# Application of Travel Time Data and Statistics to Travel Time Reliability Analyses 

Handbook and Support Materials

July 2023

## FOREWORD

Over the past decade, the collection and dissemination of travel time data and summary statistics have grown exponentially. The increased availability of these data has led to the adoption of new monitoring and measuring activities by States and metropolitan planning organizations to evaluate the performance of the transportation system. Travel time data is available in numerous forms. This report provides a guide and supporting material for working with these data in the development of travel time reliability performance assessment and reporting.

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| SI* MODERN METRIC) CONVERSION FACTORS |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| APPROXIMATE CONVERSIONS TO SI UNITS |  |  |  |  |
| Symbol | When You Know | Multiply By | To Find | Symbol |
| LENGTH |  |  |  |  |
| in | inches | 25.4 | millimeters | mm |
| ft | feet | 0.305 | meters | m |
| yd | yards | 0.914 | meters | m |
| mi | miles | 1.61 | kilometers | km |
| AREA |  |  |  |  |
| $\mathrm{in}^{2}$ | square inches | 645.2 | square millimeters | $\mathrm{mm}^{2}$ |
| $\mathrm{ft}^{2}$ | square feet | 0.093 | square meters | $\mathrm{m}^{2}$ |
| $\mathrm{yd}^{2}$ | square yard | 0.836 | square meters | $\mathrm{m}^{2}$ |
| ac | acres | 0.405 | hectares | ha |
| $\mathrm{mi}^{2}$ | square miles | 2.59 | square kilometers | km ${ }^{2}$ |
|  |  | VOLUME |  |  |
| fl oz | fluid ounces | 29.57 | milliliters | mL |
| gal | gallons | 3.785 | liters | L |
| $\mathrm{ft}^{3}$ | cubic feet | 0.028 | cubic meters | $\mathrm{m}^{3}$ |
| $y^{3}{ }^{3}$ | cubic yards | 0.765 | cubic meters | $\mathrm{m}^{3}$ |
| NOTE: volumes greater than 1,000 L shall be shown in $\mathrm{m}^{3}$ |  |  |  |  |
| MASS |  |  |  |  |
| oz | ounces | 28.35 | grams | g |
| lb | pounds | 0.454 | kilograms | kg |
| T | short tons (2,000 lb) | 0.907 | megagrams (or "metric ton") | Mg (or "t") |
| TEMPERATURE (exact degrees) |  |  |  |  |
| ${ }^{\circ} \mathrm{F}$ | Fahrenheit | $\begin{gathered} 5(\mathrm{~F}-32) / 9 \\ \text { or }(\mathrm{F}-32) / 1.8 \end{gathered}$ | Celsius | ${ }^{\circ} \mathrm{C}$ |
| ILLUMINATION |  |  |  |  |
| fc | foot-candles | 10.76 | lux | 1 x |
| fl | foot-Lamberts | 3.426 | candela/m ${ }^{2}$ | $\mathrm{cd} / \mathrm{m}^{2}$ |
| FORCE and PRESSURE or STRESS |  |  |  |  |
| Ibf | poundforce | 4.45 | newtons | N |
| $\mathrm{lbf} / \mathrm{in}^{2}$ | poundforce per square inch | 6.89 | kilopascals | kPa |
| APPROXIMATE CONVERSIONS FROM SIUNITS |  |  |  |  |
| Symbol | When You Know | Multiply By | To Find | Symbol |
| LENGTH |  |  |  |  |
| mm | millimeters | 0.039 | inches | in |
| m | meters | 3.28 | feet | ft |
| m | meters | 1.09 | yards | yd |
| km | kilometers | 0.621 | miles | mi |
| AREA |  |  |  |  |
| $\mathrm{mm}^{2}$ | square millimeters | 0.0016 | square inches | $i n^{2}$ |
| $\mathrm{m}^{2}$ | square meters | 10.764 | square feet | $\mathrm{ft}^{2}$ |
| $\mathrm{m}^{2}$ | square meters | 1.195 | square yards | $\mathrm{yd}^{2}$ |
| ha | hectares | 2.47 | acres | ac |
| $\mathrm{km}^{2}$ | square kilometers | 0.386 | square miles | $\mathrm{mi}^{2}$ |
| VOLUME |  |  |  |  |
| mL | milliliters | 0.034 | fluid ounces | fl oz |
| L | liters | 0.264 | gallons | gal |
| $\mathrm{m}^{3}$ | cubic meters | 35.314 | cubic feet | $\mathrm{ft}^{3}$ |
| $\mathrm{m}^{3}$ | cubic meters | 1.307 | cubic yards | $\mathrm{yd}^{3}$ |
| MASS |  |  |  |  |
| g | grams | 0.035 | ounces | oz |
| kg | kilograms | 2.202 | pounds | lb |
| Mg (or "t") | megagrams (or "metric ton") | 1.103 | short tons (2,000 lb) | T |
| TEMPERATURE (exact degrees) |  |  |  |  |
| ${ }^{\circ} \mathrm{C}$ | Celsius | 1.8C+32 | Fahrenheit | ${ }^{\circ} \mathrm{F}$ |
| ILLUMINATION |  |  |  |  |
| 1 x | lux | 0.0929 | foot-candles | fc |
| $\mathrm{cd} / \mathrm{m}^{2}$ | candela/m2 | 0.2919 | foot-Lamberts | $f 1$ |
| FORCE and PRESSURE or STRESS |  |  |  |  |
| N | newtons | 2.225 | poundforce | Ibf |
| kPa | kilopascals | 0.145 | poundforce per square inch | lbf/in ${ }^{2}$ |

[^0]
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## LIST OF ACRONYMS

| ASD | aftermarket safety device |
| :--- | :--- |
| BSM | basic safety message |
| Caltrans | California Department of Transportation |
| ELPR | electronic license plate reader |
| FHWA | Federal Highway Administration <br> geographic information system |
| GIS | Global Positioning System |
| GPS | Highway Capacity Manual |
| HCM | identification |
| ID | level of service |
| LOS | level of travel time reliability |
| LOTTR | media access control |
| MAC | mean absolute deviation |
| MAD | measure of effectiveness |
| MOE | mean travel time index |
| MTTI | National Cooperative Highway Research Program |
| NCHRP | National Performance Management Research Data Set |
| NPMRDS | performance measurement system |
| PeMS | third performance management rule |
| PM3 | planning time index |
| PTI | quality control |
| QC | roadside unit |
| RSU | Second Strategic Highway Research Program |
| SHRP 2 | State route |
| SR | traffic message channel |
| TMC | travel time index |
| TTI | median travel time index |
| TTI50 | 80th percentile travel time index |
| TTI80 | vehicle-hours traveled |
| VHT | vehicle-miles traveled |
| VMT |  |

## CHAPTER 1. INTRODUCTION

## TASK PURPOSE

The purpose of this work is to provide a handbook for the application of travel time data to travel time reliability analyses. The handbook covers several topics including:

- Data sources for reliability
- Data processing methods for reliability
- Reliability measure creation and comparison, highlighting differences and similarities in the use of data from different sources

The intent of the handbook is twofold:

1. To provide practitioners with the ability to understand the differences in reliability measures derived from the different data sources
2. To document the steps needed to turn high-resolution travel time data into reliability performance measures

## ISSUES SURROUNDING RELIABILTY

Defining reliability up to this point has largely been a technical exercise aimed at practitioners and researchers. For example, in the original Future Strategic Highway Research Program, reliability was defined as: "...how travel times vary over time (e.g., hour-to-hour, day-to-day)." ${ }^{1}$ This definition has persisted and formed the basis for developing reliability performance measures and analytical methods. From an analyst's perspective, reliability is often depicted as a travel time distribution to convey variability, such as is shown in figure 1. Additional measures that describe the size and shape of the travel time distribution such as the semistandard deviation also have been used. Essentially, reliability is just a characteristic of overall congestion rather than a distinct phenomenon-how congestion varies over time.

It is generally acknowledged that the travel time distribution is used to measure reliability, but how is travel time itself defined? Travel time is measured in a variety of ways with a variety of different data (direct, indirect, and purely synthetic) and all of these methods have been used to calculate reliability. There has been almost no resource material describing these various data and methods and the implications they have on the values of reliability measures. The specific issues dealt with in this project are described below.

[^1]

Source: Transportation Research Board, National Academy of Sciences.
Figure 1. Graph. Example travel time distribution and associated reliability measures. ${ }^{2}$

## Trip-Based Travel Time Reliability

Because of the nature of the data that have been available, nearly all reliability reporting is based on the facility perspective. The data measurements used relate to the performance of a facility, not an end-to-end trip as made by travelers. Trip performance can be synthesized from facility-based data using the virtual probe method ${ }^{3}$, but how well this method represents actual vehicle travel times has not been determined.

A comprehensive mobility measurement program will involve using both trip- and facility-based measures because they both inform analysis about the nature of mobility in a region:

- Many transportation investments are focused on improving and managing facilities, so facility-based measures are highly useful to planners and engineers. This focus is particularly true for operations and capacity improvements as well as some types of demand management.

[^2]- Other transportation investments-as well as land-use and development policies-are more oriented to the entire trip-making process, so understanding trip performance informs us about our customers' (i.e., travelers) transportation system experience.
- Emerging operations strategies-such as active transportation and demand management and integrated facility management-also need to consider the entire trip-making process.

Data from vendors are now becoming available that allow trip-based measures to be developed; these data track the location and time of individual vehicles and are described throughout this handbook. However, trip-based reliability measurement poses its own challenges. Facility measurement describes the nature of congestion to which travelers are exposed. When using these data, analysts are left to decide the origin and destination of a trip. Trip measurement includes factors in addition to congestion exposure-how travelers interact with the entire landscape. Regarding trips, travelers are generally free to change departure times and routes and, in some cases, destinations and modes as well. In this project, the research team fixed the origins and destinations to compare trajectory data to facility-based data.

Over time, however, trip purposes and destinations change, resulting in multiple definitions of what a "trip" is even though it may be measured with the same measure. For example, a work trip could have the same start time and route as well as exclusively use a car every day. Alternately, these factors could vary to different degrees. Measuring a true trip from the traveler's perspective entails measuring a variety of factors, many of which are beyond the control of transportation agencies. Finally, measuring trip performance can be viewed as how participants (travelers and businesses) adapt to the landscape. This adaptation no doubt includes congestion avoidance (e.g., selecting origins and destinations to minimize congestion exposure) and associated costs, which are not captured in trip-based measures.

## Standard Processing Procedures

Standard processing procedures for calculating performance measures from high-resolution data do not exist. Analysts use different methods for performing quality control (QC), imputation/handling of missing data, aggregating data, and computing measures, resulting in different values for performance measures created from the same data.

Because little detailed data collected under rigorous controls exist for comparison, QC procedures for travel time data are primitive. For freeway detectors, where volumes and speed measurements exist, checks can be made against traffic flow parameters but deciding how far astray a value should be before it is considered erroneous is problematic. For vehicle probe data, the situation is even more restrictive. Cross-checking travel time data against disruption data (i.e., weather, incidents, and work zones) would be a way of verifying that low speeds are legitimate, but this project did not deal with data from these other data sources.

## CHAPTER 2. DATA SOURCES FOR RELIABILITY

This section documents the data sources and collection methods for producing travel time values. These values are the basis for developing the travel time distribution from which reliability measures are derived. The discussion in this section focuses mainly on emerging data sources, especially the trajectory data now available from travel time vendors. The state of the practice is limited in many respects primarily because, up to only recently, most of the continuously collected data that have been available do not represent true travel times as measured by vehicle movement.

## FREEWAY DETECTORS

Freeway detectors have been a source of speed data for several decades.

- Sensor: A variety of collection methods exist, including inductive loops, microwave radar, active infrared, passive infrared, acoustic array, and video image processing.
- Spatial attribute: Point
- Temporal attribute: Continuous
- Measurement type: Instantaneous- measurements are aggregated in the field at 20-second intervals.
- Direct data measurements: All of the sensors can produce volume, lane occupancy on a lane-by-lane basis at specific points. Inductive loop, microwave radar, active infrared, and video image-processing sensors also can provide vehicle classification, though some sensor types (e.g., radar) only provide length-based classifications rather than the Federal Highway Administration (FHWA) Traffic Monitoring Guide's 13-class scheme. ${ }^{4}$
- Indirect measurements derived from data: Speed, travel time
- QC methods: Sensor outages or other events could result in missing or erroneous data at various dates and times. Active infrared, passive infrared, and video image-processing performance is affected by inclement weather, such as heavy rain, snow, and dense fog. Likewise, depending on placement and configuration, low-speed traffic movement can influence radar measurements.

