Algorithms for Studying the Impact of Travel Time Reliability Along Multisegment Trucking Freight Corridors

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Performance measures allow planners and engineers to monitor and evaluate transportation facilities or projects and to justify the allocation of funds among alternative transportation improvement options. To capture the impact of corridor congestion on freight vehicles, new tools and methodologies are developed to analyze data from commercial vehicles and produce performance measures such as travel time, speed, and travel time reliability. Because long freight corridors comprise segments with varying reliability characteristics, the objective was to develop a programming logic that would use available truck Global Positioning System data to (*a*) identify natural segments or regions in a corridor between urban centers, Interstate junctions, or rural areas and (*b*) estimate corridorwide impact of travel time unreliability. The case study presented investigates the I-5 corridor in Oregon. The research applies statistical techniques to compute vehicle travel time and reliability for freight movements within each segment. The proposed methodology has been used successfully to identify distinct segments and characteristics of travel time reliability in freight corridors. Travel time information was used to compute cost effects of delays within rural and urban areas along the I-5 corridor. The research presents an advance in the processing and aggregation of Global Positioning System truck data to produce succinct yet informative performance measures and segments.

Since the adoption of performance measures (PM) by departments of transportation, the traditional focus has been on the movement of passenger vehicles (*1*). As a result, PM used by many agencies may not appropriately capture the needs of all roadway users, including freight vehicles. Currently, there are neither specific freight performance measures (FPMs) in use by public agencies nor rough estimations of travel time reliability to and from major economic centers. For the freight industry, delay and congestion not only negatively affect the businesses that rely on efficient and timely deliveries but also increase vehicle emissions and the cost of transporting goods. To improve the functionality of transportation networks and make efficient use of funds, it is crucial that public agencies develop tools with which to assess existing system performance for all modes.

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Just-in-time production systems reduce the amount of inventory available at distribution centers or retailers and increase the need for products or parts to arrive at the scheduled time. For example, a late delivery may delay scheduled production or product delivery, causing manufacturers to incur steep financial losses. Carriers may also face steep penalties and additional costs when a breakdown in the supply chain takes place. Without a reliable transportation network, it is difficult for carriers to schedule a departure time that will ensure an on-time arrival at the destination.

Although this research is specific to one freight mode (trucking), the research and tools developed can be expanded and adapted to develop PM for other modes. This paper uses reliability of travel time as the PM for freight movement, defined as the time taken by a driver to travel between an origin and a destination. *NCHRP 618* recommends the use of 90th and 95th percentile travel times for a given route or trip as the simplest indicator of travel time reliability (*2*). The 90th and 95th percentile travel times are intended to reflect the travel time delays that can occur during heavy congestion (*2*). Travel time information is easy to interpret and is desired by the general traveling public, as well as freight carriers. This research uses 50th, 80th, and 95th percentile travel time to represent variability in rural and urban areas.

BACKGROUND AND LITERATURE REVIEW

Mobility affects the freight industry because it limits the ability of vehicles to move between origins and destinations (*3*). Measures used to quantify mobility include travel time, reliability, and delay. These PM are highly dependent on the location, rural or urban, of a corridor segment. Urban centers tend to have greater traffic volumes at certain times of the day, especially in morning and evening peak periods, which contribute to recurring congestion. Rural traffic volumes and mobility tend to be more consistent throughout the day. Therefore, it is important to develop tools that can identify roadway segments that have similar land use characteristics.

Loop sensor data have been used successfully to identify truck volume and acquire travel time and speed information on Interstates. Truck transponder data [weigh in motion (WIM) data] have also been used to gather travel time information, as well as characteristics of the freight vehicle and load. More recently, Global Positioning System (GPS) technologies have emerged as a method for collecting freight-specific data. McCormack et al. (*4*) and Quiroga and Bullock (*5*) have described the challenges associated with the use of GPS data to develop PM for freight and passenger vehicles.

Loop Sensor Data

Loop sensor data have been used to estimate freeway performance (e.g., travel time, speed, and vehicle count) for general-purpose vehicles and to identify and study bottlenecks at regional and link levels (*6, 7*). However, loop sensors are limited in their ability to differentiate among vehicle types traveling along a freeway and to provide disaggregate data by mode. Researchers at the University of Washington have studied the reliability of dual loop detectors in providing accurate vehicle count and speed results by vehicle type (*8, 9*). These researchers have also used single loop detectors to differentiate between vehicles by incorporating video footage. Although this method may be time-consuming and requires calibrations, their findings show promise in integrating single loop detectors with video footage to differentiate between general-purpose vehicles and freight vehicles with reasonable accuracy in count and speed estimates. However, dual loop detectors were found to be less reliable and could not reasonably estimate between vehicle types during congested periods (*8*).

