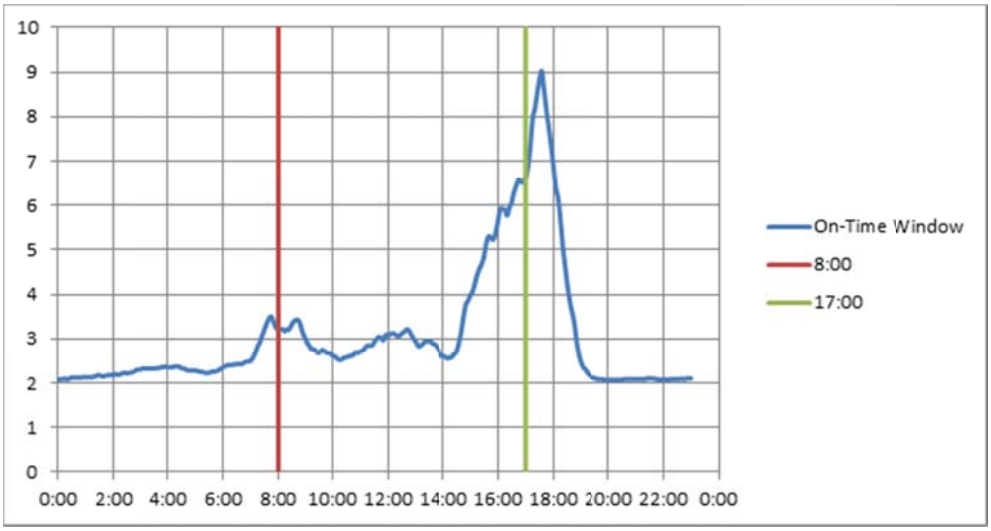


Exhibit D-77: Lengths of the On-Time Window as a function of the Departure Time

By reviewing the plot it is possible to see that the smallest on-time window occurs at 10:15 AM. Its width is technically 2.52 min.

Identify how to Maximize the Probability of an On-Time Delivery (FP3)

In this use case, the trucking company wants to know when a truck needs to leave and what route it should follow to maximize the probability of an on-time delivery. This is important for time-sensitive shipments.

Table D-44: Identify how to Maximize the Probability of an On-Time Delivery (FP3)

User	Trucking Company
Question	When should a truck leave and what route should it use to maximize the likelihood of an on-time delivery?
Steps	1. Select the origin and destination. 2. Define the on-time window (earliest to latest delivery time). 3. Assemble TT-PDFs by time-of-day and route (and perhaps network operating condition). 3. Find the route and departure time that maximizes the probability of arriving within the on-time window.
Inputs	A database of TT-PDFs for truck travel times by time of day and route under the network operating conditions of interest.
Result	When to leave and what route to use to maximize the probability of making an on-time delivery.

Step 1 involves selecting the origin and destination. In this case, the OD-pair shown in Exhibit D-1were used again, with the origin at point A and the destination at point B.

Step 2 is to define the on-time window, or the timeframe during which shipments are considered to be delivered on-time. The half hour from 4:00 PM to 4:30 PM was selected.

Step 3 involves assembling the TT-PDFs by time of day and route. The TT-PDFs mentioned in FP1 was used, for the CA 163 route under normal conditions.

Step 4 involves finding the route and departure time that maximizes the probability of arriving within the on-time window. The same Monte-Carlo simulation technique used in the traveler use cases was employed to generate individual vehicle travel times for each route. Exhibit D-78 shows the results. From the graph it can be seen that for all the three routes the departure times between 15:50 and 16:05 maximize the on-time percentage.

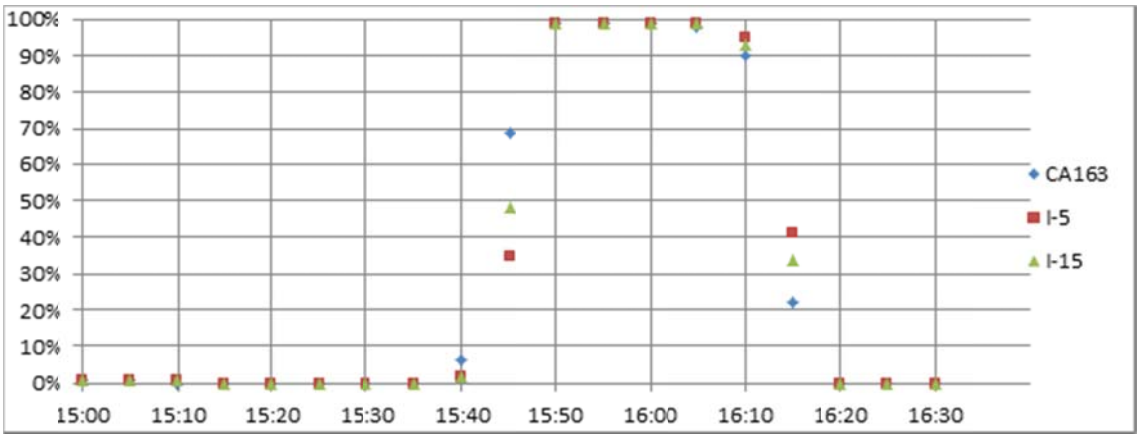


Exhibit D-78: Effects of the Departure Time on the On-Time Percentage

Assess the On-Time Probability for a Scheduled Shipment (FP4)

A user wants to obtain the probability of an on-time arrival based on a scheduled departure time, a desired delivery time, and route. This information helps the trucking company assess whether a proposed delivery schedule incorporates too much risk of not being on-time.

