

# Using Truck Probe GPS Data to Identify and Rank Roadway Bottlenecks

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**Abstract:** This paper describes the development of a systematic methodology for identifying and ranking bottlenecks using probe data collected by commercial global positioning system fleet management devices mounted on trucks. These data are processed in a geographic information system and assigned to a roadway network to provide performance measures for individual segments. The authors hypothesized that truck speed distributions on these segments can be represented by either a unimodal or bimodal probability density function and proposed a new reliability measure for evaluating roadway performance. Travel performance was classified into three categories: unreliable, reliably fast, and reliably slow. A mixture of two Gaussian distributions was identified as the best fit for the overall distribution of truck speed data. Roadway bottlenecks were ranked on the basis of both the reliability and congestion measurements. The method was used to evaluate the performance of Washington state roadway segments, and proved efficient at identifying and ranking truck bottlenecks. DOI: [10.1061/\(ASCE\)TE.1943-5436.0000444](https://doi.org/10.1061/(ASCE)TE.1943-5436.0000444). © 2013 American Society of Civil Engineers.

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## Introduction

This research was undertaken to develop a process by which the Washington State Department of Transportation (WSDOT) could use global positioning system (GPS) probe data from trucks to locate and quantify roadway bottlenecks. Once bottlenecks are located, WSDOT can use this information to more effectively guide and prioritize infrastructure investment.

Roadway bottlenecks have been defined in different ways in various studies. Daganzo (1997) suggested that an active bottleneck is a restriction that separates upstream queued traffic and free-flowing downstream traffic. Bertini and Myton (2005) similarly defined a bottleneck as a point upstream of which there is a queue and downstream of which there is freely flowing traffic. They considered a bottleneck to be active when it meets these conditions and to be inactive when there is a decrease in demand or a spillover from a downstream bottleneck. Ban et al. (2007) defined bottlenecks as sections of the roadway that have either capacities less than or demand greater than other sections. Chen et al. (2004)

described freeway bottlenecks as certain freeway locations that experience congestion at nearly the same time almost every day.

For this research, the authors defined a bottleneck as a poorly performing roadway segment on the basis of speed measurements and statistical predictability derived from truck GPS data. The development of predictability was based on the hypothesis that speed, estimated from GPS receiver data, can be statistically represented by either a unimodal or bimodal probability density function, estimated for different time periods during the day. The authors used a set of ensembles for each period of the day across one year to represent traffic performance for a particular time period. Furthermore, the authors hypothesized that the observed distributions can be approximated by a mixture of two Gaussian distributions, and a Gaussian mixture model can be fit to the speed data to estimate parameters that can be used to classify the performance into the following three categories: (1) unimodal and reliably slow, (2) unimodal and reliably fast, and (3) bimodal and unreliable. The authors tested these hypotheses in this research.

The authors selected reliability as the bottleneck indicator because it is critical in judging the performance of the transportation system. In the field of engineering, reliability is defined as “the probability that an entity will perform its intended function satisfactorily or without failure for a specified length of time under the stated operating conditions at a given level of confidence” (Kececioglu 1991). The concept of reliability has been extended to transportation primarily for measuring the (un)certainly of travel time. Researchers have used different definitions of travel time reliability. For example, Emam and Al-Deek (2006) described it as the probability that a trip between a given origin-destination pair can be made successfully within a specified time interval. Shaw (2002) defined it as the variability between the expected and actual travel time. Lyman and Bertini (2008) considered it to be the consistency or dependability in travel times, as measured from day to day and/or across different times of the day. This research hypothesized

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that roadway reliability can be evaluated by using truck speed distribution and classified the reliability performance of segments into three categories, as described previously.

The bottleneck identification and ranking process presented in this research used GPS data obtained from commercial fleet management devices in trucks. As these GPS devices become more prevalent in vehicles, GPS data are becoming an increasingly common and valuable source of roadway data. Processing the raw GPS data to identify bottlenecks for this effort involved the following procedures:

1. Geocode and process the GPS data. Utilizing geographical information system (GIS) techniques, the state's roadway network was partitioned into individual segments, and then the truck GPS data were filtered and assigned to those segments for further analysis.
2. Evaluate freeway performance. Statistical methods, in addition to some other metrics, were applied to evaluate the travel reliability and overall performance of each roadway segment and identify the truck bottleneck locations.
3. Rank the bottlenecks. Truck bottlenecks were ranked on the basis of a range of measures, including travel reliability, congestion measures, and the importance of the segments to freight mobility.

Each procedure is subsequently explained, and the bottleneck ranking results are described in detail. This process provides an efficient tool for transportation professionals to use in identifying and locating truck bottlenecks. Such information will help guide investments designed to relieve existing bottlenecks and improve the overall performance of the freight network.