Truck Transponder Data

Since the early 2000s, researchers have investigated the use of truck transponder data as a source for truck travel time information. If a transponder-equipped vehicle can be tracked at two sequential WIM stations, their time stamps can be used to generate information regarding the trip travel time and later aggregated to produce freeway link performance measures such as travel time distributions and reliability. This approach is similar to methods used along toll roads and, more recently, methods that incorporate media access control addresses from portable devices to study arterial performance measures.

However, truck transponder data present several challenges (*10*). First, generally there are long distances between WIM stations. The driver of a freight vehicle has the opportunity to stop, rest, refuel, or make deliveries before the vehicle is tracked at the next station. Algorithms must be incorporated to filter out trucks that stop while traveling through the corridor because their slower travel time information would severely bias the results. Second, relatively few trucks are equipped with transponders, and a large sample size is needed for link travel time to be accurately estimated from the truck data.

Truck GPS Data

Commercial GPS technologies are emerging as an effective form of data collection and are showing potential to contribute to the study of freight movements. However, there are challenges in using GPS data provided by the freight industry.

The first challenge involves the availability of GPS data. Although many carriers use GPS to monitor fleets, a carrier's scheduling and logistics practices are proprietary and not commonly shared. Early work by Greaves and Figliozzi in Australia discussed the use of passive GPS devices to identify truck trips and presented future applications and limitations of the data source (*11*). Recent research efforts by McCormack et al. have presented the challenges involved in acquiring data; their work highlighted the process of purchasing GPS data from private vendors to establish a GPS freight database with success (*4*).

The second challenge is the behavior of truck drivers. Trucks behave much differently from passenger vehicles because truck drivers have mandatory rest periods, must follow lane restrictions, must adhere to strict schedules, and must make stops for deliveries and pickups throughout the day. This type of travel behavior can be captured by GPS data more readily than other types of data. However, algorithms are needed for identifying and recognizing these behaviors so that local and freeway performance, as well as travel between key origin–destination pairs, can be studied.

FHWA is sponsoring research at several universities and, in partnership with the American Transportation Research Institute (ATRI), has made GPS data from freight vehicles accessible to universities for investigating new methods for developing FPM in urban and rural areas. The research in this paper used such data provided by ATRI.

METHODOLOGY FOR CORRIDOR SEGMENTATION

Literature investigating freight performance measures that use freight-specific data (e.g., WIM, commercial GPS) informed the methodologies developed in this research to study travel time reliability on multisegment corridors.

Commercial GPS data from ATRI, covering the I-5 corridor in Oregon, were used in this research. The approach relies on increases and decreases in truck volume along the corridor to identify changes in segments (i.e., urban segments, rural segments). Truck volume is used because volume or traffic flow per lane is the key factor associated with congestion and reduced travel speed, as indicated in the *Highway Capacity Manual* (*12*). Along a freeway corridor, changes in traffic volumes take place at interchanges. It is assumed in this research that segments along corridors (as well as the total number of lanes) are defined between interchanges. If a finer spatial resolution is needed after an initial segmentation that uses volumes, a second segmentation that uses speeds can be applied. The same methodology would apply with speeds instead of volumes.

A challenge in working with commercial GPS data is that data from trucks in congestion (exhibiting lower speeds) may be confused with data from trucks experiencing longer travel times for reasons unrelated to congestion. If proper filtering methods are not used, data from trucks that have left the Interstate to refuel, make deliveries, or rest may be analyzed and may create bias in the data set. Also, the various segments along a corridor have different speed distributions, which also vary by time of day. For this reason, truck volume is used initially to identify segments of analysis; then travel speeds are used to remove these outliers (e.g., observations that have been identified to have slower speeds for reasons unrelated to congestion). In this way, trucks traveling through segments can be filtered on the basis of travel time characteristics of each segment.

Data Description

GPS data from commercial trucks along I-5 is used for the analysis; the data were provided by ATRI. Each record or observation provides a unique truck identification, a time stamp, and latitude and longitude of the trucks. The ArcGIS linear referencing tool is used to map every GPS latitude–longitude reading to a milepost measure. The milepost measures are used to determine the direction of travel for every truck, designated as northbound (NB) or southbound (SB).