The American Association of State Highway and Transportation Officials (AASHTO) Guidelines for Traffic Data Programs ${ }^{5}$ recommends that the QC process includes one or more of the following actions:

[^3]- Reviewing the traffic data format and basic internal consistency
- Comparing traffic data values to specified validation criteria
- Marking or flagging traffic data values that do not meet the validation criteria
- Reviewing marked or flagged traffic data values for final resolution
- Imputed marked, flagged, or missing traffic data values with best estimates (while still retaining original data values and labeling imputed values as estimates)

Common validation criteria for freeway detector data include the following:

- Univariate and multivariate range checks-Involves validating data against an expected minimum, maximum, or range of expected values for a single variable (e.g., volume, occupancy, or speed) or a combination of variables (e.g., maximum consecutive identical volume, occupancy, and speed values, combinatory checks)
- Spatial and temporal consistency-Involves validating the consistency of data compared to adjacent locations (either across lanes or upstream and downstream monitoring locations) or previous periods
- Detailed diagnostics-Involves validating individual vehicle data at a detector location using detailed diagnostic tests, such as individual vehicle velocity versus moving median velocity and headway versus on-time feasible range of vehicle lengths. These criteria entail detailed diagnostic data from traffic detectors that are typically not available from archived data sources

Turner recommended the following validity criteria for detector data (table 1) in the report titled, "Quality Control Procedures for Archived Operations Traffic Data: Synthesis of Practice and Recommendations." ${ }^{6}$ Turner also recommended the following practices:

- Recognize that validity criteria are only one part of a comprehensive quality assurance process that does more than just discard suspect data that already have been collected.
- Provide metadata to document QC procedures and results.
- Provide metadata to document historical traffic sensor status and configuration.
- Use database flags or codes to indicate failed validity criteria.
- Implement, at a minimum, a basic foundation for data validity criteria (table 1 ).
- Further develop other spatial and temporal consistency criteria for detector data.
- Use, when feasible, visual review to supplement the automated validity criteria.
- Processing procedures: Travel times between detectors are assumed based on spot speeds.

[^4]Table 1. Validity criteria for freeway detector data. ${ }^{7}$

| Validity Criteria | Default Parameters |
| :---: | :---: |
| Prescreening criteria | - |
| Controller error codes (e.g., $-1,255$, etc.) | N/A |
| Check consistency of elapsed time and poll cycles | N/A |
| Check for duplicate records (location ID, date, time identical) | N/A |
| If volume $=$ occupancy $=$ speed $=0$, then set speed $=$ missing/null (no vehicles present) | N/A |
| Univariate range criteria | - |
| Minimum volume | Zero vehicles |
| Maximum volume | 3,000 vehicles per hour per lane (adjust for appropriate time interval) |
| Minimum occupancy | 0 percent |
| Maximum occupancy | 100 percent |
| Minimum speed | 0 mph |
| Maximum speed | 100 mph |
| Multivariate logical consistency | - |
| Maximum consecutive identical volume and occupancy and speed values (including volume $=$ occupancy $=$ speed $=0$ ) | Number of reporting intervals that corresponds to 30 consecutive minutes (maximum) with no vehicles detected |
| If volume $>0$ and speed $=0$ then invalid | N/A |
| If volume $=0$ and speed $>0$ then invalid | N/A |
| If volume $=$ speed $=0$ and occupancy $>0$ then invalid | N/A |
| If occupancy $=0$ and volume $>$ volume $_{\text {max }}$ (based on maximum possible volume when occupancy value is truncate to 0 ) | ```\mp@subsup{Volume }{\mathrm{ max }}{=} (2.932\timesSPEED }\times\mathrm{ ELAPSED_TIME)/600``` |

-no data; $\mathrm{N} / \mathrm{A}=$ not applicable; $\mathrm{ID}=$ identification.
The lane-by-lane detector volumes and spot speeds are translated into station-, link-, and facility-level statistics using the following steps: ${ }^{8}$

- Freeway detector data is aggregated in the field to 20 - or 30 -second averages (speeds and lane occupancies) and sums (volumes). These are usually further aggregated to 5-minute intervals.

[^5]- For each 5-minute interval, the lane-by-lane data at each detector location are combined into a station across all lanes in a direction. The traffic volume is summed across all lanes, while a weighted average speed is calculated based on traffic volume in each lane. The weighted average speeds represent the time-mean speeds at a specific station.
- The 5-minute station data are expanded to links by assuming that each detector has a zone of influence equal to half the distance to the detectors immediately upstream and downstream from it. The measured speeds and volumes are assumed to remain constant within each zone of influence, and travel times along each link are calculated by dividing the equivalent link length by the average travel speed.
- The 5-minute link data are aggregated with adjacent links to form analysis facilities. The beginning and end points of the analysis facilities are based on logical breakpoints, such as major highway interchanges or other locations where traffic conditions are expected to change because of traffic or roadway characteristics. Facility travel times for each 5-minute interval are calculated as the summary of link travel times. Whenever a link travel time is missing, the whole facility travel time for that 5-minute interval may be set to a null value. To minimize the harmonic fluctuations associated with speed data, an average facility speed for each 5 -minute interval is calculated as the facility length divided by facility travel time. These speeds represent space-mean speeds across the analysis facility.


## TRAFFIC SIGNAL DETECTORS

- Sensor: Advanced controllers in signal cabinets record high-resolution signal event data that consist of a log of discrete events such as changes in detector and signal phase states.
- Spatial attribute: Point
- Temporal attribute: Every 0.1 second
- Measurement type: Signal event data are recorded at the highest time resolution of the controller ( 0.1 second). The signal controller-generated events are outputted in sets of four bytes per event: one byte for the event code type, one byte for the event parameter (for signifying detector numbers and phases), and two bytes for the timestamp of when the event occurred. The event code type specifies the type of event that occurred:
- Event code IDs 0-20. Active phase events: Indicate phase-related status changes, such as activation or termination.
- Event code IDs 21-30. Active pedestrian phase events: Indicate pedestrian-related phase status changes.
- Event code IDs 31-40. Barrier/ring events: Indicate barrier and yellow permissive events.
- Event code IDs 41-60. Phase control events: Indicate phase hold, call, and omit status changes.
- Event code IDs 61-80. Phase overlap events: Indicate overlap status changes.
- Event code IDs 81-100. Detector events: Indicate detector activity and error status changes.
- Event code IDs 101-130. Preemption events: Indicate preemption status changes.
- Event code IDs 131-170. Coordination events: Indicate coordinated timing status changes, such as cycle length and split times.
- Event code IDs 171-199. Cabinet/system events: Indicate controller property-related status changes, such as alarms, clock updates, and power failures.
- Event code IDs 200-255: User-defined events: Indicate user-defined events.
- Direct data type measurements: Data types include signal event data, cycle times, and phase intervals.
- Indirect measurements derived from data: Direct data can be integrated with vehicle count event data to produce measurements for delay, queue length, and green/red occupancy ratio.
- QC methods: They include hardware maintenance that enable proper collection of high-quality event data and communications systems that ensure signal controller clocks are synchronized. The QC process also includes ensuring proper coordination of inductive loop detectors to the signal detectors.
- Processing/calculation procedures: Day, et al. documented a workflow for developing operational performance measures from postprocessed signal event data, as shown in figure 2. ${ }^{9}$ The first step is to obtain event data from the field. The next step is to extract the cycle times and phase intervals from the data, which provides the set of relevant time intervals to support performance measurement. Once the cycles and phase intervals are defined, it is possible to integrate the vehicle count event data to yield measures of effectiveness (MOEs) as follows:
- Produce visualizations: The raw event data yields several graphical tools for characterizing signal performance, such as flow profiles and coordination diagrams.
- Compute vehicle MOEs: Vehicle counts are compiled on any phase with a working count detector. These support cycle-by-cycle performance measures for a lane, lane group, or phase.
- Compute estimated delay: A record of vehicle arrivals at the intersection can be measured using upstream or setback/advance detectors. This measure provides a means of estimating delay and queue length.
- Compute nonvehicle MOEs: MOEs for nonvehicle modes, such as pedestrians and transit vehicles, may be generated using Global Positioning System (GPS) trajectories of transit vehicles or pedestrian pushbutton actuation times.

[^6]The next step is to compile the cycle-by-cycle performance measures, which produces a series of data tables that may be aggregated for reporting purposes.

The report Performance Measures for Traffic Signal Systems: An Outcome-Oriented Approach documents the requisite data elements recommended for various performance measures. ${ }^{10}$

Limitations: This method uses high-resolution data loggers at the signals and is thus available for a small percentage of signals that have this capability. It also is a very indirect method for deriving travel times. Unless it is integrated with re-identification (ID) detectors, it only gives delay at the signal and ignores segment travel times between intersections.


Source: Purdue University.
Figure 2. Flow chart. Performance measure analysis workflow. ${ }^{11}$

[^7]
## VEHICLE RE-ID TECHNOLOGIES: BLUETOOTH®, ELECTRONIC LICENSE PLATE READERS, AND TOLL TAG READERS

- Sensor: There are a variety of collection methods, including Bluetooth detection, electronic license plate readers (ELPRs), and toll tag readers.
- Bluetooth ${ }^{\circledR}$ and Wi-Fi detection systems use roadside readers to actively search for in-range devices and capture the unique media access control (MAC) address of each device.
- ELPR use optical cameras to capture images of license plates of oncoming or receding traffic and use video image processing to "read" the license plates. License plate numbers can then be matched at sensor locations downstream to generate travel times.
- Toll tag readers detect the unique radio frequency IDs of motorists' automated toll tags at reader locations and calculate travel times based on the arrival time at each location.
- Spatial attribute: Line segment comprised reader pairs
- Temporal attribute: Continuous, but typically aggregated at 5-, $15-, 30$-, and 60 -minute epochs
- Measurement type: Travel times are directly measured based on a unique vehicle identifier (e.g., MAC address, license plate, or toll tag ID) and timestamp at fixed reader locations.
- Direct data measurements: All of the collection methods can produce vehicle travel times and speeds between reader locations.
- Indirect measurements derived from data: Travel time reliability and other travel time-based performance measures.
- QC methods: Variety of statistical methods developed primarily for ELPRs. Vendors typically have various methods of ensuring reasonable data, including removing errors and mixing in historical values to have smoother and fuller trendlines. However, most vendors consider these methods proprietary.
- Processing procedures: The travel time of an individual vehicle along a road segment is obtained by comparing the time when the vehicle is detected at the beginning of the segment to the time when the vehicle is detected at the end of the segment.
- Limitations: These data systems are based on the use of algorithms capable of discarding erroneous data. Data processing should account for unusual travel times caused by route choices, such as:
- Vehicle exits the facility to make an intermediate stop, then re-enters the facility later.
- Vehicle chooses an indirect route.
- Vehicle is detected at one device, undetected at next device, then detected at a later time or in the opposite direction.
- Penetration rate is relatively low (between 2 and 6 percent of traffic). Depending on local conditions, this method may not provide a statistically reliable sample of overall traffic speeds.
- Bluetooth ${ }^{\circledR}$ and Wi-Fi detectors do not provide lane-by-lane disaggregation.

Singer et al. noted the following additional limitations: ${ }^{12}$

- Some Bluetooth ${ }^{\circledR}$ systems only report detected vehicles within a 10 -second inquiry window, so all vehicles detected within this window will report the same detection time, leading to possible travel time inaccuracies, especially over short segment lengths. Each inquiry window could have up to eight detections, making it difficult for the system to match vehicles at multiple detector locations during heavy-traffic periods. However, newer generations of Bluetooth ${ }^{\circledR}$ detection systems utilize asynchronous input/output, allowing data to be output as soon as it is read.
- Accurate travel times depend on the spacing of readers. Long spacings can mask bottlenecks. For Bluetooth ${ }^{\circledR}$ systems, the nondirectional sensors may detect devices on nearby roadways, parking lots, and other surrounding areas. While data-processing algorithms can identify and remove much of the "noise" from the dataset, it is best to install readers such that unintended detections are minimized.
- ELPRs depend on a clear view of license plates; therefore, the system is sensitive to any factors that reduce visibility, such as precipitation, lens fog, line-of-sight obstructions, low ambient lighting, and license plates that are dirty, obstructed, missing, or have low character contrast. Not all States require vehicles to have a front license plate, so detection rates may be higher if rear plates are used.
- Toll tag readers are only feasible on routes where a significant percent of vehicles have toll tags. As with Bluetooth $\circledR$, the appropriate positioning of toll tag readers is essential to achieve high detection rates. For example, multiple readers may be needed to cover all lanes of a roadway. However, a single reader may be sufficient if there is a large number of detectable vehicles and match rates are high enough to generate accurate travel times.
- Another consideration for toll tag readers is the potential for reader failure. Although device failure depends on many implementation factors (e.g., operating temperature, power conditioning), the potential for failure should be considered.