## Literature Review

Several studies have been devoted to identifying roadway bottlenecks. The following is a brief review of those bottleneck identification techniques.

Cambridge Systematics (2005) made an initial effort to identify and quantify highway truck bottlenecks on a national basis. They located bottlenecks by identifying highway sections that were highly congested, as indicated by a high volume of traffic in proportion to the roadway capacity (the volume-to-capacity ratio), and then estimated the truck hours of delay at the bottlenecks by using a queuing-based model. Finally, they classified the bottlenecks into different groups by constraint type and ranked them by hours of delay. The limitations of this approach were related to the quality of the input data, because most data were derived and did not directly account for real-world truck behavior.

The American Transportation Research Institute (ATRI) assessed and ranked U.S. freight bottlenecks by using truck GPS data (ATRI 2011). ATRI used truck GPS data to calculate the average miles per hour below free-flow speed on the segment of interest. This number was multiplied on an hourly basis by the number of trucks on that section of roadway to produce an *hourly freight congestion value*. The sum of 24 hourly freight congestion values was then calculated to produce the total freight congestion value, which was used to rank the severity of the bottlenecks. Limitations of this approach were that it was valid only for the bottlenecks pre-selected for the list, and some bottlenecks may not have been identified.

Chen et al. (2004) developed an algorithm for locating active freeway bottlenecks and estimating their delay impact on the basis of loop detector data. The algorithm used the presence of a sustained speed differential between a pair of upstream-downstream detectors to identify bottlenecks and could automatically calculate

bottlenecks' spatial extent and time duration. However, the algorithm was limited by data availability, in particular by the detector location and spacing. If the detectors were widely spaced, it was difficult to detect the speed change and determine whether the bottleneck was active. In addition, this method was based on single-day data and could be affected by incidents and day-to-day traffic variations.

Ban et al. (2007) proposed a percentile-speed-based approach by using loop detector data from multiple days to identify and calibrate freeway bottlenecks. Bottleneck identification occurred on a speed contour map (SCM) automatically. This method converted the speeds on the SCM into either 0 or 1, depending on whether the speed was higher than a congestion threshold, and identified the areas marked by 1s to obtain the queue length and time duration of the bottleneck. A drawback of the method was that it was based on the assumptions of continuous freeway detection and low day-to-day traffic variation.

Standard travel time reliability measures used by FHWA include the 90th or 95th percentile travel time and the buffer index, which is the extra time needed to allow the traveler to arrive on time (FHWA 2011). This index is computed as the difference between the 95th percentile travel time and the mean travel time, divided by mean travel time. Emam and Al-Deek (2006) used dual-loop detector data to develop a new methodology for estimating travel time reliability. Four statistical distributions were tested for travel time data: Weibull, exponential, lognormal, and normal. On the basis of the developed best-fit distribution (lognormal), they computed the travel time reliability as the probability that a trip between a given origin-destination pair could be made within a specified time interval. In comparison to existing reliability measures, the new method showed higher sensitivity to geographical locations and a potential for estimating travel time reliability as a function of departure time.

The research presented in this paper differs from previous approaches in that it is based on GPS measurements obtained from individual probe vehicles, rather than on general measures of traffic performance. Therefore, the performance of the trucks did not need to be inferred from roadway performance measures but rather was measured directly. On the basis of the statistical distribution of truck spot speeds measured by GPS units, the authors developed a methodology for evaluating the travel reliability of roadway segments, and utilized this new reliability measure to assess and prioritize roadway bottlenecks.

## GPS Data Processing

The GPS data utilized in this study were collected for nine months from approximately 6,000 trucks per day traveling on roads throughout Washington State. The commercial in-vehicle GPS devices report, through cellular technology, both at preset intervals (every 10–15 min) and when the trucks stop. The resulting GPS data set included measurements of an individual truck's longitude and latitude, the truck's ID (scrambled for privacy), instantaneous (spot) speeds estimated by the GPS receiver, and a date and time stamp. Other variables in the data set included GPS signal strength, travel heading, and the truck's status if stopped, e.g., parked with engine on or off. More details about the data collection effort and the GPS-based performance measures program can be found in McCormack et al. (2010) and Ma et al. (2011).

The GPS data processing included the following three steps: (1) segment the road network, (2) add attribute information to the segments, and (3) geocode and match the GPS data with road segments.

## Segmenting the Road Network

The authors obtained WSDOT's entire road network, with the associated roadway attributes, as a digital network in ArcGIS-compatible format. ArcGIS was used to divide this network into the segments on which analysis was performed. The segmenting was based on ramps, signalized intersections, and any location where the speed limit changed. The authors further divided any segment longer than 3 mi into shorter segments. Because most roadways involve two-way travel, the increasing and decreasing milepost attributes from the WSDOT linear referencing model were used to determine the travel direction of each roadway segment. In essence, except for a few one-way roads, each roadway segment was processed as two segments, one for each travel direction. This segmentation process resulted in approximately 22,000 statewide analysis segments.