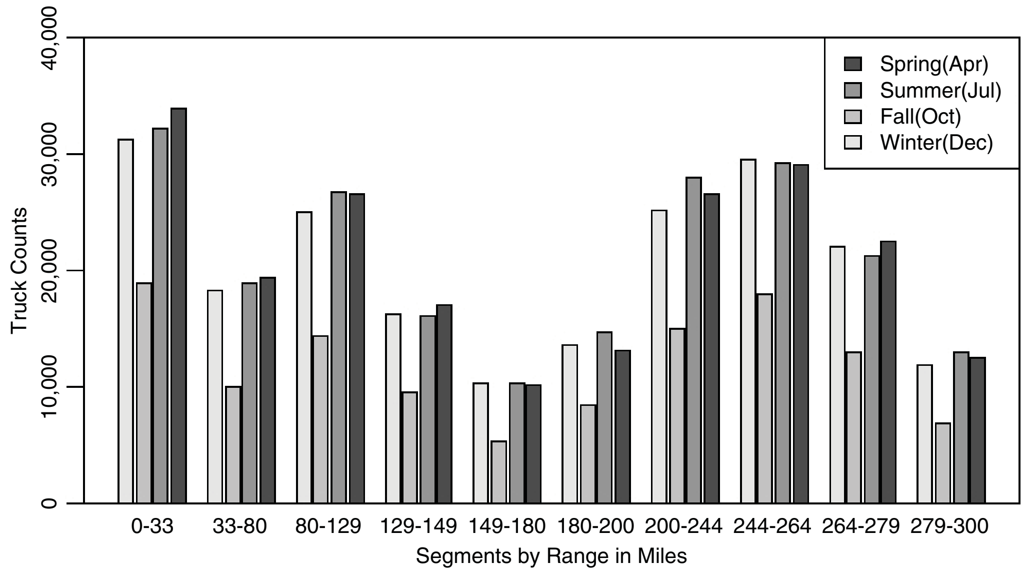


FIGURE 1 Truck counts across segments for April, July, October, and December 2007.

The GPS data are then arranged in database tables with the postgreSQL database tools and finally are simulated to generate travel time distributions with scripts written in PHP and Shell.

Segment Distribution

The following sequence is used to identify segments along the corridor:

1. Truck counts are determined for every mile and travel direction (NB or SB) by applying queries and scripts on the previously arranged database tables.
2. A cumulative truck count function (CTCF) is drawn for the cumulated truck counts. This CTCF allows the identification of any sudden rise and fall in truck counts occurring in a particular area of the corridor.
3. Smoothing of the data is performed on the CTCF with a moving average of length 20 mi.
4. These three processes are repeated for months in the various seasons of the year to capture any seasonal effects on truck counts.

Segment Analysis

Location of significant changes in truck density and time of the year and seasonal variations are two factors used to analyze the truck density patterns. Truck density patterns are used to break the corridor into a number of segments falling within rural and urban areas.

SEGMENTATION RESULTS

The results correspond to NB I-5 only. Commercial GPS data for April, July, October, and December 2007 were analyzed. These months were chosen to represent seasonal variations in truck travel and traffic volumes. Truck counts were first determined for 1-mi segments. The counts are similar for April, July, and December. Counts for October are consistently the lowest. Results for the month of July are presented here because those counts are highest or second highest along the corridor. Figure 1 presents the truck counts per segment for the 4 months analyzed.

Figure 2*a* presents the CTCF for NB I-5 during July 2007, given as a percentage of the total count per mile. It was verified that the

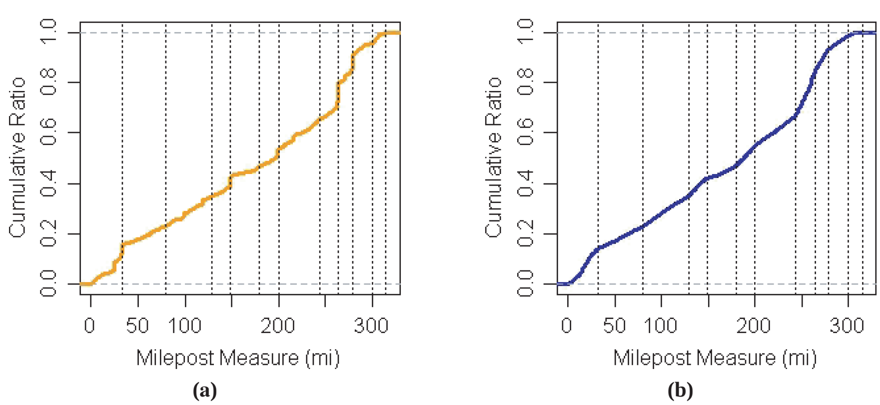


FIGURE 2 Cumulative truck count ratio: (*a*) collected data and (*b*) smoothed data, 20-mi moving average (data from July 2007).