## VEHICLE PROBE DATA FROM COMMERCIAL SOURCES

- Sensor: Vehicle probe data is collected through a combination of GPS-derived vehicle locations and times, instantaneous speeds from onboard devices, and public agency detectors. These data are used to generate travel time information by aggregating the high-resolution raw data on vehicle locations in time and space. Several commercial vendors provide vehicle probe data. The National Performance Management Research Data Set (NPMRDS) is one such data setthat FHWA makes available for use by certain public agencies.

[^8]- Spatial attribute: Polyline
- Temporal attribute: Various aggregations-Most typical ones being 5-, 15-, 30-, and 60 -minute epochs (i.e., periods)
- Measurement type: Average travel time on segments aggregated by epoch. The segments are designated as traffic message channels (TMCs) and roughly correspond to roadway segments between interchanges or intersections. Some vendors provide smaller geographic units than TMCs.
- Direct data measurements: None. Data are aggregated from direct measurements of GPS-equipped devices.
- QC methods: Appendix C of the National Cooperative Highway Research Program (NCHRP) Report 854 provides an example analysis of coverage, completeness, and validity for NPMRDS data. ${ }^{13}$ The coverage analysis compared the directional miles between the National Highway System NPMRDS geographic information system (GIS) map network and the full TMC-encoded network used by commercial sources. The completeness analysis examined the percentage of time data that was available for specific 5-minute periods. Finally, the validity analysis examined the differences between car and truck speeds. The researchers recommended to remove (or cap) speeds that were unreasonably high. An appropriate speed cap, if desired, should consider the functional classification of the roadway (freeway or arterial) and the speed data being investigated ("truck" or "passenger car" or "all vehicles"). After completing the QC process for the data, average speeds should be computed for the temporal and spatial aggregation levels desired:
- Establish free-flow (i.e., low volume) travel speed.
- Calculate congestion performance measures.
- Limitations: The current generation of vehicle probe data from commercial sources (e.g., NPMRDS version one and version two) are essentially spot speeds assigned to a link, and travel times are synthesized from these data. Travel times on a road segment are the average of vehicles; they do not reflect directly measured travel times except where path processing is used. This data source is not truly reflective of travel times over time and space. In addition, the raw data are aggregated data and not true measurements. This aggregation reduces the variability in the data, which is problematic for reliability calculations.

Some providers also may offer incident information, predictive travel time algorithms, and fusion of data from other sources (e.g., roadway sensors). One challenge of using vendor-

[^9]provided data may be combining third-party data with data collected directly by a State or local agency (e.g., roadway sensor data).

Also, probe speed data does not capture travel times for every epoch of every road segment. Therefore, users typically have two overall choices to obtain data. One option is data that reflect direct field measurement and would contain measurement gaps when no probes are detected. The other would fill in these measurement gaps with imputed data. Using either choice has shortcomings. If one uses direct field measurements only, the road segments and epochs that have measurements may be reflective of higher traffic with lower speeds and greater unreliability, thereby over-representing these conditions in an aggregate analysis. On the other hand, using gap-filled data may artificially smooth the data in a way that would dampen fluctuation in the reliability analyses.

Lastly, while the TMC is theoretically a standard, TMC definition varies depending upon the vendor providing the data, making data integration challenging. Similarly, the TMC network may not fit transportation agency applications as it may span multiple major intersections. Typically, a time-consuming conflation effort is developed to integrate probe speed data with a department of transportation's network.

Vehicle trajectory data: Recently vendors have started to make available the high-resolution data on vehicle locations in time and space. From these data, vehicle trajectories can be derived that overcome many of the assumptions of the widely available facility-specific travel times. With trajectory data, it is possible to compute the actual travel times of vehicles between points, e.g., origins and destinations for an entire trip.

## RIDE-HAILING COMPANIES

- Sensor: Ride-hailing companies are sometimes considered nonstandard sources but are still a valuable (and underutilized) source of travel time data that State and local agencies could use. Zone-to-zone travel times are synthesized from GPS trace pings from drivers operating on a company's network. All drivers use a smartphone to handle the logistics of their trips through a ride-hailing company's network. In 2017, a ride-hailing company made its travel time data available to the public via its movement data analysis tool. ${ }^{14}$ All data is anonymized and aggregated to ensure no personally identifiable information or user behavior can be found using the tool.
- Spatial attribute: Polyline
- Temporal attribute: Continuous, but reporting is intermittent
- Measurement type: The ride-hailing company's application records latitude, longitude, and a timestamp (date/time) every 4 seconds. These GPS trace pings are used to provide navigational routing, fare calculations, driver-rider matching, and user-experience elements (e.g., display the location of the ride-hailing company-affiliated vehicles in the

[^10]ride-hailing company's rider application). When aggregated, the GPS trace pings can be used to derive average travel times between zones in a given region.

- Direct data measurements: Data types include device/vehicle trajectories and paths. These data can be aggregated to produce average travel times between two zones for a given time and date. Zones defined for a region are commonly based on census tracts, traffic analysis zones, or neighborhoods.
- Indirect measurements derived from data: Travel time analyses and origin-destination matrices may be developed from these data.
- QC methods: Travel time statistics are removed for zone pairs that either do not meet:
- A minimum number of trips: In general, there should be at least five trips between origin and destination during the period examined.
- A minimum count of unique riders necessary to preserve rider privacy (e.g., at least three different customers)
- Limitations: Cortright noted several limitations to these data. ${ }^{15}$ The movement tool provides trip times only for origin-destination pairs that have a sufficient number of trips (undertaken by the ride-hailing company's drivers) to enable them to calculate average trip times. While this is not a problem in dense, urban environments, data are sparse in lower density areas and for suburb-to-suburb trips. In addition, this ride-hailing company filters out trips that do not meet minimum thresholds for data privacy as well as origin-destination pairs that have fewer than 30 observations in a given month. Another limitation is that this ride-hailing company lacks data on traffic volumes.


## CONNECTED VEHICLES

- Sensor: Vehicle-to-infrastructure communication allows vehicles and infrastructure to communicate with one another via dedicated short-range communications transceivers. Infrastructure can communicate location-specific or general messages to vehicles, such as curve speed warning, road condition warning, weather information, and incident/detour information. Vehicles can communicate their presence to infrastructure, enabling features such as traffic signal actuation, automatic toll payment, incident detection, and general information sharing (i.e., traffic volume and travel time).
- Spatial attribute: Varies
- Temporal attribute: Continuous
- Measurement type: A probe data breadcrumb log stores vehicle location, heading, speed, and path history as part of the basic safety message (BSM), as summarized in table 2.

[^11]This information is stored on aftermarket safety devices (ASD) onboard the vehicle and is communicated to roadside units (RSUs).

Table 2. BSM core data fields. ${ }^{16}$

| BSM Core Data Fields |  |
| :--- | :--- |
| msgCnt | Message count |
| Id | Temporary ID of vehicle |
| secMark | Message time |
| Lat | Latitude of vehicle |
| Long | Longitude of vehicle |
| Elev | Elevation of vehicle |
| Accuracy | ASD estimation of location sensor accuracy |
| Transmission | State of the vehicle's transmission |
| Speed | Vehicle speed |
| Heading | Vehicle heading |
| Angle | Steering wheel angle |
| accelSet | Vehicle acceleration state in all three axes |
| Brakes | Vehicle braking status |
| Size | Vehicle size |

In addition, a finer path history called "crumbData" may be collected, as summarized in table 3 .
Table 3. Crumb data fields. ${ }^{17}$

| Optional CrumbData | Description |
| :--- | :--- |
| elevationOffset | The elevation offset from the BSM's CoreData:elev field |
| Heading | Vehicle heading at the time offset of this crumb |
| latOffset | The latitude offset from the BSM's CoreData:lat field |
| lonOffset | The longitude offset from the BSM's CoreData:lon field |
| posAccuracy | Position accuracy with regard to multiple axes |
| Speed | Vehicle speed at time = BSM time + this crumb's time offset |
| timeOffset | The time offset from the time of the parent BSM |

- Direct data measurements: The probe data breadcrumb data yields measurements of travel times at the vehicle level. The RSU travel time source data is collected from a single passing BSMs to facilitate travel time computations for the traffic control system.

[^12]These data are limited and used by the transportation management center to develop link travel times to compare the connected-vehicle data with other travel time data sources.

- Indirect measurements derived from data: Not applicable.
- QC methods: The Connected Vehicle Pilot Deployment Program Data Management Plans for Tampa, $\mathrm{FL}^{17}$, and New York City, NY ${ }^{18}$, outline key data quality attributes (i.e., validity, reliability, precision, integrity, and timeliness) to ensure data collected and produced in the pilot projects result in reliable analytical results. Scheduled and unscheduled data quality audits are conducted to identify erroneous data from data streams. Once discovered and assessed, there are three ways to process erroneous data: - Delete-If it is determined that the data has no significant value or impact to the overall data set, application, or performance measure, the data may be deleted.
- Flag-If it cannot be determined that the data has significant value, cannot be parsed from its erroneous components, or impact to the overall data set, application, or performance measure is undetermined, the data may be retained but flagged to be omitted from certain analysis.
- Correct-If it is determined that the data has significant value, can be parsed from its erroneous components, or has a negligible impact on the overall data set, application, or performance measure, then the data may be retained. They can be flagged as corrected or further cleaned. Corrected data can be included or may be omitted from certain analysis.

Another critical component of data quality for the Tampa pilot is the configuration management plan, including procedures for submitting and approving any proposed design change. In addition, an ongoing log of current and historical configurations are documented, such as software and firmware versions/dates, device serial numbers, and maintenance and repair activities:

- Processing procedures: The BSM's core data (and if configured, crumb information) is uploaded daily to the transportation management center through RSUs. Breadcrumb data structures are stored on the ASD and uniquely tagged and processed separately at the transportation management center for mobility analytics. Figure 3 depicts a high-level view of where and how data flows from ASDs and RSUs to the transportation management center for subsequent analysis, sanitization, analysis, backup, archive, and export.
- Limitations: These data provide the most direct measurement of travel times as experienced by users. This method relies on appropriate processing algorithms to achieve high accuracy. The data management plan for the pilots notes that the travel time data may be used at the transportation management center for measuring segment travel times

[^13]where there is no instrumentation. A major limitation currently is the limited market penetration of this technology, leading to a lack of data for systematic analysis.

## SUMMARY OF TRAVEL TIME DATA SOURCES

Table 4 summarizes the characteristics of travel time data sources used for reliability analysis.


Figure 3. Diagram. ASD event and breadcrumb data collection and processing sequence.
Source: Federal Highway Administration, October 2017. Connected Vehicle Pilot Deployment Program Phase 2, Data Management Plan—New York City, FHWA-JPO-17-454.