## Adding Attribute Information to the Segments

Within the GIS, a 50-ft buffer was added around the analysis segments. The resulting polygon or area was given identifying attributes from different state roadway network GIS layers. Some of these attributes already existed in the state highway GIS files, e.g., state route ID and posted speed limit. The authors added other attributes to the segments, including the Washington State Freight and Goods Transportation System (FGTS) freight tonnage classification, the compass heading (0–360) of the roadway, lowest and highest milepost measures of a segment, and the segment length. These attributes were used to identify the characteristics of each segment and geocode the truck GPS data in the next step.

## Geocoding and Matching the GPS Data with Road Segments

The authors compared the location and heading of the GPS points throughout all of Washington State (approximately 250,000 GPS location records per day) to the segmented linework and filtered out any GPS measurements taken from trucks that were not traveling along a WSDOT route.

The GPS points were filtered in the following two-step process:

- Step 1: The location of each point was compared with the state route segments created. Points that fell outside of a zone or buffer created around each segment (roughly 50 ft from the roadway's center) were eliminated.
- Step 2: The heading of each point was compared with the closest heading of a short section of the analysis segment. Points with a difference in heading of greater than 15 degrees were eliminated. Points with a difference in heading of 15 degrees or less were retained and tagged with a value indicating whether travel was in an increasing or decreasing direction. This process filtered out trucks traveling along intersecting or non-state route roadways, and it also identified which direction (such as north- or southbound) on a roadway segment a truck was traveling. Finally, each truck's GPS records were assigned to the segment.

## Roadway Performance Evaluation

In this research, the authors used several measures, based on the processed truck GPS data, to evaluate the performance of roadway segments. The authors considered both congestion and reliability measures. Travel reliability reflects the level of consistency in transportation service for a mode, trip, route, or corridor for a time period. Unreliable travel conditions over a roadway section indicate

that the travel time on the section is unpredictable; such a section may indicate a bottleneck and be a concern to truckers.

## Congestion Measures

The authors used the following two congestion measures in this research to evaluate roadway performance: average speed, and the frequency with which congestion exceeded a certain threshold.

Average speed was used to indicate the general travel condition of trucks over the freeway segments. Zhao et al. (2011) found that aggregated GPS speed estimates match loop detector speeds and capture travel conditions over time and space.

The magnitude of congestion was also estimated from the frequency of truck speeds falling below a threshold speed. WSDOT uses a threshold of less than 60% of posted speed to indicate congestion (WSDOT 2010). The authors used this metric as one of the congestion measures in this paper because it could reflect the severity of truck congestion on the freeway segment.

## Travel Reliability Measures

Travel reliability was estimated for different time periods (AM, midday, PM, and night) on the basis of truck speed distribution. Reliability was classified into the following three categories: reliably slow, reliably fast, and unreliable. The authors hypothesized that roadway performance predictability and reliability could be statistically measured. This measurement was based on speed, as estimated with spot speed data from GPS receivers. The speed data could be statistically represented by either a unimodal or bimodal probability density function estimated for a certain time period. Additionally, the authors hypothesized that the data for representing roadway performance over a certain period could be constructed from ensembles collected across one year.

The authors proposed using this performance reliability measure to capture the roadway behavior of interest to truck operators. For example, truck operators want to be able to predict roadway delay and variations to help them make business and operational decisions about contracting, timing, and routing. The authors evaluated the travel speed for each segment and were able to model reliable (or consistent) trucks performance on a roadway segment as a unimodal distribution of truck speeds. The authors were able to represent unreliable travel performance (variable speeds) as a bimodal distribution of truck travel speeds. The ability of WSDOT to identify unreliable segments will help it directly respond to measures of interest to trucking operators.

The ability to represent GPS data statistics with a bimodal distribution was tested by fitting the truck speed data to a mixture of two Gaussian distributions and evaluating the goodness of the fit. The probability density function of a mixture of two Gaussian distributions is

$$f(x) = \alpha \cdot n(x, \mu_1, \sigma_1) + (1 - \alpha) \cdot n(x, \mu_2, \sigma_2) \quad (1)$$

$$n(x, \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \cdot \exp\left[-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right] \quad (2)$$

where for  $i = 1, 2$  and with  $0 < \alpha < 1$ , the function  $f(x)$  has the following five parameters:

- $\alpha$  is the mixing proportion of the first normal distribution,
- $\mu_1$  and  $\sigma_1$  are the mean and standard deviation of the first normal distribution, and
- $\mu_2$  and  $\sigma_2$  are the mean and standard deviation of the second normal distribution.