TABLE 1 Segment Summary, NB I-5, July 2007 GPS Data

Segment ID	Segment Mileposts	Truck Counts	Nearby Locations on I-5 NB
1	0–33	18,861	Pacific Hwy. 99, Crater Lake Hwy., and International Medford Airport
2	33–80	9,998	Pacific Hwy. 99
3	80–129	14,392	Pacific Hwy., Northeast Stephens St., Roseburg Airport
4	129–149	9,454	Pacific Hwy., Eagle Valley Rd., Umpqua Hwy. 99
5	149–180	5,284	Near Eugene
6	180–200	8,427	Near Eugene
7	200–244	14,929	Eugene–Corvallis
8	244–264	18,002	Salem, Woodburn
9	264–288	12,898	Wilsonville, Tualatin, Junction I-205
10	288–300	6,892	Portland Junction I-84 (Figure 3*a*)

same sudden rise and fall in truck counts throughout the corridor take place at the same locations across the four chosen months (i.e., the cumulative distribution plots for the chosen months are similar to the plot shown for July). To present a clearer trend regarding the rise and fall in truck count rates, the data were smoothed by averaging over a 20-mi length (i.e., a moving average of 20 mi in length), shown in Figure 2*b*.

The start and end of each segment and nearby points of interest (urban areas, major highway junctions, etc.) are given in Table 1. Table 1 presents each segment identification, the segment mileposts, truck counts, and nearby locations or points of interest. Truck count results reflect the month of July 2007 only.

As expected, higher truck counts tend to occur in segments near urban areas (e.g., Eugene–Corvallis–Salem; all in Oregon). In the Portland area, counts are lower because of an alternative truck route (I-205) and the truck traffic splits. Figure 3 shows the identified segment locations for NB I-5. As depicted in the maps and supported in the results presented in Table 1, segments in northern Oregon (Segments 6 and 7) correspond to urban areas with higher truck count density (counts per mile), whereas segments in southern Oregon (Segments 1 through 5) correspond to rural areas with lower truck count density.

Segmentation should include other considerations, such as land use and posted speed limits. For example, in Oregon, speed limits in