Table 4. Characteristics of travel time data sources used for reliability analysis.

| Data Source | Collection Method | Measurement Type | Data <br> Types Derived from Measurements | QC Methods | Processing Procedures for Reliability | Limitations for <br> Reliability Analysis |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Freeway detectors | Variety of detectors used: inductive loops, active infrared, passive infrared, acoustic array, and video image processing. | Measurements are aggregated in the field at 20-second intervals. | Volume, speed, lane occupancy on a lane-bylane basis at specific points. Some methods provide vehicle classification. | Univariate and multivariate range checks; spatial and temporal consistency; detailed diagnostics; checks against traffic flow equations. | Travel times between detectors are assumed based on spot speeds. | Point-based speeds are not truly reflective of travel times over time and space; aggregation reduces variability. |
| Traffic signal detectors | Advanced controllers in signal cabinets record high-resolution signal event data. | Signal event data (phasing, occupancy) are recorded at the highest time resolution of the controller. | Signal event data, cycle times, and phase intervals. Data can be integrated with vehicle count event data to produce measurements for delay and queue length. | None. | Workflow includes getting event data, cycle times, phase intervals, produce MOEs, compile MOEs, and aggregate and report the results. | Very indirect method of deriving travel times. |


| Data Source | Collection Method | Measurement Type | Data <br> Types Derived from Measurements | QC Methods | Processing Procedures for Reliability | Limitations for Reliability Analysis |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Bluetooth ${ }^{\circledR}$ detection | Roadside readers actively search for inrange Bluetooth devices and capture unique MAC addresses. | Unique vehicle identifier and timestamp at fixed reader locations. | Travel times and average speeds between reader locations. | Variety of statistical methods developed primarily for ELPRs. | Travel times between reader locations are directly measured. | Depends upon algorithms capable of discarding erroneous data. Other limitations include inquiry window length, spacing of readers, sensitivity to environmental conditions, adequate saturation rates, and potential for reader failure. |
| ELPR | Roadside readers optical cameras and video image processing to read license plates. | Unique vehicle identifier and timestamp at fixed reader locations. | Unique vehicle identifier and timestamp at fixed reader locations. | Variety of statistical methods developed primarily for ELPRs. | Travel times between reader locations are directly measured. | Depends upon algorithms capable of discarding erroneous data. Other limitations include inquiry window length, spacing of readers, sensitivity to environmental conditions, adequate saturation rates, and potential for reader failure. |


| Data Source | Collection Method | Measurement Type | Data <br> Types Derived from <br> Measurements | QC Methods | Processing Procedures for Reliability | Limitations for Reliability Analysis |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Toll tag readers | Roadside readers detect the unique radio frequency IDs of motorists' automated toll tags. | Unique vehicle identifier and timestamp at fixed reader locations. | Unique vehicle identifier and timestamp at fixed reader locations. | Variety of statistical methods developed primarily for ELPRs. | Travel times between reader locations are directly measured. | Depends upon algorithms capable of discarding erroneous data. Other limitations include inquiry window length, spacing of readers, sensitivity to environmental conditions, adequate saturation rates, and potential for reader failure. |
| Vehicle probe data (epoch and segment based) from commercial sources | Mix of: GPS-derived vehicle locations and times; instantaneous speeds from onboard device; and agency detectors. | Average travel time on segments aggregated to 1-5-minute intervals. | Travel times by time interval (usually 1-5 minutes) and road segment. | Range checks, analysis of coverage, completeness, and validity. | Travel times on a road segment are the average of vehicles; they do not reflect directly measured travel times except where path processing is used. | Segment-based travel times are not truly reflective of travel times over time and space; aggregation reduces variability. |


| Data Source | Collection Method | Measurement Type | Data <br> Types Derived from <br> Measurements | QC Methods | Processing Procedures for Reliability | Limitations for Reliability Analysis |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Ride-hailing companies | Zone-to-zone travel times are synthesized from GPS trace pings from drivers operating on the company's network. | The latitude, longitude, and a timestamp (date/time) are recorded every 4 seconds. | Device/vehicle trajectories and paths. Average travel times between two "zones" in a region for a given time and date. | Screening for minimum number of trips between zone pairs, or minimum count of unique riders. | Zone assignment, mean epoch, zone to zone travel time, aggregate trips, privacy constraints, release. | Trip times only available if sufficient number of trips are available within privacy constraints. Data are sparse in lower density areas and for suburb-to-suburb trips. Also lack of traffic volume data. |
| Connected vehicles | Vehicle-to-infrastructur e communication. | Vehicle location and timestamp; these data are available today from telematics providers in over 4 million vehicles in the United States. | Vehicle trajectories and paths. | Key data quality attributes include validity, reliability, precision, integrity, and timeliness. Data quality audits are conducted to delete, flag, or correct erroneous data. | Data flows from ASD to RSU, and on to the transportation management center for subsequent analysis, sanitization, analysis, backup, archive, and export. | Provide the most direct measurement of travel times as experienced by users. Rely on appropriate processing algorithms to achieve high accuracy. |

## TRAVEL TIME DATA USED IN THIS STUDY

Common travel time data sources, including vehicle probe data, detector data and trajectory data, were investigated in this study. The NPMRDS (a private-firm version) was selected for the probe data, which includes field speed data for each TMC for timestamps at 5-minute intervals. Travel times on the TMCs are determined by tracking individual vehicles over a distance and then snapping these travel times to a TMC; this is known as "path processing." Starting in 2017 (the period covered herein), the travel times in the NPMRDS are based on path processing. Both speeds and travel times are included in the data. Prior to 2017, the travel times were based on instantaneous or near-instantaneous vehicle speeds. The general data structure is shown in table 5.

Table 5. NPMRDS data sample, 2017.

| TMC_code | Measurement_tstamp | Speed |
| :--- | :--- | :--- |
| $106+05207$ | $1 / 1 / 20170: 25$ | 63 |
| $106+05208$ | $1 / 1 / 20170: 25$ | 64 |
| $106+05209$ | $1 / 1 / 20170: 25$ | 64 |
| $106+05209$ | $1 / 1 / 20170: 30$ | 62 |
| $106+05207$ | $1 / 1 / 20170: 35$ | 65 |
| $106+05208$ | $1 / 1 / 20170: 35$ | 64 |

Source: FHWA
Detector data capturing freeway traffic volumes and speeds was obtained from the California Department of Transportation's (Caltrans) performance measurement system (PeMS) data. The data structure is similar to those of the probe data, except that data are collected on each detector station rather than TMC, as shown in table 6.

The Maryland State Highway Administration provided trajectory data from a private firm, which contain vehicle locations for short-interval timestamps of each recorded trip (as shown in table 7). Although speeds and travel times are not explicitly provided in the dataset, they can be calculated based on the location and time information.

Table 6. Detector data sample—Caltrans PeMS, 2017.

| Timestamp | Station | District | Freeway | Direction | Lane_ <br> Type | Length | Total_ <br> Flow | Percent_ <br> Observed | Average_ <br> Speed |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :---: | :---: | :---: |
| $1 / 1 / 20170: 00$ | 717075 | 7 | 10 | E | ML | 0.32 | 97 | 100 | 68.5 |
| $1 / 1 / 20170: 00$ | 717077 | 7 | 10 | E | ML | 0.235 | 108 | 100 | 69 |
| $1 / 1 / 20170: 00$ | 707097 | 7 | 10 | E | ML | 0.245 | 145 | 0 | 65.1 |
| $1 / 1 / 20170: 05$ | 717075 | 7 | 10 | E | ML | 0.32 | 83 | 100 | 68.1 |
| $1 / 1 / 20170: 05$ | 717077 | 7 | 10 | E | ML | 0.235 | 84 | 100 | 67.8 |
| $1 / 1 / 20170: 05$ | 717097 | 7 | 10 | E | ML | 0.245 | 118 | 0 | 64.6 |

Table 7. Trajectory data sample, 2018.

| Tripid | Tstamp | Latitude | Longitude |
| :--- | :--- | :--- | :---: |
| 3f74eaa4-2e36-89be-dc6c-83530aa10bfe | $3 / 15 / 20183: 51$ | 38.990972 | -77.157407 |
| eb8c3e25-4f3b-875a-44c0-a53e23911f66 | $3 / 14 / 201822: 28$ | 38.9906351 | -77.1542528 |
| eb8c3e25-4f3b-875a-44c0-a53e23911f66 | $3 / 14 / 201822: 28$ | 38.9906902 | -77.1545025 |
| eb8c3e25-4f3b-875a-44c0-a53e23911f66 | $3 / 14 / 201822: 28$ | 38.9908102 | -77.1549984 |
| eb8c3e25-4f3b-875a-44c0-a53e23911f66 | $3 / 14 / 201822: 28$ | 38.9908704 | -77.1552548 |
| eb8c3e25-4f3b-875a-44c0-a53e23911f66 | $3 / 14 / 201822: 28$ | 38.9909268 | -77.155515 |
| eb8c3e25-4f3b-875a-44c0-a53e23911f66 | $3 / 14 / 201822: 28$ | 38.9909803 | -77.1557819 |
| eb8c3e25-4f3b-875a-44c0-a53e23911f66 | $3 / 14 / 201822: 28$ | 38.9910564 | -77.1563175 |
| eb8c3e25-4f3b-875a-44c0-a53e23911f66 | $3 / 14 / 201822: 28$ | 38.9910954 | -77.1565785 |

## CHAPTER 3. DATA PROCESSING FOR RELIABILITY

## SETTING SPATIAL AND TEMPORAL SCALES

The data available for measuring travel time reliability is of high resolution and it is useful to aggregate the data spatially and temporally. For performance measurement and project planning, the two most reasonable spatial scales are the facility and the trip. The Highway Capacity Manual (HCM) defines a facility as: "a length of roadway, bicycle path, or pedestrian walkway composed of a connected series of points and segments." ${ }^{19}$ A reasonable length for a facility can be determined as the roadway segments between major intersections or interchanges. In urban areas, these distances can be 3-7 miles in length. Additionally, trips can be defined between origin and destination points of interest. A trip can take a consistent path of connected roadways, or they can take any roadway path between origins and destinations.

The analyst also defines the periods to be analyzed. At a minimum, the morning and afternoon peak periods for nonholiday weekdays are a good practice used since these are the times when congestion will be most apparent. The beginning and ending times of the peak periods are based on local knowledge of traffic patterns. The ending time should be late enough to capture residual queue dispersion from the peak.

## TRAVEL TIME CALCULATION METHODS

Given the differences in the various data sources, four travel time calculation methods were explored:

- Detector
- Probe snapshot
- Probe virtual
- Trajectory

For detector data ("spot" speeds and volumes), travel times are synthesized for the lowest level of aggregation present in the data. The assumption is that the spot speeds are uniform across a length of highway equal to the half the distance to the nearest upstream and downstream detectors. Detector spacing significantly affects the accuracy of this assumption-the closer the spacing, the more reasonable the assumption. The steps in this aggregation process are shown in figure 4 and are as follows.


Source: FHWA.
Figure 4. Flow chart. Creating segment (facility) travel times. ${ }^{19}$

## Step 1: Combine Lane Data into Station Data

If data are reported by lane, the lane-by-lane data are combined into a station (e.g., all lanes in a direction). Traffic volumes are summed across all lanes, and the traffic speed is reported as a
weighted average, with weighting based on the respective lane traffic volumes. If volume data are missing for any of the lanes, the total station volume is factored up by the ratio of the total number of lanes to the number of lanes with valid data.

## Step 2: Calculate Link Statistics

Link properties are estimated from station data by assuming that each station has a zone of influence equal to half the distance to the detectors immediately upstream and downstream (the detector zone length). The measured speeds are then assumed to be constant within each zone of influence.

- Vehicle-miles of travel (VMT) is the volume times the detector zone length.
- Vehicle-hours of travel (VHT) is the VMT divided by the minimum of free-flow speed and speed.
- Travel time (in hours) is the detector zone length divided by the speed


## Step 3: Calculate Section Statistics

Section VMT, VHT, and travel time is the sum of these measures for each link within the section. If any data are missing for any of the stations, the total section VMT, VHT, or travel time is factored up by the ratio of the total section length to the total length of stations with valid data.

The following measures are the computed for the section:

- Space-mean speed is the VMT divided by VHT.
- Travel rate is the reciprocal of space-mean speed.
- Travel time is the facility length divided by the space-mean speed.

The probe snapshot method uses probe data and is based on the detector method, which develops the 5-minute facility travel times by summing up all section travel times along the facility at each given time interval. The facility travel times can be adjusted based on the ratio of sum of the section lengths and facility length if missing section data exists. Facility-level space-mean speeds can be derived from the facility travel times.

The probe virtual method relies on an algorithm that synthesizes travel times by simulating vehicles on the time/space diagram developed from probe data. A vehicle's speed at any given moment is determined by what link it is on at a given time. As it takes time for a vehicle to travel to a specific section, the traffic condition on that section could change by the time the vehicle arrives. In this way, end-to-end travel times are created and compiled into a travel time distribution from which reliability measures are calculated.

[^14]The trajectory method will be customized based on the nature of the data. For each trip that can be identified by the common trip ID from both ends of the facility, the direction of the trip is first determined based on the difference in adjacent locations. As the origin and destination ends can be defined once the direction is set, trip travel time is calculated by subtracting the earliest timestamp in the origin end from the latest timestamp in the destination end. Additionally, to account for the trips that potentially stopped or made detours, an error removal procedure was developed using mean absolute deviation (MAD) test based on travel time (figure 5):

$$
M A D=\frac{\sum_{i=1}^{n}|T T i-M|}{\mathrm{n}}
$$

## Figure 5. Equation. Formula for MAD.

Where:
$T T_{i:}=$ travel time for vehicle $i$.
$M=$ median of the 15 -minute block travel times.
$N=$ number of observations in the block.
To ensure the correct traffic context of the individual trip, trips are grouped into 15 -minute blocks first to develop the baseline travel time $(M)$. An error is defined as one that is out of the following range (figure 6):

$$
M \pm 3 M A D
$$

Figure 6. Equation. Formula for identifying errors.
In practice, the size of the block and the number of MAD (sensitivity coefficient) can be adjusted based on the field data.