A maximum likelihood method was used to fit the statistical distributions to the speed data. Truck speed data sets, collected from 10 high-volume roadway segments on Interstate 5 (I-5) through downtown Seattle, were used to test the goodness-of-fit in urban areas. The speed data were first classified into the following four time periods: AM peak (6 a.m. to 9 a.m.), midday (9 a.m. to 3 p.m.), PM peak (3 p.m. to 7 p.m.), and night (7 p.m. to 6 a.m.). The time periods were consistent with the analysis periods defined by WSDOT, and many other transportation agencies, for highway performance measure and congestion evaluation. Each time period's data were fit to the mixture of two Gaussian distributions, and the Kolmogorov-Smirnov test was applied to evaluate the fitness of distribution. The test results indicated that 36 out of 40 data sets passed the Kolmogorov-Smirnov test. The average test statistic is 0.04, with 56% of the K-S test statistic below 0.04, and only 5% of the test statistic above 0.06.

To evaluate the applicability of the mixture of two Gaussian distributions to rural highways, the authors used truck speed data sets collected from 10 segments on U.S. 395 in rural Stevens County in eastern Washington State for goodness-of-fit tests. The authors fit 24 hours of truck speed data to the statistical distribution without differentiating time periods. The test results indicated that 8 out of 10 data sets passed the Kolmogorov-Smirnov test. The average test statistic was 0.06. Therefore, the hypothesis that truck speed distributions could be statistically represented by a bimodal probability density function was accepted as true.

A mixture of two Gaussian distributions was used in this research to fit the truck speed data during different time periods. On the basis of the estimated parameters, the authors proposed the following set of rules to evaluate whether travel conditions on the freeway segment are defined as unreliable, reliably slow, or reliably fast:

- The travel condition is defined as unreliable if and only if  $|\mu_1 - \mu_2| \geq |\sigma_1 + \sigma_2|$ ,  $\alpha \geq 0.2$ , and  $\mu_1 \leq 0.75 \cdot V_p$  ( $V_p$  is the posted speed); otherwise, it is defined as reliable, and
- If the travel condition is defined as reliable, the second step is to evaluate whether it is reliably slow or reliably fast on the basis of the average speed. It is defined as reliably slow if  $v \leq 0.75 \cdot V_p$ . Otherwise, it is defined as reliably fast.  $v$  is the average speed computed as one of the congestion measures.

The first rule incorporates both statistics and engineering judgment. The first condition,  $|\mu_1 - \mu_2| \geq |\sigma_1 + \sigma_2|$ , is the statistical rule for evaluating whether a mixture of two normal distributions is bimodal (Schilling et al. 2002).

The second condition,  $\alpha \geq 0.2$ , is included to complement the first condition because, from an engineering point of view, the travel condition would still be considered reliable if  $\alpha$  value were very small. This would indicate that the probability of truck speeds falling within the low-speed regime was very small. The threshold value for  $\alpha$  is 0.2 because a clustering analysis of I-5 corridor data found 0.2 to be a conservative estimate of the break point between different speed clusters (Fig. 1).

K-means clustering is employed to identify the break point between different speed clusters. This method partitions the points in a data matrix into a specified number of clusters to minimize the within-cluster sums of point-to-cluster-centroid distances. Truck speed data collected on the I-5 segments were selected as the sample for estimating the threshold value for  $\alpha$ , and vector  $[|\mu_1 - \mu_2|/|\sigma_1 + \sigma_2|, \alpha]$ , computed from the statistical fitting result for each segment, was used as the input data for the clustering. This method was applied by randomly choosing starting data points as the cluster centers to partition the input data into two clusters. Fig. 1 shows the clustering results and that 0.3 was the critical value for  $\alpha$ , partitioning the data points into two clusters. The condition

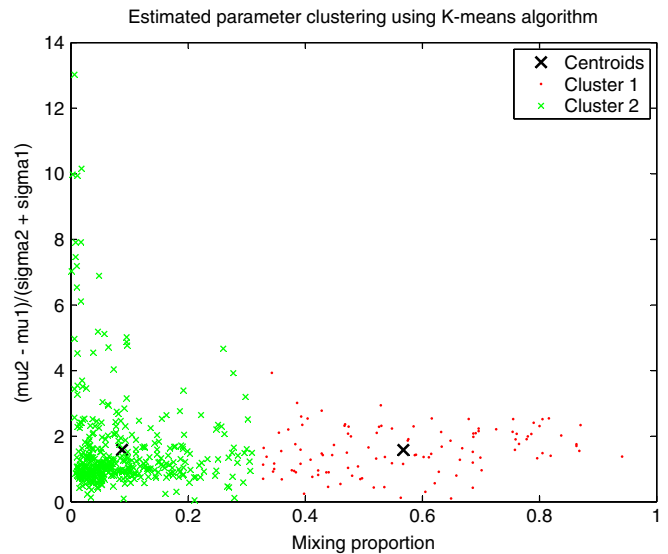


Fig. 1. Two-cluster analysis results using the K-means clustering method for I-5 freeway segments