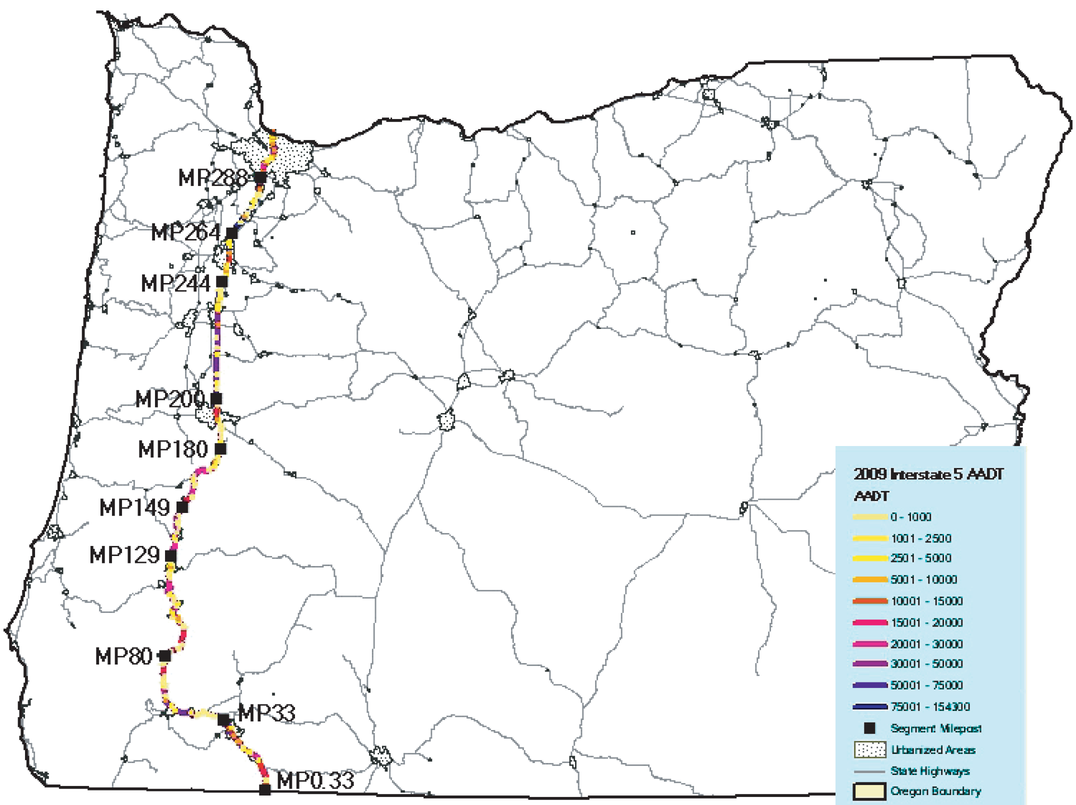


FIGURE 3 Segments identified along I-5 with Highway Performance Monitoring System volume data.

urban areas are lower than those in rural areas. To remove outliers, time-of-day level can affect the posted speed limit (night versus day). Similarly, recurrent congestion levels affect the lower speed thresholds.

Finally, identified segments can be mapped against geographic information system data (e.g., against Highway Performance Monitoring System data) to validate the results of the proposed corridor segmentation. With corridor segments identified, each corresponding to rural or urban areas, it is possible to analyze segments independently.

METHODOLOGY FOR ESTIMATION OF RELIABLE TRAVEL TIMES

This section presents the algorithm used to estimate truck travel time distributions for each segment. The parameters, variables, and output of the algorithm used to estimate the travel time distribution are as follows below.

Parameters

m_{0i} = initial milepost for segment i (i.e., start point of a segment in miles),
m_{1i} = final milepost for segment i (i.e., end point of a segment in miles),
$m_{1i} - m_{0i}$ = length of segment in miles,
$b_{ri} = f_i(|m_{1i} - m_{0i}|)$—buffer radius or the radius of influence in miles around the start and end points of a segment where $|m_{1i} - m_{0i}|$ is the length of the chosen segment,
f_i = factor to determine size of radius of influence,
mean_{cur} = total time/number of trucks—mean of the time stamp readings for segment being analyzed,
$\text{mean}_{\text{prev}}$ = mean of time stamp readings for a previous segment,
$n_{\min,i}$ = minimum acceptable number of trucks trips,
$s_{\min,i}$ = minimum acceptable truck speed, and
$s_{\max,i}$ = maximum acceptable truck speed.

Variables

m_{start} = actual start point for a truck in miles,
m_{end} = actual end point for a truck in miles, and
n_{actual} = actual number of truck trips in a segment as obtained from the data.

Outputs

t_{95} = travel time 95th percentile,
t_{80} = travel time 80th percentile, and
t_{50} = travel time 50th percentile.

It is assumed that the vehicle travel time within a segment is normally distributed.

The algorithm is as follows:

Step 0. Preprocessing

Determine the minimum number of trucks or observations ($n_{\min,i}$) required for each segment i. The value of $n_{\min,i}$ will depend on the required accuracy for the travel time estimations. The number of valid observation will depend on the following factors: (*a*) segment length, (*b*) time period, and (*c*) density of counts the given segment and time period.

Step 1. Initiate the iterations.

Pick the first segment, $i = 1$.

Step 2. Identify trips start and end points.

A truck may have several readings in a given segment. To find the most representative travel time for the segment, for each truck in the segment do the following:

(a) Find m_{start} that is closest to m_{0i} and lies within the buffer radius b_{ri}.

(b) Find the end point of the truck trip m_{end} for the same day that is closest to m_{1i} and lies within the buffer radius b_{ri}.

(c) If steps a and b are successful, then a travel time is obtained and added to the list of travel times for the segment.

Step 3. Number of travel time observations.

Count the number of truck trips obtained for the segment or the list size: n_{actual}.

Step 4. Verify that $n_{\text{actual}} \geq n_{\min,i}$.

If the number of minimum observations is not reached, output a warning message. It would be necessary to add more observations: (*a*) increasing the time period length or (*b*) finding a segment that better represent truck trips or GPS observation intervals. Go back to Step 1 and continue with the next segment $i = i + 1$.

Step 5. Calculate travel times.

Calculate travel time distribution for all the trucks by finding the difference in the time stamp between their consecutive m_{start} and m_{end} readings. This time difference is the actual time required by a truck to cross the segment.

Step 6. Remove outliers.

Calculate the minimum and maximum travel time ranges based on the length of the segment and the value of the parameters $s_{\min,i}$ and $s_{\max,i}$. Parameters $s_{\min,i}$ and $s_{\max,i}$ should be segment dependent because typical travel speeds are affected by land use (e.g., rural versus urban), posted speed limits, and congestion.