## ANALYSIS PROCEDURES

The analysis procedure developed in this study includes data extraction, data transformation, data aggregation and measures calculation.

## Data Extraction

The candidate facilities were first determined based on the facility characteristics (e.g., roadway type, congestion level) and the travel time data availability along the facilities. The data extraction step uses the input of a dataset with larger geographical coverage and the facility definition, and outputs the dataset specifically for the selected facility.

For the probe and detector data, the TMCs or detector stations representing the subsections of a road can be identified once its physical extent is determined. The road dataset can be produced by subsetting the entire dataset based on the TMCs or detector stations. TMCs and detector stations are directional therefore data for each direction can be extracted separately.

As no subsection structure exists in the trajectory data, a method that utilizes the trajectory trip ID and timestamp was developed. This method starts by defining two polygons at both ends of a facility. The polygons should be as small as possible to avoid capturing trips on other facilities
but big enough to fully cover the two travel directions of the facility end. Trajectory data points that fall within the polygons can be extracted separately according to their respective polygons. The common trip ID and timestamp can then be used to establish the information of the trips that traveled from one end to the other.

One polygon that covers the entire study facility is not good practice as it cannot guarantee that all trips start at one end and traveled to the other end. Trips entered or left in the middle of the facility from/to a side street also could be included in the extracted dataset, which could skew the travel time calculation. Depending on the facility geometry, one big polygon also might contain data points on adjacent streets, which could further complicate the calculation.

## Data Transformation

This step transforms the raw extracted data and produces the clean section-level speeds and travel times for different data sources and travel time calculation methods.

For probe data, the general process includes:

1. Read the extracted NPMRDS speed statistics.
2. Read the NPMRDS TMC definition file.
3. Create a template using the number of unique TMCs and all time intervals.
4. Merge the NPMRDS speed statistics to the template.
5. Fill gaps in the merged file.
6. Optional speed adjustment if probe virtual method is used.
7. Additional date and time preparations for use in the aggregation step.

Step 1 reads the extracted speed statistics, and step 2 reads the TMC definition file that includes the basic characteristics, such as TMC length and order.

To use the probe virtual method, the dataset is ideally without data gaps both temporally and geographically. Any missing data could create issues for the probe virtual method to properly simulate a vehicle to create the simulated speeds. Step 3 creates a template that includes all associated TMCs and covers all time intervals. The merged dataset in step 4 has a bigger dimension as it contains the missing fields from the original NPMRDS. These gaps are filled in step 5 by interpolating the missing information.

The original probe average speed estimates contain the speeds at given times and is a snapshot in nature. Step 6 is needed if the probe virtual method is used. As described in the travel time calculation methods section of this document, the probe virtual method simulates an average vehicle's movement on the space/time diagram and updates the average speeds with consideration of the arrival time on a specific section. The implementation steps include:

- Calculate the section travel time based on section length and speed.
- Prepare the subsections at any given time interval by sorting the data by datetime and TMC order.
- Virtually simulate the vehicle movements by calculating the arrival time interval of a section based on the section travel times. The resulting arrival time interval (virtual) must be later than the original starting timestamp (snapshot).
- Sort by TMC code and datetime to adjust the snapshot speeds to virtual simulated speeds.

As the probe virtual method looks to replace an original speed on a specific TMC with a speed on the same TMC but at a later time interval, it is critical to ensure that the replacement only happens within the same TMC, and the process does not go beyond the last record of the dataset.

Step 7 produces additional fields according to the datetime information for later use. For example, the "day of the week" field is used to distinguish between weekdays and weekends; the "hours" field is used to define peak periods; and the "date" field serves as the basis to define holidays. For detector data, the method is largely the same as the probe snapshot as both are based on the Second Strategic Highway Research Program (SHRP 2) L03 method. The only difference is that detector data uses detector station definition file instead of the TMC definition file with NPMRDS.

For trajectory data, three main steps to transform the data include:

- Determine the direction of a trip by comparing timestamps of a specific trip ID at both ends.
- Calculate facility-level travel time by finding the difference of the latest timestamp in the destination end and the earlies timestamp in the origin end.
- Exclude errors (e.g., stops and detours) by applying the MAD test described in the travel time calculation method section of this document.


## Data Aggregation

This step aggregates the section-level data to facility-level speeds and travel times for calculation of performance measures. Spatial and temporal aggregation were already discussed in this document. The concept is to create a distribution of travel times for a facility for the periods of interest. From this distribution of facility travel times, all reliability measures can be created. The facility travel times can be adjusted based on the ratio of sum of the section lengths and facility length if missing section data exists. Facility-level space-mean speeds can then be derived from the facility travel times. This step is not as necessary for the trajectory data as the transformed trajectory data is at facility level. The resulting dataset of this procedure is used to develop the performance measures, such as planning time index (PTI) and mean travel time index (MTTI).

The next step is to aggregate the facility data at various datetime into 5 -minute interval by grouping the data by time. The facility speed at a 5 -minute interval is used to develop speed distribution figures to better understand the traffic patterns as well as to complete the QC review of the analysis process.

## Measures Calculation

Table 8 shows the reliability performance measures used in this study that are calculated based on the aggregated speed/travel time data.

The dataset at the facility level is used to calculate the PTI, 80th percentile travel time index (TTI80), MTTI, median travel time index (TTI50), semistandard deviation, pct_spd, and third performance management rule (PM3) level of travel time reliability (LOTTR). The procedure includes the following steps:

- Define peak periods based on the field context. In this study, 7-9 a.m. and 4-6 p.m. were defined for facilities from Maryland, Tennessee, and Minnesota; California used 6-10 a.m. and 4-8 p.m.
- Subset the dataset based on datetime so that weekday, weekend, and holiday data can be used for different calculation purposes separately.
- Calculate free-flow speed and free-flow travel time. The authors of this document suggest computing the free-flow speed as 85 th percentile speed on weekends and holidays during 6-10 a.m. Free-flow speeds were calculated individually from each data source.
- Calculate the performance measures using nonholiday weekday data.

Table 8. Selected reliability performance measures derived from the travel time distribution.

| Reliability Performance Measure | Definition |
| :--- | :--- |
| PTI | 95th percentile travel time index (TTI) (95th percentile <br> travel time divided by the free-flow travel time). |
| TTI80 | TTI80 (80th percentile travel time divided by the <br> free-flow travel time). |
| MTTI | Mean travel time divided by the free-flow travel time. |
| TTI50 | Median travel time divided by the free-flow travel time. |
| Semistandard deviation | The standard deviation of travel time pegged to free-flow <br> travel time rather than the mean travel time (variation is <br> measured relative to free-flow travel time). |
| Failure/on-time measures | Percent of trips with space-mean speed less than 50 mph; <br> 45 mph; and 30 mph (pct_30, pct_45 and pct_50). <br> PM3 LOTTR. |
| PM3 system reliability | Percent of the person-miles traveled on the Interstate (or <br> non-Interstate National Highway System) that are <br> reliable. ${ }^{20}$ |

The computation of free-flow speed has been contentious within the profession, with no clear agreement on how it should be derived. In the development of congestion performance measures, free flow speed is used as a benchmark to determine when congestion starts. (In other applications, it is part of speed and level of service (LOS) estimation.) Some analysts suggest that by using free-flow speed as a congestion benchmark, we are measuring too much congestion. For example, the HCM indicates that freeway traffic flow shifts to the congested regime ("stop-and-go") at $50-54 \mathrm{mph}$, well below the free-flow speed. For the purpose of this study, how free-flow speed is computed is not germane where we are comparing different data

[^15]sources and computation methods. The same is true for congestion monitoring applications where trends are tracked over time. The choice of a congestion benchmark is subjective, and, like any standard, it can be informed by technical information, but ultimately it is best determined through consensus.

The use of actual speed data from vehicle probes during periods of low traffic volume, as discussed above, may be a reasonable approach to setting the free-flow speed for uninterrupted flow facilities. For signalized facilities, using this method determines something close to the midblock speeds that are not influenced by the presence of signals. During low traffic volume times, vehicles on a signalized arterial experience very little control delay. If the calculated free-flow speed is close to a facility's speed limit, then this is likely the case. Many references, including the HCM, use what is essentially the midblock speed as the free-flow benchmark; this procedure assumes that the signal has no influence when in fact its mere presence even under low traffic volume conditions will introduce delay, depending on the phasing and progression. Many researchers and practitioners feel this delay should be included in the benchmark for measuring congestion.

Fortunately, the HCM can be used as a guide. Urban street LOS thresholds are set as fractional multipliers of the (midblock) travel speeds. For this study, we used a multiplier of 0.75, which corresponds to LOS B. Another option is to apply the relationships from NCHRP Report 387. It provides a simplified method for computing the free-flow speed, which accounts for signal control delay (figure 7) ${ }^{21}$ and signal delay (figure 8 ).

$$
F F S=\frac{L}{\frac{L}{S_{m b}}+N \times\left(\frac{D}{3600}\right)}
$$

Figure 7. Equation. Formula for computing free-flow speed on signalized highways.
Where:
$F F S=$ free-flow speed, accounting for signal delay.
$L=$ length of the facility.
$S_{m b}=$ midblock speed.
$N=$ number of signals.
$D=$ average delay per signal.

$$
D=D F \times 0.5 \times C(1-g / C)^{2}
$$

## Figure 8. Equation. Formula for calculating delay per signal.

Where:
$G=$ effective green time.
$C=$ cycle length.

[^16]$D F=$ progression factor.
Defaults:
$C=120$ seconds.
$g / C=0.45$.
$D F=0.9$ for uncoordinated traffic actuated signals.
$=1.0$ for uncoordinated fixed time signals.
$=1.2$ for coordinated signals with unfavorable progression.
$=0.9$ for coordinated signals with favorable progression.
$=0.6$ for coordinated signals with highly favorable progression.
The midblock speed, $S_{m b}$, can be determined using the databased procedure for freeways. Alternately, it can be set to the speed limit.

For PM3 LOTTR percentage of reliable travel, dataset at the subsection level is used given that the calculation entails the aggregation of subsection lengths. It is not available to the trajectory data given the data structure. The calculation process includes:

- Assign the four Federally defined LOTTR periods.
- Calculate the LOTTR values for each subsection in each LOTTR period.
- Determine the reliability of subsections.
- Calculate the ratio of reliable subsections to the facility length. ${ }^{22}$

For PM3 LOTTR system reliability, facility-level data is grouped by LOTTR periods to determine whether the facility is reliable. This calculation is available to all data sources. ${ }^{23}$

[^17]
## CHAPTER 4. CASE STUDY: DEVELOPING AND COMPARING RELIABILITY MEASURES USING DIFFERENT DATA SOURCES AND ANALYTIC METHODS

## ANALYSIS FRAMEWORK

A series of case studies were conducted for comparison of the data sources in computing reliability measures. Table 9 shows a summary of the facilities selected for various analyses. Data from 2017 to 2019 were used except that the trajectory analysis only used 2018 data.

Table 9. Case study analysis plan.

| Analysis Scale | Road <br> Types | Data/Method: <br> Detector | Data Method: <br> Probe/ <br> Snapshot | Data/Method: <br> Probe/ <br> Virtual | Data/Method: <br> Trajectory |
| :--- | :--- | :---: | :---: | :---: | :---: |
| CA: multiple <br> facilities | Freeway | Y | Y | Y | - |
| MD: I-495/ <br> I-695 | Freeway | - | Y | Y | Y |
| TN: multiple <br> facilities | Freeway | Y | Y | Y | - |
| MD: River <br> Road/Rockville <br> Pike | Arterial | - | Y | Y | - |
| TN: multiple <br> facilities | Arterial | - | Y | Y | - |
| MD: multiple <br> freeways + art <br> facilities | Freeway <br> + <br> Arterial | - | Y | Y | Y |
| Urban trip <br> (MD) | - | - | - | - | Y |
| Freight trips: <br> urban + long <br> distance | - | - | Y | Y | - |

California sites:

- I- 5 between Tonopath and Hubbard
- I-405 between Artesia and Century
- U.S. 101 between Burlington and Hollywood Reservoir
- State route (SR) 91 between I-110 and I-710
- I-80 between Lagoon Valley and Leisure Town
- I- 80 between Carlson and Richmond Pkwy
- I-580 between Foothill and El Charro
- U.S. 101 between Trimble and State route 237
- I-680 between Amador Valley and Deerwood

Maryland sites:

- I-495-Old Georgetown Road in Bethesda
- I-495-Baltimore Avenue in Hollywood
- I-270—Rockville: I-495
- I-495-Georgia Avenue in Silver Spring
- I-495
- I-695
- River Road
- Rockville Pike

Tennessee sites:

- I-24-Nashville
- I-40-Knoxville
- I-75-Knoxville
- U.S. 70-Knoxville


## RESULTS

The performance measures were calculated following the procedures described in the analysis procedure section of this document. The results were visualized to assess the differences among the different data sources and travel time methods in calculating the travel time reliability.