Table D-45: Assess the On-Time Probability for a Scheduled Shipment (FP4)

User	Trucking Company
Question	What on-time probability can be expected for a scheduled shipment?
Steps	1. Select the origin, destination, and scheduled departure and delivery times. 2. Define the on-time delivery window. 3. Assemble TT-PDFs by time-of-day and route (and perhaps network operating condition). 3. Identify the probability that the truck will arrive during the on-time delivery window.
Inputs	A database of TT-PDFs for truck travel times by time of day and route under the network operating conditions of interest.
Result	The probability of being on-time given the departure time and delivery time window.

Step 1 involves selecting the origin, destination, and scheduled departure and delivery times. In this case, the OD-pair shown in Exhibit D-1 were used again, with the origin at point A and the destination at point B.

Step 2 involves defining the on-time delivery window. In this case, the on-time delivery window was defined as being from 4:00 PM to 4:30 PM.

Step 3 involves assembling TT-PDFs by time-of-day and route. In this use case, Exhibit D-78 is used.

Step 4 involves identifying the probability that the truck will arrive during the on-time delivery window. From Exhibit D-78, the probability of being on-time can be seen for given departure times. When the departure times are between 15:00 and 16:20, the probability of being on time grows from 0 to almost 1 between 15:50-16:05 and then drops back to 0.

Assess the Impacts of Adverse Highway Conditions (FP5)

The trucking company wants to obtain information concerning the likelihood that a route will involve large delays (e.g., due to inclement weather). Knowing this will reduce the likelihood of severe delays. This information would help the company assess the likelihood of a given (rural) route being closed prior to the arrival of a truck, or during the passage of the truck along the route and, if necessary, identify alternative routes. The assessment is based on a combination of current weather forecasts, current road conditions, and historical experience.

Table D-46: Assess the Impacts of Adverse Highway Conditions (FP5)

User	Trucking Company
Question	What is the likelihood that a route will involve large delays?
Steps	1. Select the origin, destination and route of interest. 2. Assemble TT-PDFs for the route and time frames during which the trips will take place. 3. Analyze the TT-CDFs to identify the likelihood that the trips will take more than various amounts of time. 4. Determine how long the trips might take and probabilities of those times.
Inputs	A database of TT-PDFs for truck trips on the route of interest during the seasons (time frames) of interest.
Result	The probability that the trip might take as long as or longer than specific amounts of time.

Step 1 involves the selecting the origin, destination and route of interest. In this case, the OD-pair shown in Exhibit D-1 were used again, with the origin at point A and the destination at point B. The route of interest is CA163.

Step 2 involves assembling TT-PDFs for the route and time frames during which the trips would take place. The TT-PDFs for the CA-163 route employed in FP1 can again be used.

Step 3 involves analyzing the TT-CDFs to identify the likelihood that the trips will take more than various amounts of time. In this case, a comparison will be made of the effects on travel time of events such as special events, incidents, weather events, and high demand.

Step 4 involves determining how long the trips might take and probabilities that those times might materialize.

Exhibit D-79 shows the travel times for CA163 under different conditions. For this route, the minimum travel time is 15.43 min and the corresponding departure time is 10:15 AM. From

Exhibit D-79 it can be seen that the biggest impact at 10:15 is special event and the travel time will grow to 21.68 min.