— Remove from the list of travel times any times that are outside the range of acceptable travel times. For example, trucks whose travel time exceeds the upper threshold may have stopped to rest, refuel, or make deliveries.

— Recalculate the size of the list of observations n_{actual}.

Step 7. Verify that $n_{\text{actual}} \geq n_{\min,i}$.

If the number of minimum observations is not reached, output a warning message. It is necessary to examine what is causing a high number of outliers. In some cases it would be possible to reincorporate trucks or observations if it is detected that an actual stop was made and this bias is properly removed from the data.

If after examining the outliers still holds that $n_{\text{actual}} \geq n_{\min}$, then segment length or speed threshold parameters may have to be reexamined. Go back to Step 1 and continue with the next segment $i = i + 1$.

Step 8. Estimate descriptive statistics for segment i.

Estimate desired percentiles, mean, standard deviation, skewness, and so forth.

Step 9. Repeat the analysis for next segments, $i = i + 1$ until all segments have been completed.

For the NB I-5 July 2007 data, the algorithm was applied to each of the mile post segments identified earlier. Results are presented in Table 2. The free-flow travel time is computed by dividing the segment length with the truck free-flow speed assumed to be 60 mph. The buffer (b_{ri}) is assumed to be 10% of the segment length, and

TABLE 2 Segment Travel Time Distributions, NB I-5, July 2007, 24-h Period

Segment ID	m_0 (mi)	m_1 (mi)	b_r (mi)	n_{actual} (count)	Free Flow (h)	Median, t_{50} (h)	t_{80} (h)	t_{95} (h)
1	3	33	3	371	0.5	1.23	1.48	1.77
2	33	80	4.7	591	0.78	1.48	1.77	2.09
3	80	129	4.9	331	0.82	1.48	1.82	2.19
4	129	149	2	155	0.33	0.74	0.918	1.11
5	149	180	3.1	216	0.52	1.22	1.49	1.8
6	180	200	2	54	0.33	0.686	0.831	0.991
7	200	244	4.4	309	0.73	1.86	2.39	2.98
8	244	264	2	151	0.33	0.799	0.988	1.2
9	264	279	1.5	268	0.25	0.828	1.01	1.22
10	279	300	2.1	99	0.35	1.11	1.36	1.64

the threshold travel speeds are assumed to be $s_{min,i}$ = 10 mph and $s_{max,i}$ = 80 mph.

The number of truck trips identified was sufficient for the travel time calculations to be performed on each segment (i.e., with the assumed parameters $n_{actual} \geq n_{min,i}$ that were always satisfied). This may not be the case if the period of analysis is smaller. The results for a shorter period, a typical afternoon peak period of 15:30 to 18:30, are presented in Table 3.

ANALYSIS OF RESULTS

The comparison of the results in Table 2 and 3 indicates that in almost all cases, the travel time percentiles are higher for the 24-h period. This is an indication that the low-speed threshold $s_{min,i}$ = 10 mph is not adequate since travel times during peak times should be longer than travel times that include low traffic periods (e.g., nighttime).

The impact of a low-speed threshold can be appreciated by observing a graph of the travel time distribution. Figure 4 presents the Gaussian kernel probability distribution graphs for the computed truck travel times for a period of 24 h (Table 2 values). Figure 5 presents the Gaussian kernel probability distribution graphs for the computed truck travel times for the period 15:30 to 18:30 (Table 3 values). The 95th percentile travel time is noted in each figure. Segment 1 of length $m_{1,1} - m_{0,1}$ = 30 mi and Segment 8 of length $m_{1,8} - m_{0,8}$ = 20 mi were chosen to facilitate comparisons and the calculation of travel speeds.

The graphs in Figures 4 and 5 show that there is a long tail of observations after a 1.25-h travel time for Segment 1 and a 0.8-h travel time for Segment 8. The corresponding speeds are 24 and 25 mph, respectively. Hence, the $s_{min,i}$ = 10 mph threshold is not adequate and captures travel times that include intermediate stops for rest, refueling, or deliveries. In some cases, when there are four or more observations for the same truck within the segment, an additional analysis of outliers indicates that trucks were indeed stopped. When there are only two observations for the same truck in the segment, it is impossible to determine the cause of the excessive travel time from the truck data alone.