$|\mu_1 - \mu_2| \geq |\sigma_1 + \sigma_2|$  is plotted against the mixing proportion because the equation indicates whether the mixture of two Gaussian distributions is statistically bimodal or not. Each point on the plot in Fig. 1 refers to one road segment during one time period.

The third condition,  $\mu_1 \leq 0.75 \cdot V_p$ , is included because, from an engineering point of view, the travel condition can still be considered reliable and free of congestion if  $\mu_1$  is higher than the congestion threshold, 75% of posted speed. This indicates that even the mean speed of the low-speed regime is above the congestion threshold, and the freeway segment is free of congestion. The authors chose 75% of posted speed because it is between 70 and 85% of posted speed, and WSDOT and other transportation agencies have adopted it as the speed threshold by which to evaluate the duration of congested periods.

The second rule is also an engineering judgment, with 75% of posted speed used as the threshold of reliability. If the average speed of the freeway segment is above 75% of posted speed, the segment is considered free of congestion and the travel condition is evaluated to be reliably fast. Otherwise, the roadway segment is experiencing traffic congestion, and the travel condition is defined as reliably slow.

### Roadway Performance Evaluation Results

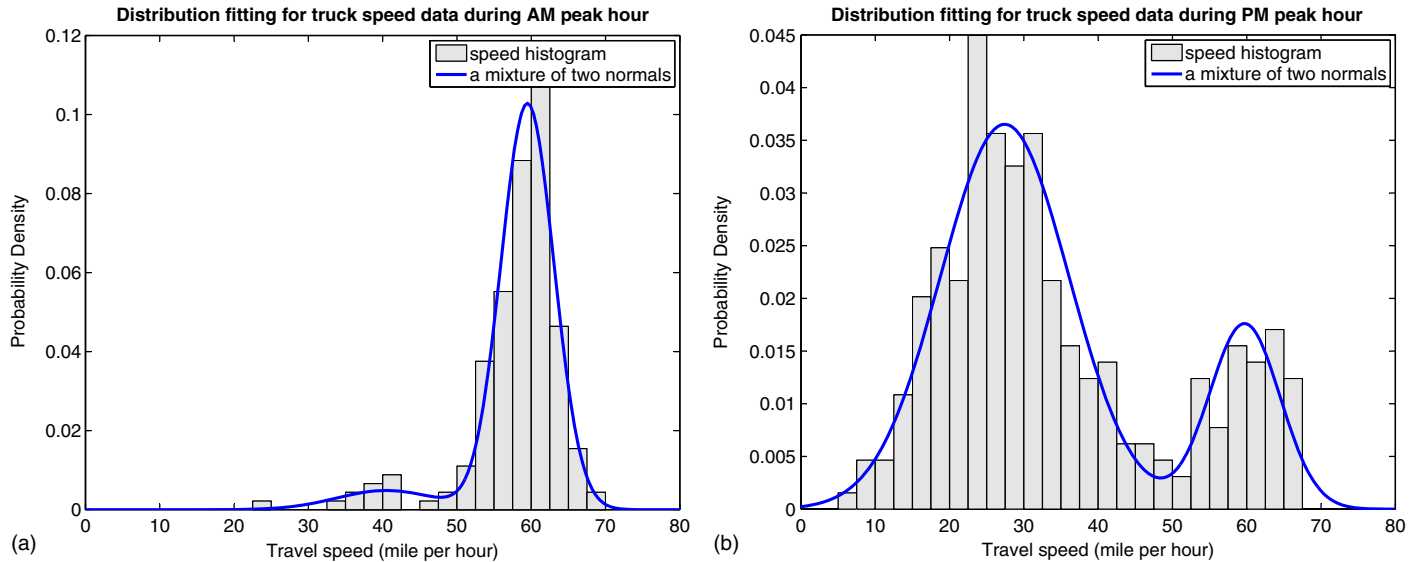
The performance of each analysis segment was evaluated by using the processed GPS data. A minimum of 200 data points per segment were required for analysis. A 0.4-mi segment on northbound I-5 north of the city of Everett was used to illustrate the bottleneck evaluation process. The average daily truck volume on this urban roadway segment is approximately 12,000. The speed distribution fitting results and travel reliability evaluation are shown in Table 1. A graphical illustration of the speed fitting results is shown in Fig. 2.