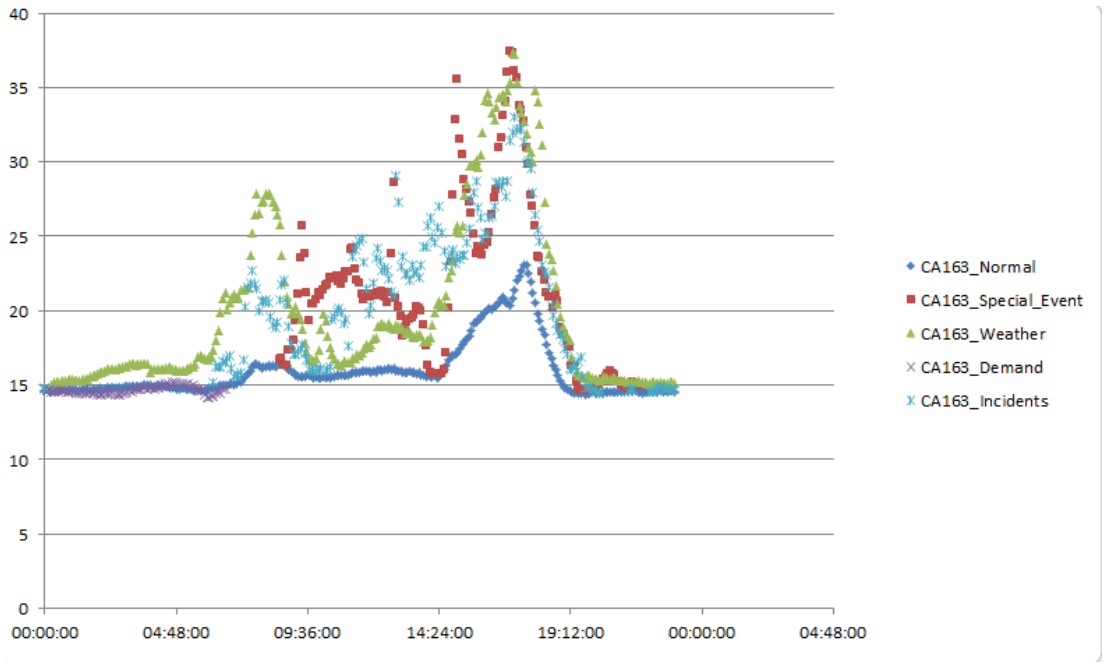


Exhibit D-79: Travel Times for CA 163

Determine the Start Time for a Delivery Route (FP6)

This use case focuses on a truck that is making multiple deliveries. The truck follows a tour from the depot to the delivery locations and back to the depot. The objective is to determine when the tour should start, or how much schedule slack (extra time) should be provided, to maximize the probability that the deliveries will all be made on-time. If the travel times and unloading times are all fixed, then no slack is needed; but if either or both are variable, as they most often are, then extra time is needed. The objective is to determine when the tour should start and what the delivery times should be so that it is most likely that all the deliveries will occur within their delivery windows. In the literature, this is referred to as the stochastic vehicle routing problem. For this use case, the important piece of information is the schedule slack. The length of the tour and the return time to the depot are ignored. (Sometimes it is not possible to do this.)

Table D-47: Determine the Start Time for a Delivery Route (FP6)

User	Trucking Company
Question	When should the truck leave – how much schedule slack should be provided – to maximize the likelihood that all of the deliveries in a tour will be on-time?
Steps	1. Select the tour (delivery route) of interest. 2. Establish the on-time windows for the destinations. 3. For every i to j pair of nodes in the tour, assemble TT-PDFs for t_{ij} for every reasonable departure time from i – i.e., either the depot or the previous delivery location. 4. For each possible departure time from the depot use the t_{ij} TT-PDFs to develop PDFs for the deliveries at each of the destinations. (This assumes the time spent making delivery is fixed.) 5. Find the departure time that maximizes the smallest of these on-time delivery probabilities or some weighted combination of them.
Inputs	A database of TT-PDFs for truck trips on the links between the delivery nodes for every reasonable departure time from the "from" node.
Result	The extra time at the beginning of the trip needed to maximize the probability that the deliveries are made on-time.

Find the Departure Time and Routing for a Set of Deliveries (FP7)

A trucking company wants to plan the schedule for a delivery route (tour) that has both flexible and inflexible deliveries. The objective is to devise a plan that minimizes cost yet ensures on-time arrival for those deliveries requiring it. This can help LTL and package delivery carriers set schedules and routings for a series of deliveries with varying degrees of flexibility. As with FP6, some of the deliveries have specific on-time windows; the others do not. Sequencing is an issue for the deliveries that do not. In the classic literature this is referred to as the stochastic vehicle routing problem with some on-time windows.

Table D-48: Find the Departure Time and Routing for a Set of Deliveries (FP7)

User	Trucking Company
Question	When does a truck need to leave and in what sequence should it make its deliveries to maximize its on-time delivery performance?
Steps	1. Select the locations to which deliveries need to be made. 2. Specify the on-time windows for those that have them. 3. Assemble TT-PDFs for all the non-stop paths between the places to be visited (because the sequence is unknown). If the TT-PDFs are time-dependent, then assemble TT-PDFs by departure time. 3. Solve the stochastic vehicle routing problem with partial on-time windows.
Inputs	A database of truck TT-PDFs for non-stop paths between the delivery locations, differentiated by departure time if necessary.
Result	A tour that that maximizes the probability that the time-constrained deliveries occur within their on-time windows. Also, for each delivery node, the range of delivery times to be expected.

Solve the Multiple Vehicle Routing Problem under Uncertainty (FP8)

A user wants to create a set of routes (tours) for pick-ups and deliveries that minimizes the number of drivers required, while ensuring that the drivers return to the depot no later than a set time. The earliest time the trucks can leave and the latest they can return are both constrained. It extends FP7 to multiple trucks and imposes a return time. Parcel delivery companies solve this problem every day. They determine how many trucks are needed, and what packages go on what trucks, so that the drivers return within the allowed time. This analysis helps parcel carriers create routes that use their drivers and vehicles as efficiently as possible, while avoiding potential costs (e.g., overtime).