## Speed and Travel Time Distributions

A few selected speed and travel time distributions are shown in figure 9-figure 24. These figures illustrate that:

- The probe snapshot and probe virtual, both using probe-derived link travel times, are reasonably close.
- Detector data generally has higher speeds as compared to the probe data.
- Trajectory data can have higher or lower speeds as compared to probe data and is generally more variable. Trajectory data also can have data gaps especially in lesstraveled arterials.


Source: FHWA.
Note: Time is the hour of the day.
Figure 9. Line graph. Speed distribution-CA I-5 NB 2017.


Source: FHWA.
Figure 10. Line graph. Travel time distribution-CA I-5 NB 2017.


Source: FHWA.
Note: Time is the hour of the day.
Figure 11. Line graph. Speed distribution-CA I-5 SB 2017.


Source: FHWA.
Figure 12. Line graph. Travel time distribution-CA I-5 SB 2017.


Source: FHWA.
Note: Time is the hour of the day.
Figure 13. Line graph. Speed distribution-MD I-695 NB 2018.


Source: FHWA.
Figure 14. Line graph. Travel time distribution-MD I-695 NB 2018.


Source: FHWA.
Note: Time is the hour of the day.

Figure 15. Line graph. Speed distribution-MD I-695 SB 2018.


Source: FHWA.
Figure 16. Line graph. Travel time distribution—MD I-695 SB 2018.


Source: FHWA.
Note: Time is the hour of the day.
Figure 17. Line graph. Speed distribution-MD I-495 and Georgia Avenue EB 2018.


Source: FHWA.
Figure 18. Line graph. Travel time distribution-MD I-495 and Georgia Avenue EB 2018.


Source: FHWA.
Note: Time is the hour of the day.

Figure 19. Line graph. Speed distribution-MD I-495 and Georgia Avenue WB 2018.


Source: FHWA.
Figure 20. Line graph. Speed distribution-MD I-495 and Georgia Avenue WB 2018.


Source: FHWA.
Note: Time is the hour of the day.
Figure 21. Line graph. Speed distribution-TN I-40/I-75 EB 2018.


Source: FHWA.
Figure 22. Line graph. Travel time distribution-TN I-40/I-75 EB 2018.


Source: FHWA.
Note: Time is the hour of the day.
Figure 23. Line graph. Speed distribution-TN I-40/I-75 WB 2018.


Source: FHWA.
Figure 24. Line graph. Travel distribution-TN I-40/I-75 WB 2018.

## PTI Results by Data Source/Method

The PTI is an important measure that indicates the reliability of a facility. This study compares the PTI values of each facility to identify potential patterns of the different data source/method.

The x-axis in figure 25 and figure 26 shows the individual facilities and the $y$-axis shows the PTI values. The plotted shapes represent the PTIs based on different data source and calculation methods. Some observations include:

- Probe snapshot and probe virtual results are very similar, with probe snapshot PTI values slightly higher than the probe virtual ones (the empty triangle-, diamond-, and circle-shaped points on the graph are close to but slightly higher than the filled shapes).
- Detector PTI values are lower than the ones from the probe-based methods (the circle shape filled with stripes are lower than the empty shapes).
- Trajectory PTI values are generally higher than that of the probe-based methods, but the opposite cases exist as well (the diamond shape filled with stripes are generally higher than the empty shapes).
- The PTI differences (height differences of the triangles) generally increase as the PTI values increase. In other words, the differences in data/method are more obvious for high PTI values.


Source: FHWA.
Figure 25. Scatterplot. Facility PTI by data/method-a.m.


Source: FHWA.
Figure 26. Scatterplot. Facility PTI by data/method-p.m.

## Relationships Between Measures by Data Source/Method

As shown in these figures:

- The PTI, TTI80, and TTI are correlated, as the three values are different percentiles of speeds over free-flow speeds.
- The PTI and TTI are somewhat correlated with semistandard deviation.
- The PTI and TTI are not well correlated to the LOTTR metric. This lack of a correlation may lead to discrepancies in determining if a facility is reliable. Further analysis of this situation is described below.


| $\square$ Snapshot | םVirtual Probe |
| :--- | :--- |

Source: FHWA.
Figure 27. Bar graph. Difference in PTI values by method, continuous trips throughout the year.


Source: FHWA.
Figure 28. Line graph. Percent difference in PTI values for continuous trips throughout the year.


Source: FHWA.
Figure 29. Scatterplot. PTI values by computation method for discrete trip start times.


Source: FHWA.
Figure 30. Scatterplot. Percent difference in PTI values for different methods, discrete trip start times.

## Examining Reliability Definitions: PTI versus PM3 System Reliability

The idea behind this analysis is to see how well a widely used reliability measure (PTI) corresponds to the PM3 measure of system reliability for individual facilities. While the PM3 measures and metrics were intended to capture system conditions, it is useful to compute metrics at a facility or project level, especially after improvements, to gauge the improvement's effect on targets. For this analysis, system reliability is computed using the same method as for the system. PTI is measured for the period in which traffic volume peaks during either a weekday a.m. or p.m. The periods for calculating PTI are the same as for computing LOTTR metrics: either on a weekday 6:00-10:00 a.m. or a weekday 4:00-8:00 p.m. Additional data were recruited for this analysis:

- Freeways: Interstates in Fairfax and Prince William County, VA; freeways in Los Angeles and San Francisco
- Signalized arterials:
- FL 319 and U.S. 90 in Tallahassee, FL
- U.S. 441 and TN 62 in Knoxville, TN
- VA 7 in Fairfax County, VA

As with the previous analyses, the data were grouped into directional facilities.

Figure 33 and figure 34 show the relationship between PM3 system reliability and PTI for Northern Virginia interstates and the California freeways used previously. The concept here is that if one measure depicts an unreliable facility, the other measure should also. For example, a $\mathrm{PTI}=3.0$ on freeways corresponds roughly to a speed of 20 mph , indicating unreliable conditions. However, the figures show that a general relationship exists, with system reliability degrading with increasing PTI as would be expected, but the data are widely scattered.

For the signalized arterial comparison, the new locations in Florida, Tennessee, and Virginia were added to those used from Maryland and Tennessee, which were used in the earlier analyses. Figure 35 again shows a general relationship between system reliability and PTI, but the correlation is much weaker.


Source: FHWA.
Figure 31. Graph. Relationship between PM3 system reliability and PTI, Northern Virginia Interstates.


Source: FHWA.
Figure 32. Graph. Relationship between PM3 rule system reliability and PTI, Los Angeles and San Francisco freeways.

Signalized Arterials


Source: FHWA.
Figure 33. Graph. Relationship between PM3 system reliability and PTI, signalized arterials in several States.

## CHAPTER 5. CONCLUSIONS

## DATA SOURCES FOR TRAVEL TIME RELIABILITY

A wide variety of travel time data are available for the development of reliability performance measures. These data are of two general types:

- Roadway based. Data from freeway detectors have a long history of use in performance measurement as they have been available for over 25 years. Speeds, volumes, and lane occupancies are collected at specific points on roadways. An advantage of these data are that volumes and speeds are paired so that detailed exposure measures can be developed. A large disadvantage is that the speeds that are taken at a point may not be reflective of actual travel time over entire roadway segments. Assumptions must be made to convert the spot speed to travel times over a distance.
- GPS based. These data are derived from tracking individual devices as users traverse the roadway network and are commonly referred to as "probe vehicle data" because their motion implies that the device is on or in a motorized vehicle. The data may be reported in its raw form - the position of devices in time and space-and referred to as "vehicle trajectory data." The actual paths (trajectories) of devices through the network can be calculated. These data can also be summarized temporally to an "epoch" (e.g., 5-minute time increments), and spatially to a unidirectional link.

Of these data types, vehicle trajectory data offer the higher resolution and therefore can be used to calculate reliability measures at any temporal and spatial level desired. For example, the travel time variability between individual vehicles on the same path and time can be ascertained. This flexibility comes with a higher cost of processing as vehicles in the raw data must be assigned to roadway segments by time. Vehicle trajectory data can also be used to monitor trip performance (including reliability) directly; trip performance must be created synthetically with other forms of travel time data.

## Results of the Case Study

- Because trajectory data measures the paths of individual vehicles, the travel time distributions display high variability in travel times compared to other sources (vehicle probe and detector) that are temporarily preaggregated (5-minute intervals for this study). The variability appears to drop during times of congestion as vehicle movements are hampered by heavy traffic flow and queues. But using pre-aggregated data obscures variability, and the resulting reliability measures are reduced in value. The question then is: "Does it matter for congestion monitoring?"; in other words, "Is the variation between vehicles an important aspect of reliability?" Vehicle-to-vehicle variation is important in the context of operations strategies, many of which are aimed at smoothing traffic flow. Within the broader context of congestion monitoring and performance reporting, preaggregated travel time data (at least at 5-minute intervals) is adequate to capture macroscopic congestion conditions.
- Reliability measures developed from trajectory data are generally higher than those developed from pre-aggregated probe data. This difference is probably due to the inclusion of vehicle-to-vehicle variation described above. However, the difference indicates that the two sources should not be combined for congestion monitoring purposes, as misleading results will ensue.
- Reliability measures developed from pre-aggregated probe data via different processing methods are reasonably close in values. Two processing methods were tested: the snapshot method and the virtual probe method. While the virtual probe method is theoretically more representative of how vehicles pass through the system, there does not appear to be a reason to choose one method over the other. For relatively short length urban facilities and trips, either method may be used, but no strong reason exists to go through the extra calculation complexity of the virtual probe method. Likewise, no strong reason exists to go through the extra calculation complexity of the virtual probe method for the development of reliability measures.
- Reliability measures developed from roadway detector data are almost always lower in value than those developed from pre-aggregated probe data, based on data from detectors in Los Angeles and San Francisco.
- All the reliability measures tested in the study were correlated with each other. The MTTI, TTI80, and PTI were strongly correlated with each other and loosely correlated with the semistandard deviation and the LOTTR metric. Understanding the relationship between TTI, TTI80, and PTI could be useful in planning applications which require that reliability measures be developed from model-developed average conditions.
- Reliability measures for long-distance trips are more sensitive to the pre-aggregated vehicle probe database processing method than for urban facilities. When considering trips that are made continuously throughout the year, the difference in processing method is generally around 5 percent, although trips exposed to a high number of urban conditions show more deviation. When discrete periods are considered, the deviation is greater. This result leads us to use the virtual probe method to develop reliability measures for long-distance trips rather than the snapshot method.
- The PM3 system reliability measure generally decreases as PTI increases for freeways, although the correlation is weak. The difference most likely lies in the nature of the measures: System reliability relies on a threshold to determine if a facility is unreliable (binary) whereas the PTI is a continuous variable. With binary variables, one facility may be only slightly over the threshold while another might be way over the threshold. In both cases, the facility is deemed to be unreliable, but the latter case is more severe, a condition captured by the PTI but ignored by the system reliability measure.

On signalized arterials, the correlation between the PM3 system reliability measure and the PTI is extremely low. In general, the reliability measures indicate that travel is more unreliable on signalized arterials (as they have higher PTI values), but the reliability may be a scaling issue. PTI is determined by assuming a free-flow or ideal travel time. On freeways, this assumption is clear but not for arterials. Many references, including the

HCM, use what is essentially the midblock speed as the free-flow benchmark; this PM3 measure assumes that the signal has no influence when in fact its mere presence even under low traffic volumes will introduce delay, depending on the phasing and progression. Many researchers and practitioners feel this delay should be included when measuring congestion. Fortunately, the HCM can be used as a guide. Urban street LOS thresholds are set as fractional multipliers of the (midblock) travel speeds. For this study, the authors of this document used a multiplier of 0.75 , which corresponds to LOS B. However, even accounting for this adjustment signalized arterial reliability is still high; the ones used the analysis are all over $\mathrm{PTI}=2.0$. A possible explanation is that on a signalized section, some portions (TMCs in our case) will be strongly influenced by the signal (e.g., approaches) while others that are some distance away will not. Another option is to apply the relationships from NCHRP Report 387, which estimate free-flow speed (including signal control delay) from midblock speed and estimated signal delay.