Taking the AM and PM periods as examples, the speed fitting results can be interpreted as follows.

During the AM peak period there are two speed operating regimes for trucks. The probability of truck travel speeds falling within the low-speed regime is 8.1%, with a mean speed of 40.5 mi/h (65.2 km/h). The probability of truck travel speeds falling within the high-speed regime is 91.9%, with a mean speed of

**Table 1.** Estimated Parameters for Speed Distribution Fitting during Different Time Periods

Time period	Mixing proportion ( $\alpha$ ) (%)	Mean 1 ( $\mu_1$ )	Mean 2 ( $\mu_2$ )	SD 1 ( $\sigma_1$ )	SD 2 ( $\sigma_2$ )	Mean	Reliability
Morning (6 to 9 a.m.)	8.1	40.5	59.5	6.7	3.6	57.9	Reliably fast
Midday (9 a.m. to 3 p.m.)	22.3	36.3	59.3	15	4.3	54.2	Unreliable
Afternoon peak (3 to 7 p.m.)	79.0	27.4	59.7	8.6	4.8	34.2	Unreliable
Night (7 p.m. to 6 a.m.)	7.7	19.4	58.3	12.2	4.6	55.3	Reliably fast

**Fig. 2.** Distribution fitting: (a) northbound I-5 segment during the AM; (b) northbound I-5 segment during the PM

59.5 mi/h (95.8 km/h). Because the mixing proportion value of the first normal distribution is lower than 0.2 and the average speed is higher than 75% of the posted speed limit, the segment is defined as reliably fast for the AM peak period. As seen in Fig. 2(a), the speed histogram presents a unimodal feature, and the truck travel speeds peak around 60 mi/h (97 km/h).

During the PM peak period, the probability of truck travel speeds falling within the low-speed regime is 79%, with a mean speed of 27.4 mi/h (44.1 km/h). The probability of truck travel speeds falling within the high-speed regime is 21%, with a mean speed of 59.7 mi/h (96.1 km/h). Because the estimated parameters meet the conditions  $|\mu_1 - \mu_2| \geq |\sigma_1 + \sigma_2|$ ,  $\alpha \geq 0.2$ ,

**Table 2.** Top 20 Worst-Performing Segments on T-1 Category Corridors

Rank	Route name	Starting milepost	Ending milepost	Frequency of speed below 60% of posted speed (%)	Mean speed [mi/h (km/h)]	Speed limit [mi/h (km/h)]	Length [(mi) (km)]
1	I 5	1.3	0.4	100.0	24.3 (39.1)	60 (96.6)	1 (1.6)
2	SR 501	0.2	0.1	100.0	20.2 (32.5)	60 (96.6)	0.2 (0.3)
3	SR 167	6.5	6.7	85.7	20.3 (32.7)	35 (56.3)	0.1 (0.2)
4	I 99	20.7	21.0	80.4	22.4 (36)	60 (96.6)	0.3 (0.5)
5	SR 410	2.5	4.5	79.7	25.9 (41.7)	55 (88.5)	2 (3.2)
6	SR 99	21.8	22.0	78.2	21.8 (35.1)	60 (96.6)	0.2 (0.3)
7	I 5	127.5	125.9	76.1	31 (49.9)	60 (96.6)	1.6 (2.6)
8	SR 512	0.0	0.2	72.7	26.5 (42.6)	60 (96.6)	0.2 (0.3)
9	I 18	0.2	0.4	68.2	22.7 (36.5)	35 (56.3)	0.2 (0.3)
10	SR 167	6.2	6.1	67.2	16.3 (26.2)	35 (56.3)	0.1 (0.2)
11	SR 181	5.9	6.0	66.3	25.4 (40.9)	50 (80.5)	0.1 (0.2)
12	SR 7	52.3	52.5	65.9	17.6 (28.3)	35 (56.3)	0.2 (0.3)
13	SR 18	0.2	0.0	65.8	19.6 (31.5)	35 (56.3)	0.2 (0.3)
14	SR 181	6.0	5.9	65.8	19.6 (31.5)	40 (64.4)	0.1 (0.2)
15	SR 99	21.5	21.7	65.6	28.6 (46)	60 (96.6)	0.1 (0.2)
16	SR 432	6.7	6.4	63.6	18.7 (30.1)	35 (56.3)	0.2 (0.3)
17	SR 16	0.3	0.0	62.9	27.9 (44.9)	55 (88.5)	0.4 (0.6)
18	I 90	49.8	47.8	61.1	37.4 (60.2)	65 (104.6)	2 (3.2)
19	SR 181	3.4	3.2	60.6	25.4 (40.9)	50 (80.5)	0.2 (0.3)
20	I 90	50.5	49.8	58.3	35.9 (57.8)	35 (56.3)	0.6 (1)

## Example of a Truck Bottleneck on a Congested Urban State Highway



- Location: SR-167 southbound, east of SR-161, Puyallup, WA
- Length: 0.24 mile
- Daily truck volume: 2,400
- Truck percentage of total traffic: 6.3%
- Average truck travel speed: 33 mph
- Posted Speed: 60 mph
- Percentage of travel speed below 60% of posted speed limit: 48%
- The SR 167 extension project will relieve this truck bottleneck and improve access to the Port of Tacoma and industrial lands.