Table D-49: Solve the Multiple Vehicle Routing Problem under Uncertainty (FP8)

User	Trucking Company
Question	How many trucks and drivers are needed to make a set of deliveries, what departure times should be used and how should the trucks be routed to maximize on-time deliveries and pick-ups?
Steps	1. Select the locations for pick-ups and deliveries. 2. Identify the on-time windows for those that have them. 3. Assemble TT-PDFs for the paths between the places to be visited. If the TT-PDFs for the paths vary by time-of-day, then assemble TT-PDFs for each departure time for each path. 3. Solve the stochastic multiple vehicle routing problem.
Inputs	A database of TT-PDFs for truck trips on paths between the locations to be visited (including the depot), differentiated by departure time where

	necessary.
Result	A set of tours (pick-up and delivery sequences) that minimizes the number of trucks and drivers required while maximizing the on-time delivery percentages and complying with the maximum allowed return. Also, for each destination, the range of pick-up or delivery times to be expected.

Alter Delivery Schedules in Real-Time (FP9)

In this use case, the trucking company needs to alter the delivery schedules for one or more trucks in real time due to some type of unexpected event. An incident on a freeway might have created severe delays on one or more of the paths the trucks were planning to use. The trucking company would note the estimated severity of the incident, identify which delivery vehicles are affected (based on their present positions and deliveries yet to be made), and generate new tours for each to minimize the impact of the incident on the on-time delivery likelihoods. This analysis is particularly helpful to parcel carriers that would have to revise their tours due to unexpected sources of delay that occur on the roadway system while deliveries are in progress.

Table D-50: Alter Delivery Schedules in Real-Time (FP9)

User	Trucking Company
Question	How should the existing multi-vehicle delivery schedule be altered because of a disruption in the network?
Steps	1. Identify the locations to which deliveries need to be made for each vehicle. 2. Identify those vehicles that are affected by the disruption. 2. Re-affirm the on-time windows for each remaining delivery. 3. Update the TT-PDFs for the paths between the places to be visited based on the network disruption. If the paths and TT-PDFs are time-dependent, then differentiate by departure time. 3. Solve the stochastic vehicle routing problem for the remaining delivery locations based on the updated TT-PDFs.
Inputs	Updated TT-PDFs for truck trips on paths from one location to another, differentiated by departure time if necessary.
Result	A new delivery schedule that maximizes the on-time probabilities. Also, for each destination, the range of delivery times to be expected.

Freight Customers

The following use cases demonstrate monitoring system functionalities that are helpful for freight customers.

Minimize Shipping Costs due to Unreliability (FC1)

A user wants to ship packages from an origin to a destination with minimum costs due to unreliability. That means there is a cost for being early and late, akin to a utility function. The analysis helps customers identify the shipping methods that will meet their specifications at the lowest cost.

Table D-51: Minimize Shipping Costs due to Unreliability (FC1)

User	Freight Customer
Question	How can the shipping costs due to unreliability be minimized?
Steps	1. Select the origin and destination. 2. Assemble costs and the PDFs for travel times for various shipping options. 3. Identify the costs of being early and late by certain amounts. 4. Compute the expected cost of each option based on its TT-PDF.
Inputs	A database of TT-PDFs for various shipping options and the costs of being early and late by certain amounts.
Result	The shipping option with the lowest cost due to unreliability.

Step 1 involves selecting the origin and destination. In this use case, we assume an origin and destination between which there are four routes for delivery options.

Step 2 involves assembling costs and the PDFs for travel times for various shipping options. In this use case, we assume 4 routes of which each route has a specific travel time distribution for delivery options. The assumed on-time window is 100 minutes to 110 minutes.

Exhibit D-80 shows the CDFs for travel times for the four routes.