The distributions of the coefficients of variations for all segments, as depicted in Figure 6, show the impact of $s_{min,i}$. A change in the slope is observed around 25 mph, and the distributions tend to have less variability when $s_{min,i}$ > 35 mph. However, increasing $s_{min,i}$ also increases the risk of wrongfully removing observations that reflect congested conditions if bottleneck travel times are less than $s_{min,i}$ and the length of the bottleneck is considerable in relation to the segment length (*13*). The value of the parameter $s_{max,i}$ is less significant since the left tail is naturally bounded by 0.

The most efficient method for calibrating $s_{min,i}$ is to use an alternative travel time estimation system, such as loop detectors. This method was successfully applied in the Portland region (*14*). Future research should include application of these methods to estimate travel time distributions such as lognormal or beta. These should be investigated because these distributions may prove to be a better fit. Additionally, smaller case studies could be conducted on segments

TABLE 3 Segment Travel Time Distributions, NB I-5, July 2007, 15:30 to 18:30 Period

Segment ID	m_0 (mi)	m_1 (mi)	b_r (mi)	n_{actual} (count)	Free Flow (h)	Median, t_{50} (h)	t_{80} (h)	t_{95} (h)
1	3	33	3	40	0.5	1.07	1.24	1.43
2	33	80	4.7	55	0.78	1.4	1.63	1.88
3	80	129	4.9	26	0.82	1.09	1.2	1.32
4	129	149	2	21	0.33	0.707	0.853	1.02
5	149	180	3.1	13	0.52	0.775	0.912	1.06
6	180	200	2	11	0.33	0.765	0.911	1.07
7	200	244	4.4	21	0.73	1.13	1.34	1.57
8	244	264	2	14	0.33	0.773	0.955	1.16
9	264	279	1.5	32	0.25	0.781	0.952	1.14
10	279	300	2.1	6	0.35	0.944	1.12	1.33

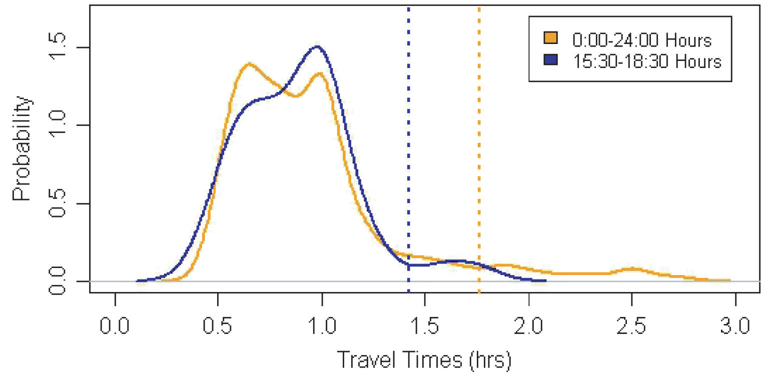


FIGURE 4 Segment 1 travel time distributions, 24-h versus 15:30-to-18:30 period (dashed lines indicate corresponding 95th percentile).

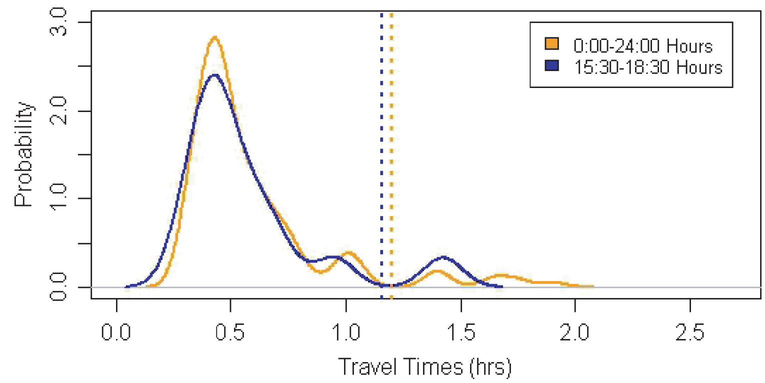


FIGURE 5 Segment 8 travel time distributions, 24-h versus 15:30-to-18:30 period (dashed lines indicate corresponding 95th percentile).