## APPENDIX A. STEPS AND PYTHON CODE FOR RELIABILITY DATA PROCESSING

This appendix presents the procedures and example Python code that can be used to process travel time data for the purpose of constructing reliability measures.

## DATA PROCESSING FOR RELIABILITY

## Data Extraction and QC

## Data extraction:

1. Determine the candidate facilities.
2. Identify TMCs that are associated with the facility: One way is to obtain the TMC definition file associated with the facility, plot the TMC locations (latitude/longitude) using a GIS program, and visually identify the TMCs that are located between the starting and ending points of the facility.
3. Obtain the probe data by providing the geographical limits of the facility.
4. Refine the facility data by subsetting the raw data based on desired TMCs.

## QC:

1. Review data documents.
a. Data structure and field data types:
i. The data documents provide data specifications, including description of the data columns, data types, and data lengths, as well as how raw data is collected and processed.
ii. This information is critical for understanding the data characteristics and quality for choosing the data columns to be included in the analysis, and for determining how data is imported.
b. Probe data time interval:
i. Data time interval not only determines the datetime dimension of the data, but also helps to identify data gaps and detect irregular data points along the datetime dimension.
c. If data gaps exist or imputed, data are used to fill gaps.
d. Built-in QC mechanism from the data source, e.g., detector health and percent of imputed data from PeMS detector data.
2. Prepare summary statistics of key variables.

- Some of the summary statistics include:
- Mean, standard deviation, and range
- Number of values, number of null values
- Number of distinct values
- For the "speed" field, the summary statistics (i, ii and iii) can be produced on the entire dataset (facility), by facility direction, by TMC and by TMC and date/time.
- For "measurement_tstamp," summary statistics ii and iii can be derived to understand if any duplicates or missing data exists.

3. Identify data gaps:

- Missing/null values
- Missing certain TMC/date/time interval combinations

Based on the nature and extent of the gaps, the following decisions can be made:

- Whether the data is usable or not
- If the data can be used, then if the data can be used as is or the gaps should be filled.
- If the gaps need to be filled, then what strategies should be employed to fill the gaps.

4. Identify errors.

- Data that are not physically possible, e.g., speed $=-5 \mathrm{mph}$
- Data that are not realistic, e.g., speed $>150 \mathrm{mph}$
- Data that are significantly different from rest of the dataset, e.g., data during incident

Based on the actual cases, decisions can be made as whether the errors should be excluded or adjusted.
5. Detect other data issues:

- Duplicate observations
- Illogical TMC/date/time interval (e.g., datetime values can be problematic because of importing with incorrect format)

6. Visualize variable distributions:

- Common sense check
- Can detect directional issues


## Spatial and Temporal Aggregation: Development of the Travel Time Distribution

## Probe Data

The probe snapshot method uses probe data and is based on the SHRP 2 L03 method, which develops the 5-minute facility travel times by summing up all section travel times along the facility at each given time interval. ${ }^{24}$ The facility travel times can be adjusted based on the ratio of sum of the section lengths and facility length if missing section data exists. Facility-level space-mean speeds can be derived from the facility travel times.

[^18]The probe virtual method relies on an algorithm that synthesizes travel times by simulating vehicles on the time/space diagram developed from probe data. A vehicle's speed at any given moment is determined by what link it is on at a given time. As it takes time for a vehicle to travel to a specific section, the traffic condition on that section could change by the time the vehicle arrives. In this way, end-to-end travel times are created and compiled into a travel time distribution from which reliability measures are calculated. The following figures contain the Python code for conducting reliability analyses.

## Data Transformation: Produce "Clean" Section-Level Data.

1. Read the extracted NPMRDS speed data:

- Import "tmc_code," "measurement_tstamp" and "speed" columns.
- Specify the "tmc_code" type as string, and "speed" type is float.

```
df_types = {'tmc_code':str, 'speed': np.float64}
df_cols = ['tmc_code', 'measurement_tstamp', 'speed']
df=}= pd.read_csv('%s/%s' %(csvFolder, file), dtype=df_types, usecols=df_cols)
df['measurement_tstamp'] = pd.to_datetime(df['measurement_tstamp'])
```

Source: FHWA.
Figure 34. Code for reading NPMRDS data.

- Find distinct "tmc_code" and "measurement_tstamp" combinations to check and remove if duplicates exist.
- Find distinct "tmc_code" of the facility.

```
df_dups = df[df.duplicated(['tmc_code', 'measurement_tstamp'], keep=False)]
df = df.groupby(['tmc_code', 'measurement_tstamp'], as_index=False).mean()
tmc_list = df['tmc_code'].drop_duplicates()
```

Source: FHWA.
Figure 35. Code for reading TMC data.
2. Read the NPMRDS TMC definition file:

- Import "tmc," "miles," "road_order" and "aadt" columns.
- Subset the dataset based on the distinct "tmc_code" identified in the previous step.
- Sort the dataset by "road_order."


Source: FHWA.
Figure 36.Code for reading TMC definition data.
3. Create a data template by using the number of unique TMCs and all the time intervals as dimensions:

- The TMC dimension is the set of the distinct "tmc_code."
- The datetime dimension is based on the starting/ending datetime and the time interval.
- Create the template with the dimension as the Cartesian product of the TMC and datetime dimension.
- The template does not include any data.


Source: FHWA.
Figure 37. Code for creating the data template.
4. Merge the NPMRDS speed data to the template:

- Merge the template and NPMRDS data based on "tmc_code" and "measurement_tstamp" fields.
- The merge is a left join that joins the NPMRDS data to the template, keeping the dimension of the template.
- The new dataset (data) has a large dimension comparing to the original NPMRDS data and data gaps ("tmc_code" and "measurement_tstamp" without "speed") are introduced in the merging process.
- Sort the data by "tmc_code" and "measurement_tstamp."

```
df1 = pd.merge(npmrds_template, df,
    on=['tmc_code', 'measurement_tstamp'], how='left')
df1.sort_values(by=['tmc_code', 'measurement_tstamp'], inplace=True)
```

Source: FHWA.
Figure 38. Code for Reading Merging TMC and Travel Time Data.
5. Fill gaps in the merged dataset using interpolation:

- Investigate the nature and extent of the data gaps in data.
- Since the probe virtual method depends upon no gaps both temporally and geographically to simulate the vehicle movements, gaps are filled if this method is to be performed.
- Fill gaps using interpolation with appropriate method (e.g., linear, nearest, etc.).
- Perform an additional QC check to make sure all gaps have been filled.

```
df.interpolate(method='nearest', inplace=True)
df.fillna(method='bfill', inplace=True)
df.fillna(method='ffill', inplace=True)
df_test = df.loc[df['speed'].isna()]
```


## Source: FHWA.

Figure 39. Code for data QC check.
6. Additional datetime preparations from data, for use in aggregation step:

- Produce "day of the week" field to distinguish between weekdays and weekends.
- Produce "hour" field to define peak periods.
- Produce "date" field to define holidays.
- Produce "time" field as the time of the day dimension.


Source: FHWA.
Figure 40. Code for creating additional temporal variables.
7. Calculate section travel time:

- Merge the data and TMC definition based on "tmc_code" field.
- The merge is a left join that gives the data the "miles," "road_order" and "aadt" fields.
- Calculate the section travel time based on section length ("miles") and speed.

```
df1=pd.merge(df1, df_tmc, left_on='tmc_code',
    right_on='tmc', how='left')
df1.drop(['measurement_tstamp', 'tmc'], axis=1, inplace=True)
df1['tt']=df1['miles']/df1['speed']
```

Source: FHWA.
Figure 41. Code for calculating section travel time data.
8. Probe virtual method speed adjustment, if used:

- Prepare the subsections at any given time interval, by sorting the data by datetime and TMC order ("tmc_code," "date" and "road_order").
- Calculate cumulative time " tt _cum" and cumulative time step " tt _step."
- Virtually simulate the vehicle movements by calculating the arrival time interval of a section based on the section travel times. The resulting arrival time interval (virtual) must be later than the original starting timestamp (snapshot).
- Sort by TMC code and datetime to replace the snapshot speeds by virtual simulated speeds.
- Ensure that the replacement only happens within the same TMC, and the process does not go beyond the last record of the dataset.

```
df.reset_index(drop=True, inplace=True)
df.loc[:, 'speed_adj']=np.nan
df['tt_cum']=df.groupby(['date', 'time'], as_index=False)['tt'].transform('cumsum')
df['tt_step']=df['tt_cum'].floordiv(5/60)
# Fill 'speed_adj' at current time with actual speed at a later time
df=df.sort_values(by=['tmc_code', 'date', 'time'])
df.reset_index(drop=True, inplace=True)
# Fill according to same TMC
num_rows=len(df.index)
for idx, row in df.iterrows():
    if int(idx+row['tt_step'])<=num_rows-1: ##ensure it doesn't go beyond the final row
        while (row['tt_step']>=0):
            ##same tmc
            if df.at[int(idx+row['tt_step']), 'tmc_code']==df.at[int(idx), 'tmc_code']:
                df.at[int(idx), 'speed_adj']=df.at[int(idx+row['tt_step']), 'speed']
                    print(idx)
                        break
            else: ##different tmc
                    row['tt_step']=row['tt_step']-1
    else: ##use last row
        df.at[int(idx), 'speed_adj']=df.at[int(num_rows)-1, 'speed']
df.loc[:, 'speed_adj']=df['speed_adj'].ffill()
df['tt_adj']=df['miles']/df['speed_adj']
```

Source: FHWA.
Figure 42. Code for creating travel times using the virtual probe method.
Data Aggregation: Produce Aggregated Facility-Level Data.

1. Aggregate section-level data to facility-level at each given datetime:

- Group data by datetime.
- Calculate the facility travel time and length by adding all section travel time ("tt" and length ("miles") at each given time.
- Adjust facility travel time based on the ration of sum of the section lengths and facility length, in case missing section data exists.
- Calculate facility-level space-mean speeds.

```
# Aggregate to route
df1_route=df1.groupby(['date', 'time'], as_index=False) \
    .agg({'tt': 'sum', 'miles': 'sum', 'hour': 'first', 'dow': 'first'})
df1_route['tt_adj']=df1_route['tt']/(df1_route['miles']/route_length)
df1_route['speed']=route_length/df1_route['tt_adj']
```

Source: FHWA.
Figure 43. Code aggregating travel times to the section level.
2. Aggregate facility data to a specific time interval (e.g., 5-minute interval):

- Filter to nonholiday weekday dataset based on the "date" and "hour" fields.
- Group data by the specific time interval.
- Calculate mean facility travel times.
- Calculate corresponding facility speeds.

```
# Aggregate to 5min interval, excluding weekends & holidays
df1_route_wkd=df1_route.loc[(df1_route['dow']>=1) & (df1_route['dow']<=5) \
    & (~df1_route['date'].isin(holiday))]
df1_route_sum=df1_route_wkd.groupby(['time'], as_index=False) \
    .agg({'tt_adj': 'mean', 'hour': 'first'})
df1_route_sum['speed']=route_length/df1_route_sum['tt_adj']
df1_route_sum['tt_adj_min']=df1_route_sum['tt_adj']*60
```

Source: FHWA.

## Figure 44. Code for aggregating travel time data to different temporal levels.

## Creating Reliability Measures: Step-by-Step Calculation

## PTI

1. Define peak periods based on the field context. Normally 7-9 a.m. and 4-6 p.m. should be used, but the peak periods can be shifted or extended based on field traffic conditions.
2. Use the facility-level travel time/speed dataset developed in the first step of the Data Aggregation section in this document.
3. Subset the dataset to weekday, weekend and holiday based on the datetime field.
4. Calculate free-flow travel time as 85 th percentile speed on weekends and holidays during 6-10 a.m.
5. Calculate corresponding free-flow speeds.
6. Calculate PTI as the 95th percentile travel time during nonholiday weekday peak period (a.m. or p.m.) divided by free-flow travel time.
```
df1_route_wkd_am=df1_route_wkd.loc[(df1_route_wkd['hour']>=7) & (df1_route_wkd['hour']<9)]
df1_route_wkd_pm=df1_route_wkd.loc[(df1_route_wkd['hour']>=16) & (df1_route_wkd['hour']<18)]
# Route FFS
ffs = df1_route.loc[((df1_route['dow']>=6) | (df1_route['date'].isin(holiday))) & \
    (df1_route['hour']>=6) & (df1_route['hour']<10),'speed'].quantile(0.85)
fftt = df1_route.loc[((df1_route['dow']>=6) | (df1_route['date'].isin(holiday))) & \
    (df1_route['hour']>=6) & (df1_route['hour']<10), 'tt_adj'].quantile(0.15)
# Planning index
TTI95_AM = df1_route_wkd_am['tt_adj'].quantile(0.95)/fftt
TTI95_PM = df1_route_wkd_pm['tt_adj'].quantile(0.95)/fftt
```

Source: FHWA.
Figure 45. Code for creating free-flow speeds and travel times as well as the PTI from aggregated travel time data.