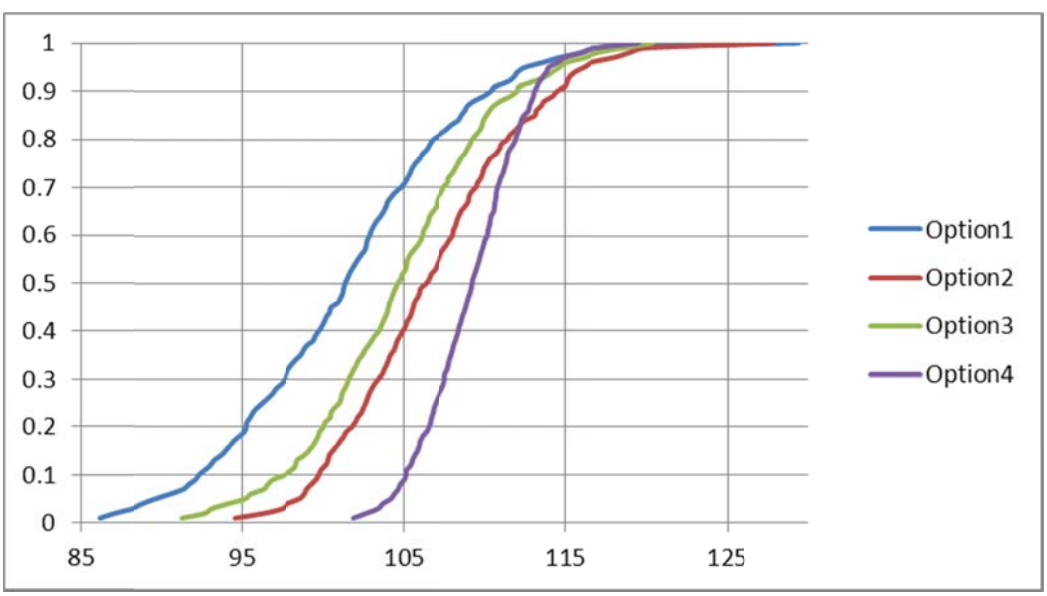


Exhibit D-80: Arrival Travel Times for four routes

From

Exhibit D-80, we can perceive that the four options have different minimum travel time but do not vary much. In this step, we need to calculate the cost for traveling as well as the cost for being early or late. Therefore, we need to get the travel time for the whole trip including arrivals and returns. We use the same method as getting the arrival travel times to get the total travel times for four routes.

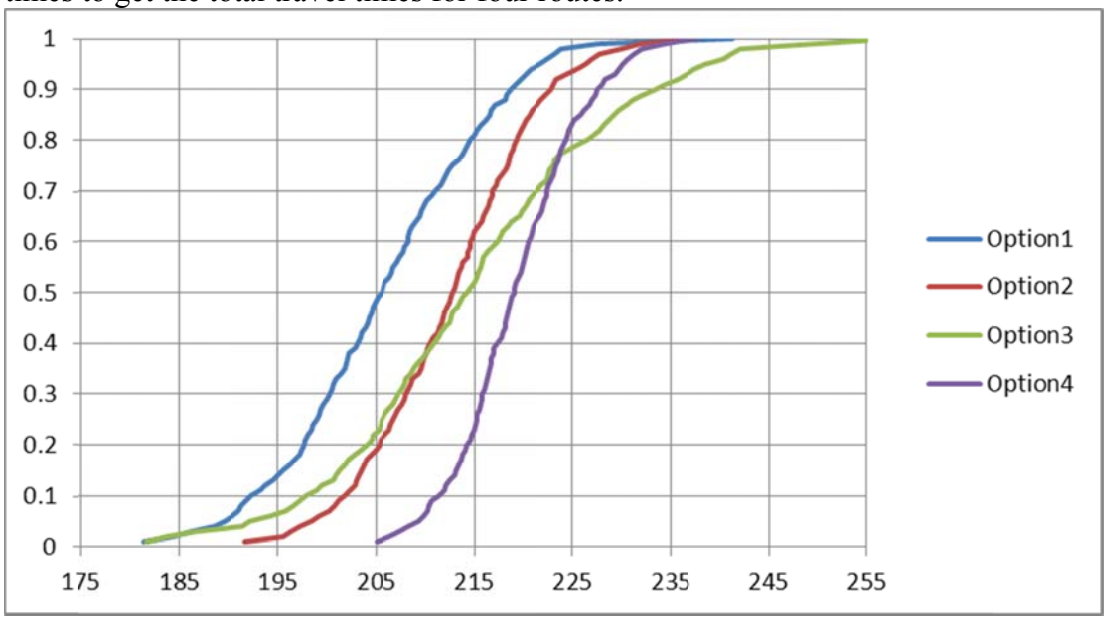


Exhibit D-81 shows the total travel times for four options.