Time Period	Reliability
AM	Unreliable
Midday	Unreliable
PM	Unreliable



**Fig. 3.** Example of the bottleneck information as used by WSDOT (with permission from the Washington State Department of Transportation)

and  $\mu_1 \leq 0.75 \cdot V_p$ , the segment is defined as unreliable for the PM peak period. The speed histogram in Fig. 2(b) demonstrates this evaluation, showing the bimodal feature.

In summary, the evaluation showed that during the midday and PM periods, travel conditions on the northbound I-5 segment

are unreliable. During the AM and night periods, travel conditions are reliable. The average truck travel speed on this segment is 50 mi/h (80.5 km/h), and the frequency of truck speed falling below 35 mi/h (56.3 km/h) is 21%.

## Truck Bottleneck Ranking

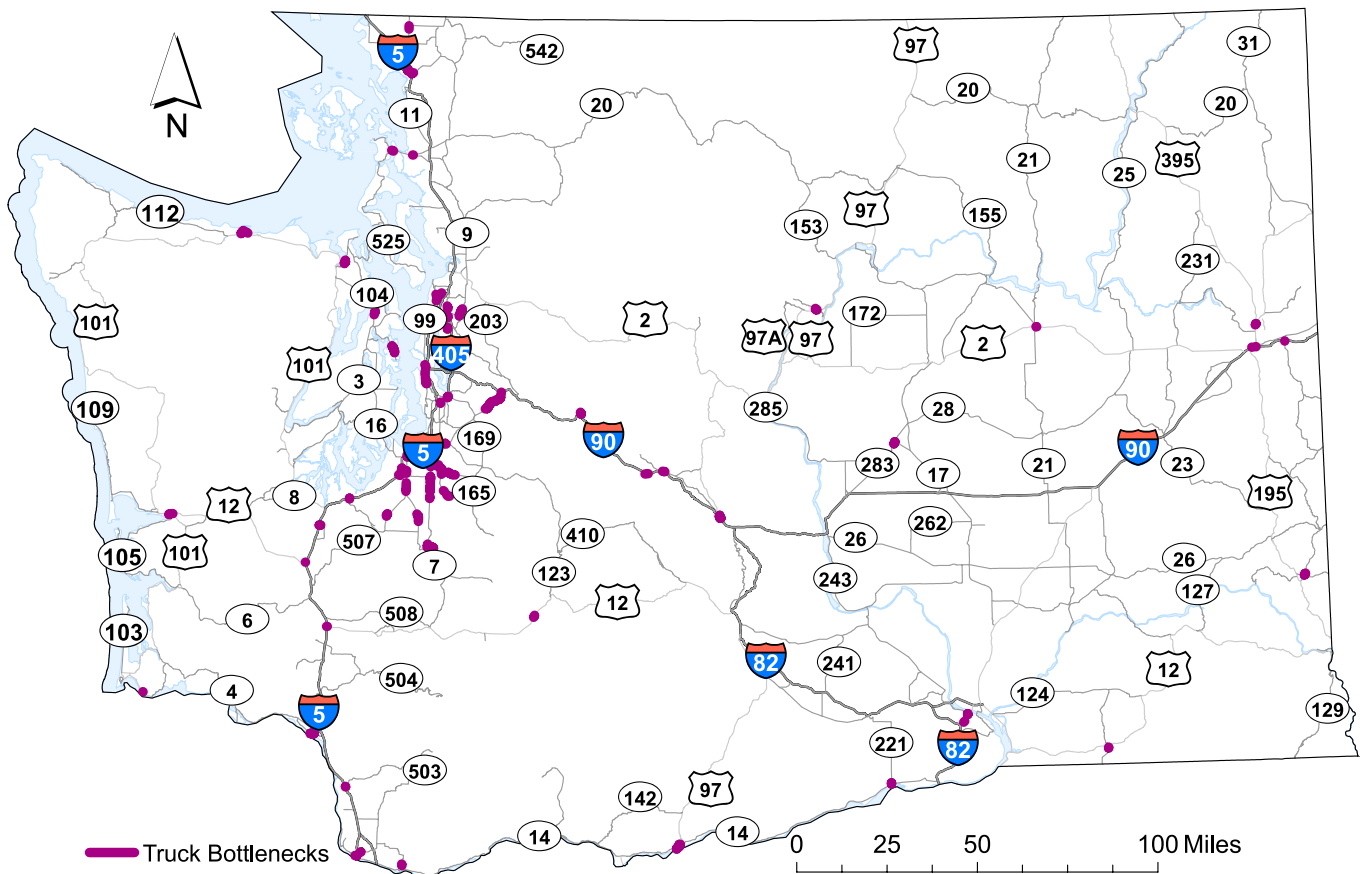
A process was developed for ranking the truck segments on the basis of their level of (un)reliability and congestion severity. The Department of Transportation can use this process to prioritize investments in infrastructure improvements. Both the congestion and reliability measures discussed previously were included in this process.