## TTI80

1. Perform the same steps as step $1-5$ in the PTI calculation.
2. Calculate TTI80 as the 80th percentile travel time during nonholiday weekday peak period (a.m. or p.m.) divided by free-flow travel time.
```
# 80th percentile index
TTI80_AM = df1_route_wkd_am['tt_adj'].quantile(0.80)/fftt
TTI80_PM = df1_route_wkd_pm['tt_adj'].quantile(0.80)/fftt
```

Source: FHWA.
Figure 46. Code for creating the TT80 measure.

## TTI50

1. Perform the same steps as step $1-5$ in the PTI calculation.
2. Calculate TTI50 as the mean travel time during nonholiday weekday peak period (a.m. or p.m.) divided by free-flow travel time.


Source: FHWA.
Figure 47. Code for creating the MTTI.

## Semistandard Deviation

1. Perform the same steps as step $1-5$ in the PTI calculation.
2. Calculate std as the standard deviation of travel time pegged to free-flow travel time (rather than the mean travel time) during nonholiday weekday peak period (a.m. or p.m.).
```
# Semi-standard deviation
df1_route_wkd_am.loc[:, 'std_temp']=(df1_route_wkd_am['tt_adj']-fftt)**2
semi_std_am = (df1_route_wkd_am['std_temp'].sum())/(df1_route_wkd_am['std_temp'].count())
df1_route_wkd_pm.loc[:, 'std_temp']=(df1_route_wkd_pm['tt_adj']-fftt)**2
semi_std_pm = (df1_route_wkd_pm['std_temp'].sum())/(df1_route_wkd_pm['std_temp'].count())
```

Source: FHWA.
Figure 48. Code for creating the semistandard deviation.
Percent of Trips with Space-Mean Speed less than 30/45/50 mph (pct_30, pct_45 and pct_50)

1. Perform the same steps as step $1-3$ in the PTI calculation
2. Calculate pct_30/45/50 as the total number of observations with speeds below the specific thresholds divided by the total number of observations during nonholiday weekday peak period (a.m. or p.m.).
```
#% of trips under 30/45/50 mph
num_am = df1_route_wkd_am['speed'].count()
num_pm = df1_route_wkd_pm['speed'].count()
pct30_am = (df1_route_wkd_am.loc[df1_route_wkd_am['speed']<=30,
pct45_am = (df1_route_wkd_am.loc[df1_route_wkd_am['speed']<=45,
pct50_am = (df1_route_wkd_am.loc[df1_route_wkd_am['speed']<=50,
pct30_pm = (df1_route_wkd_pm.loc[df1_route_wkd_pm['speed']<=30,
pct45_pm = (df1_route_wkd_pm.loc[df1_route_wkd_pm['speed']<=45,
pct50 pm = (df1_route_wkd pm.loc[df1_route wkd pm['speed']<=50,'speed']).count ()/num_pm
```

Source: FHWA.
Figure 49. Code for creating the percent of trips operating at different speed thresholds.

## PM3 LOTTR

1. Perform the same steps as step $1-3$ in the PTI calculation.
2. Calculate LOTTR as the 80 th percentile travel time divided by median travel time during nonholiday weekday peak period (a.m. or p.m.).
```
LOTTR_route = df1_route_wkd['tt_adj'].quantile(0.80)/df1_route_wkd['tt_adj'].quantile(0.50)
LOTTR_AM = df1_route_wkd_am['tt_adj'].quantile(0.80)/df1_route_wkd_am['tt_adj'].quantile(0.50)
LOTTR_PM = df1_route_wkd_pm['tt_adj'].quantile(0.80)/df1_route_wkd_pm['tt_adj'].quantile(0.50)
```

Source: FHWA.
Figure 50. Code for creating LOTTR metric (step 1).

## PM3 Percent Length Reliable

1. Define peak periods based on the field context. Normally $7-9$ a.m. and $4-6$ p.m. should be used, but the peak periods can be shifted or extended based on field traffic conditions.
2. Use the section-level travel time/speed dataset developed in the Data Transformation section of this document.
3. Subset the section-level dataset to create nonholiday weekday and weekend datasets.
4. Assign four LOTTR periods based on the Federal PM3 hour definition.
```
# tmc level
df1_wkd = df1.loc[(df1['dow']>=1) & (df1['dow']<=5) & (~df1['date'].isin(holiday))]
df1_wke = df1.loc[(df1['dow']>=6) | (df1['date'].isin(holiday))]
# Assign LOTTR Periods
df1_wkd.loc[(df1_wkd['hour']>=6) & (df1_wkd['hour']<10), 'LOTTR_PERIOD']=1
df1_wkd.loc[(df1_wkd['hour']>=10) & (df1_wkd['hour']<16), 'LOTTR_PERIOD']=2
df1_wkd.loc[(df1_wkd['hour']>=16) & (df1_wkd['hour']<20), 'LOTTR_PERIOD']=3
df1_wke.loc[(df1_wke['hour']>=6) & (df1_wke['hour']<20), 'LOTTR_PERIOD']=4
# Combine
df_lottr = pd.concat([df1_wkd.loc[df1_wkd['LOTTR_PERIOD']>=1],
    df1_wke.loc[df1_wke['LOTTR_PERIOD']>=1]])
```

Source: FHWA.

## Figure 51. Code for creating LOTTR metric (step 2).

5. Merge with the TMC definition dataset for the TMC length field "miles."
6. Group the dataset by TMC and LOTTR period.
7. Calculate LOTTR values (80th percentile travel time divided by median travel time) for each TMC and LOTTR period.
8. Merge the dataset with the TMC definition data.
9. Determine the reliability of each TMC by comparing the LOTTR values with the 1.5 threshold value.
10. Calculate the ratio of total reliable TMC length to the facility length.
```
# Calculate LOTTR, tmc-level
df_lottr_sum = df_lottr.groupby(['tmc_code', 'LOTTR_PERIOD'],
                                    as_index=False)[['tt']].apply(lottr_80_50)
df_lottr_sum.reset_index(inplace=True)
df_lottr_sum.rename(columns={'tt': 'LOTTR'}, inplace=True)
# Get miles from TMC
df_lottr_sum = pd.merge(df_lottr_sum, df_tmc,
    left_on=['tmc_code'], right_on=['tmc'], how='left')
df_lottr_max = df_lottr_sum.groupby(['tmc_code'], as_index=False) \
    .agg({'LOTTR':'max', 'miles':'first'})
#LOTTR measure 1: % of sub-segment length that's reliable
LOTTR_route_pct = (df_lottr_max.loc[df_lottr_max['LOTTR']<1.5, 'miles'].sum()) \
    /(df_lottr_max['miles'].sum())
```

Source: FHWA.
Figure 52. Code for creating LOTTR metric (step 3).
This measure is not available for the trajectory data, as the trajectory data does not have subsections.

## PM3 System Reliability

1. Perform the same steps as step 1-4 in the PM3 percent length reliable calculation.
2. Aggregate the dataset to facility-level by group datetime.
3. Group the dataset by LOTTR period.
4. Calculate LOTTR values (80th percentile travel time divided by median travel time) for each LOTTR period.
5. Determine the reliability of the facility by comparing the LOTTR values with the 1.5 threshold value.
```
# aggregate to route
df_lottr_route = df_lottr.groupby(['date', 'time'], as_index=False) \
    .agg({'tt': 'sum', 'miles': 'sum', 'hour': 'first',
        'dow': 'first', 'LOTTR_PERIOD': 'first'})
df_lottr_route_sum = df_lottr_route.groupby(['LOTTR_PERIOD'], as_index=False)
    [['tt']].apply(lottr_80_50)
if df_lottr_route_sum['tt'].max() < 1.5:
    LOTTR_REL = 'Reliable'
else:
    LOTTR_REL = 'Unreliable'
```

Source: FHWA.
Figure 53. Code for creating system reliability measure.
U.S. Department of Transportation

Federal Highway Administration
Office of Operations
1200 New Jersey Avenue, SE
Washington, DC 20590
https://ops.fhwa.dot.gov
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[^0]:    *SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

[^1]:    ${ }^{1}$ Transportation Research Board of the National Academies of Sciences, Engineering, and Medicine. 2003. NCHRP Report 510: Interim Planning for a Future Strategic Highway Research Program. Washington, DC: National Academy of Sciences. https://www.nap.edu/read/21949/chapter/5.

[^2]:    ${ }^{2}$ Transportation Research Board of the National Academies of Sciences, Engineering, and Medicine. 2014. Incorporating Travel Time Reliability into the Highway Capacity Manual, Transportation Research Board. Report No. S2-L08-RW-1. Washington, DC: Transportation Research Board. https://www.nap.edu/download/22487.
    ${ }^{3}$ In this method, a time-space matrix of facility-based travel times is prepared. The movement of vehicles across the matrix is then simulated.

[^3]:    ${ }^{4}$ Federal Highway Administration. 2016. Traffic Monitoring Guide. Washington, DC: Federal Highway Administration. https://www.fhwa.dot.gov/policyinformation/tmguide/.
    ${ }^{5}$ American Association of State Highway and Transportation Officials. 2009. AASHTO Guidelines for Traffic Data Programs. http://dl1.wikitransport.ir/book/AASHTO_Guidelines_for_Traffic_Data_Programs_2009.pdf.

[^4]:    ${ }^{6}$ Turner, S. 2007. Quality Control Procedures for Archived Operations Traffic Data: Synthesis of Practice and Recommendations. Report No. Work Order 03-007. Washington, DC: Federal Highway Administration. http://worldcat.org/digitalarchive/content/cdm266301.cdmhost.com/CBT/p266401coll4/0000077587/qc procedures. pdf.

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    ${ }^{8}$ Liao, C-F. 2018. Investigating Inductive Loop Signature Technology for Statewide Vehicle Classification Counts. Report No. MN/RC 2018-31. St. Paul, MN: Minnesota Department of Transportation. http://www.dot.state.mn.us/research/reports/2018/201831.pdf.

[^6]:    ${ }^{9}$ Day, C. M., D. M. Bullock, H. Li, S. M. Remias, A. M. Hainen, R. S. Freije, A. L. Stevens, J. R. Sturdevant, and T. M. Brennan. 2014. Performance Measures for Traffic Signal Systems: An Outcome-Oriented Approach. West Lafayette, IN: Purdue University.
    https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1002\&context=jtrpaffdocs.

[^7]:    ${ }^{10}$ Day, C. M., D. M. Bullock, H. Li, S. M. Remias, A. M. Hainen, R. S. Freije, A. L. Stevens, J. R. Sturdevant, and T. M. Brennan. 2014. Performance Measures for Traffic Signal Systems: An Outcome-Oriented Approach. West Lafayette, IN: Purdue University. https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1002\&context=jtrpaffdocs.
    ${ }^{11}$ Day, C. M., D. M. Bullock, H. Li, S. M. Remias, A. M. Hainen, R. S. Freije, A. L. Stevens, J. R. Sturdevant, and T. M. Brennan. 2014. Performance Measures for Traffic Signal Systems: An Outcome-Oriented Approach. West Lafayette, IN: Purdue University.
    https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1002\&context=jtrpaffdocs.

[^8]:    ${ }^{12}$ Singer, J., A. E. Robinson, J. Krueger, J. E. Atkinson, M. C. Myers. 2013. Travel Time on Arterials and Rural Highways: State-of-the-Practice Synthesis on Rural Data Collection Technology. Report No. FHWA-HOP-13-029. Washington, DC: Federal Highway Administration. https://ops.fhwa.dot.gov/publications/fhwahop13029/fhwahop13029.pdf.

[^9]:    ${ }^{13}$ Transportation Research Board of the National Academies of Sciences, Engineering, and Medicine. 2017. NCHRP Research Report 854: Guide for Identifying, Classifying, Evaluating, and Mitigating Truck Freight Bottlenecks. Washington, DC: National Academy of Sciences. https://www.nap.edu/login.php?action=guest\&record id=24807.

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