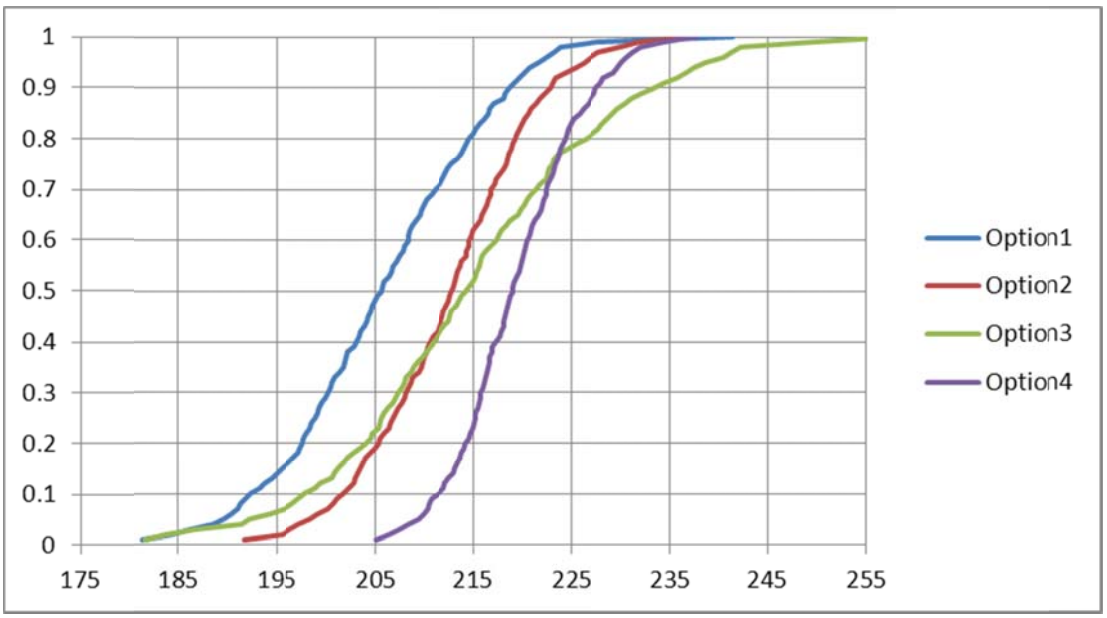


Exhibit D-81: Total Travel Times for Four Routes

To get the cost for total travel time, we assume that the rate is 0.01$/minute.

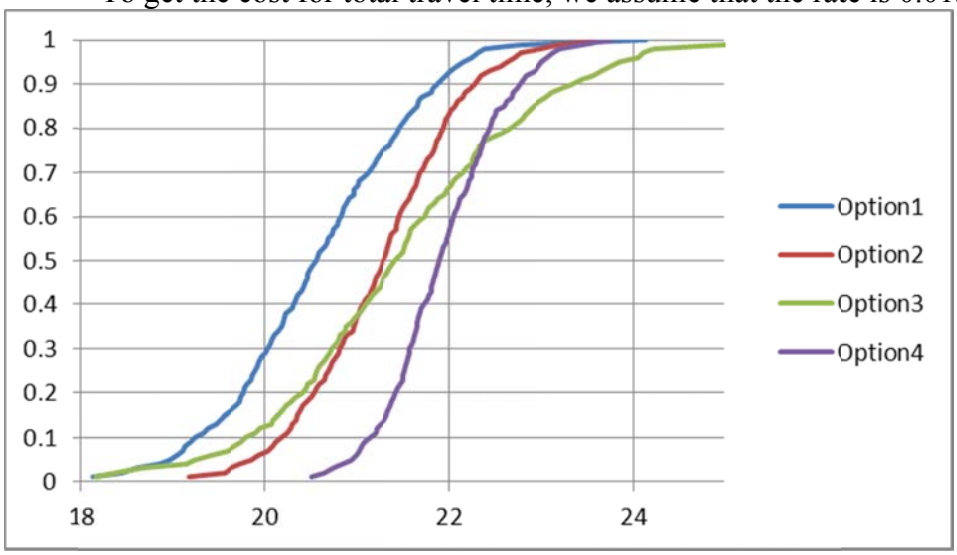


Exhibit D-82 shows the cost for total travel time.