The rules for the ranking process are as follows:

First identify all the roadway segments within at least one time period that are unreliable or reliably slow. Then rank these segments by the frequency that congestion exceeds a certain threshold. Higher priority is given to the segments with a higher frequency of congested travel.

These rules consider travel reliability to be the most important factor for ranking roadway segments because the trucking industry is more concerned with travel reliability than with mean travel speed. Roadway segments that are determined to be reliably fast during all time periods are excluded from the ranking list because those segments do not have a congestion problem, and their travel condition is predictable. In addition, because the importance of various truck bottlenecks could change in light of different freight

## Truck Bottlenecks in Washington State



**Fig. 4.** Bottlenecks identified in Washington State

mobility factors, bottlenecks are only compared within the same freight roadway (freight and goods transportation system, FGTS) classification, and a separate ranking list is developed for each category.

As an example, the 20 worst-performing segments for the highest level FGTS categories within the central Puget Sound area were identified, as shown in Table 2.

Table 2 shows the ranking results of the top 20 worst-performing segments on T-1 category corridors (T-1 corridors are roadways carrying more than 10 million annual gross truck tonnage). By combing the adjacent segments on the same freeway, the authors identified the following major truck bottlenecks:

- I-5 mile point (MP) 0.4–1.3,
- State route (SR) 18 MP 0–0.4,
- I-90 MP 47.8–50.5,
- SR 99 MP 20.7–22,
- SR 167 MP 6.0–6.7,
- SR 181 MP 5.9–6.0, and
- SR 410 MP 2.5–4.5.

Most of these bottlenecks were located within the central Puget Sound area, indicating that the most severely congested spots were concentrated there. However, the authors' evaluation results did not explain what caused these bottlenecks.

These results demonstrated that the proposed ranking rules are useful for ranking roadway segments and identifying the locations of the worst bottlenecks. WSDOT has taken this information and developed a one-page handout designed to support its infrastructure planning and capital development programs (Fig. 3).

Fig. 4 shows the locations of the worst 80 truck bottlenecks identified by this ranking process. WSDOT is currently evaluating bottleneck locations that fall within or adjacent to proposed WSDOT projects to determine whether any solutions could be incorporated into the scoped of work being developed. WSDOT is also considering incorporating the remainder of the 80 locations into future corridor studies.

## Conclusions

On the basis of fleet management GPS probe data from trucks, this research developed both congestion and reliability measures for evaluating the performance of roadway segments and further identifying and ranking truck bottlenecks. This paper classified the travel reliability of roadway segments into the following three categories: unreliable, reliably slow, and reliably fast. This system was based on the hypothesis that roadway reliability is statistically predictable and truck speed distribution can be represented by either a unimodal or bimodal probability density function over a certain time period. The Kolmogorov-Smirnov test was used to test the distribution's goodness-of-fit for the mixture of two Gaussian distributions.

This reliability measure was used to evaluate the performance of a truck transportation network by fitting the collected truck speed data with a mixture of two Gaussian distributions, and then using a set of rules, based on the estimated distribution parameters, to determine whether the travel condition was (1) unreliable, (2) reliably slow, or (3) reliably fast. The poorly performing segments were identified and ranked on the basis of both reliability and congestion measurements.

The new methodology proved efficient in identifying the worst truck bottlenecks within WSDOT's roadway network. This research provides an effective tool for decision makers to use in systematically locating the worst bottlenecks and pinpointing the locations where bottleneck alleviation may provide the greatest benefit.

## Notation

The following symbols are used in this paper:

- $F(x)$  = empirical cumulative distribution function (CDF);
- $f(x)$  = probability density function of a mixture of two Gaussian distributions;
- $G(x)$  = standard CDF;
- $\alpha$  = mixing proportion of the first normal distribution;
- $\mu_1, \sigma_1$  = mean and standard deviation of the first normal distribution; and
- $\mu_2, \sigma_2$  = mean and standard deviation of the second normal distribution.

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