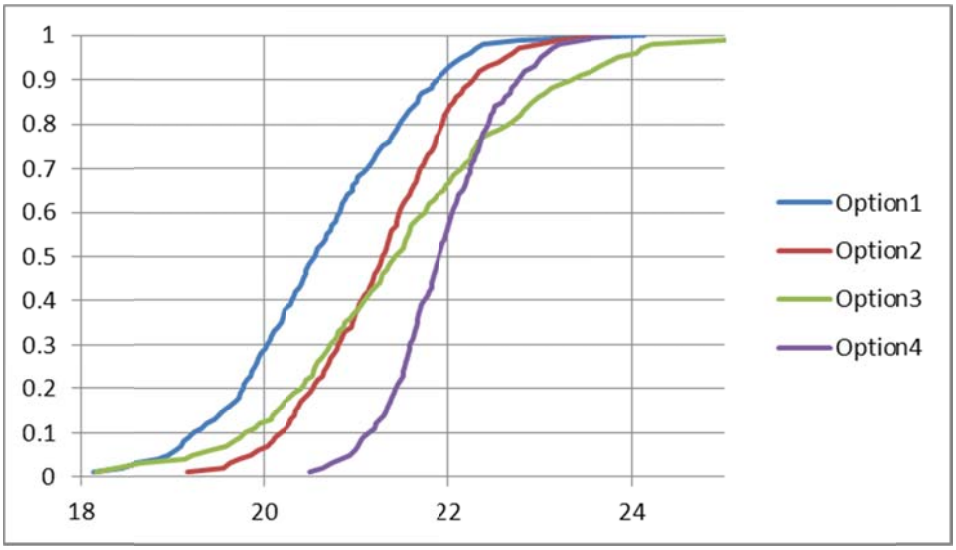


Exhibit D-82: Cost For Total Travel Time

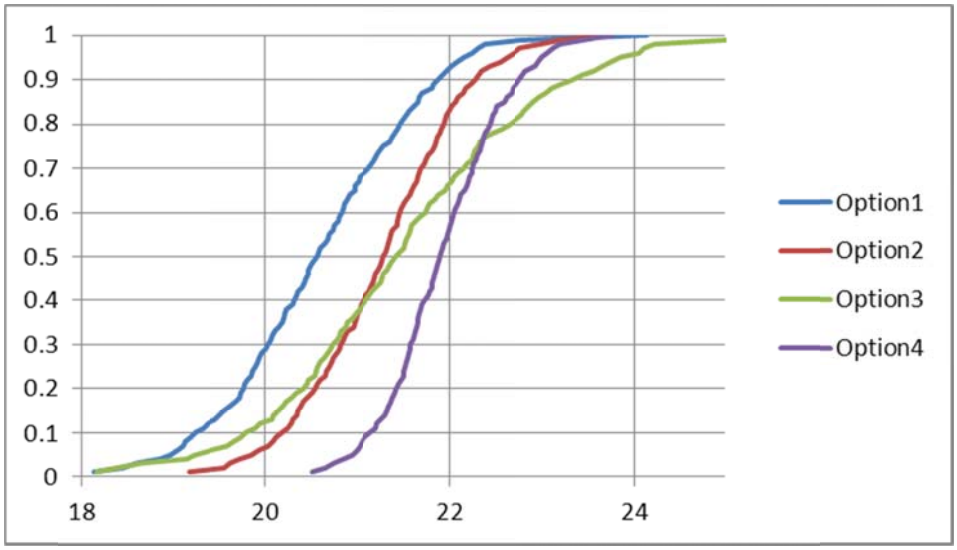
From 

Exhibit D-82, we know that the cost for travel time is consistent with total travel time. Options with less travel time have less travel time cost.

Step 3 involves identifying the costs of being early and late by certain amounts. In regard to the arrival travel time, we assume the on-time window is from 100 minutes to 110 minutes. The penalty rate for being early is $1/minute while the penalty rate for being late is $2/minute.

Exhibit D-83 shows the cost for penalties of the four options.

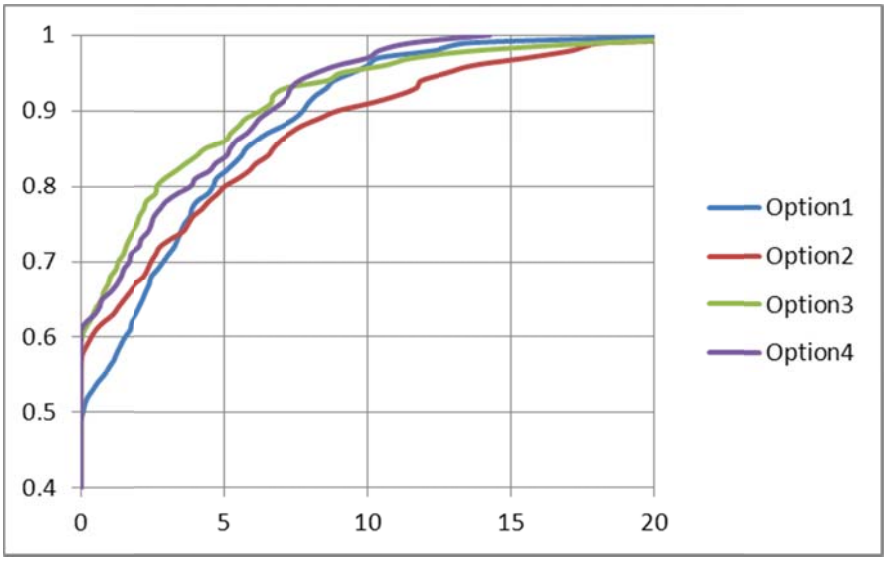


Exhibit D-83: Cost for On-Time Penalty

Exhibit D-83 shows that for almost 93% probability, option 3 is the best option among the 4 options while option 4 is the best option when probability is larger than 93%.

Step 4 involves computing the expected cost of each option based on its TT-PDF. We calculate the cost for the whole trip including the penalty rate for being late or early as

well as arrival travel time and return travel time. Exhibit D-84 shows the cumulative distribution function.

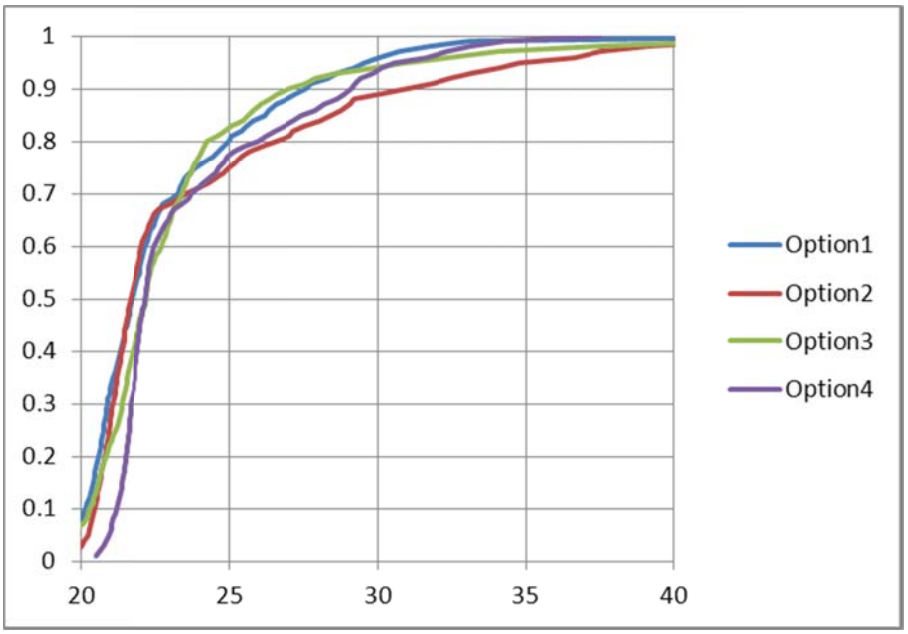


Exhibit D-84: Cost for the Whole Trip(Travel Time and Penalty)

From Exhibit D-84, we can perceive that when probability is below 40%, the best option is option 4.When probability is greater than 40% and smaller than 70%, the best option is option 2 while the best option is option 3 when probability is 75% to 95%. When probability is near 100%, either option 4 or 1 is good to choose.

Determine Storage Space for Just-in-Time Deliveries (FC2)

A user wishes to set up a just-in-time delivery system and wants to know how much storage space is needed at the receiving location. Because shipments may arrive late, some stock needs to be carried in inventory; and since shipments may be early, some storage space for those arrivals needs to be provided. This information helps size the facility.

Table D-52: Determine Storage Space for Just-in-Time Deliveries (FC2)

User	Freight Customer
Question	How much storage space is needed given the reliability of deliveries for a just-in-time manufacturing facility?
Steps	1. Select the manufacturing facility of interest. 2. Assemble PDFs for the deviations from intended delivery times. Separate this out by shipment size and by origin if there are different reliabilities. 3. Determine a tolerable stock-out probability. 4. Build a Monte Carlo model of the storage facility given the PDFs for delivery time deviations and determine how large the on-site storage needs to be to ensure that the stock-out probability is met.
Inputs	A database of PDFs for deviations from intended delivery times separated out by shipment sizes and origin.
Result	A three-dimensional tradeoff surface between travel time, on-time performance, and shipping cost. Given weights among these three, the optimal shipping option can be selected.

Find the Lowest Cost Reliable Origin (FC3)

A user needs items shipped to a location by a specified time, while minimizing shipping costs. This use case is similar to FC1 but more than one origin is possible. This information helps a customer assess the tradeoff between cost and delivery reliability.

Table D-53: Find the Lowest Cost Reliable Origin (FC3)

User	Freight Customer
Question	What origin provides the most reliable deliveries at an acceptable cost?
Steps	1. Select the destination of interest and the possible origins. 2. Define reliable delivery (e.g., percent within the on-time window). 3. Define two cost functions – one related to travel time and the other related to whether the shipment is early or late. 4. Assemble TT-PDFs as well as PDFs for the deviations from intended delivery times by origin. 6. Select the origin that has the best CDF for cost.
Inputs	A database of PDFs for travel times an deviations from intended delivery times by origin.
Result	The origin with the best CDF in terms of cost.

Find the Warehouse Site with the Best Distribution Reliability (FC4)

A user wants to site a distribution center so that it maximizes delivery reliability to the destinations it serves. Several sites are possible. The number of truck trips to each location served is important because the best choice needs to account for the trip frequency. The times of day are also important because the travel time reliability varies depending on when the deliveries take place.

Table D-54: Find the Warehouse Site with the Best Distribution Reliability (FC4)

User	Freight Customer
Question	What warehouse location has the best delivery reliability?
Steps	1. Select the possible warehouse sites, the destinations to be served, the number of truck trips per week to those destinations, and the times when the deliveries would take place. 2. Assemble TT-PDFs for trips from the warehouse sites to the destinations for the times when the deliveries would take place. 3. Identify the warehouse site that maximizes the likelihood that trucks will be on-time in reaching the destinations.
Inputs	A database of TT-PDFs for truck trips from the warehouse sites to the destinations for the times when the deliveries would take place.
Result	A rank ordering of the warehouse sites based on the truck-trip-weighted reliability of reaching the destinations on-time.

REFERENCES

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2) Daniel Boyle, John Pappas, Phillip Boyle, Bonnie Nelson, David Sharfarz, and Howard Benn. *TCRP Report 135: Controlling System Costs: Basic and Advanced Scheduling Manuals and Contemporary Issues in Transit Scheduling.* Transportation Research Board of the National Academies, Washington, D.C., 2009.