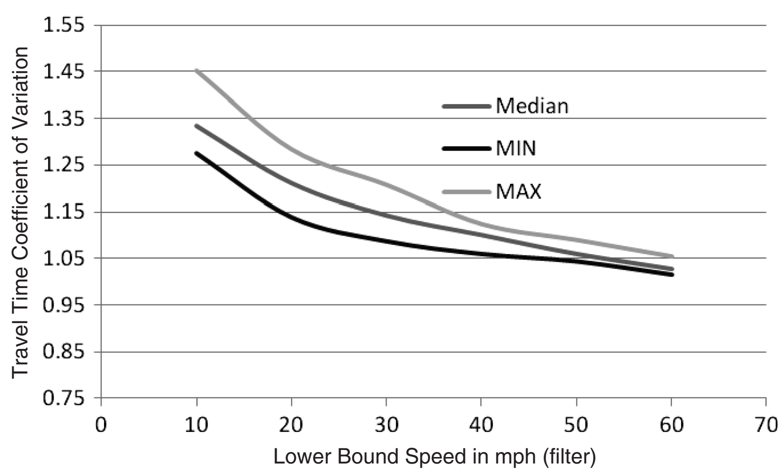
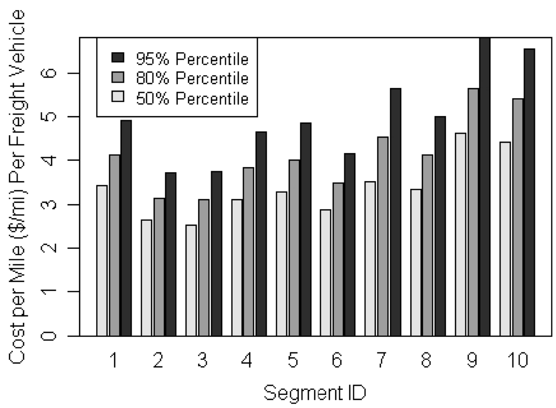
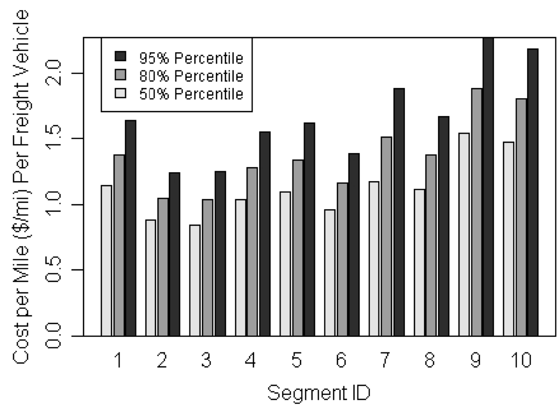


FIGURE 6 All segments, travel time coefficients of variation of speed parameter $s_{\min,i}$.



(a)



(b)

FIGURE 7 Cost per mile per freight vehicle: (*a*) daily operating cost and (*b*) additional daily travel time cost due to unreliable travel time only.

for various times of day (or weekend versus weekday) to capture variation in travel time distributions and allow comparison among segments by type (urban versus rural). The analysis presented in this research is a launching point for further studies and investigations and offers an example of application of the research methods.

ESTIMATED COST OF TRAVEL TIME RELIABILITY

The impact of travel time reliability on operating and travel time costs can be estimated by using the predicted travel times with the 50th, 80th, and 95th percentiles across each segment of the corridor. The figure for average operating cost, $83.68 per hour, was derived during recent research by ATRI and is used to estimate operating cost per mile (*15*). The figure for average value of time for freight vehicles in Oregon, $27.85 per hour, was adjusted to reflect 2010 prices and is used to estimate travel time cost per mile (*16*).

For each segment along the corridor, Figure 7 presents the daily operating cost per mile per freight vehicle and presents daily travel time cost per mile per freight vehicle for travel below free-flow conditions (i.e., the cost of delay for travel time at 50%, 80%, and 90% confidence intervals). As shown in the figure, costs per mile per freight vehicle are greater near urban areas, and the Portland–Vancouver (Washington) area and surrounding cities achieve the highest cost per mile per freight vehicle (Segments 9 and 10). The urban areas show greater differences in costs among the travel times at 50th, 80th, and 90th percentiles. Smaller cities, such as Eugene and Salem (Segments 6 and 8) also achieve moderate cost per mile per freight vehicle, as does the area surrounding the key junction of I-5 and Pacific Highway (Segment 4). The remaining rural areas achieve lower cost per mile, with little difference between travel times with 50%, 80%, and 90% confidence intervals.

Higher costs near urban centers are a direct result of the increase in the variability (i.e., decrease in reliability) of travel time within these areas, caused by recurring and nonrecurring congestion. Variability in travel time presents a particular challenge for the freight industry, as carriers must meet scheduling demands of their customers. Figure 8 compares free-flow travel time and travel time at the 50th, 80th, and 90th percentiles by depicting the increase in cost above free-flow cost.

CONCLUSIONS

Estimation of travel time reliably plays a crucial role in timely delivery of goods and is dependent on such as time of operation, location of the corridor, and corridor characteristics (urban or rural

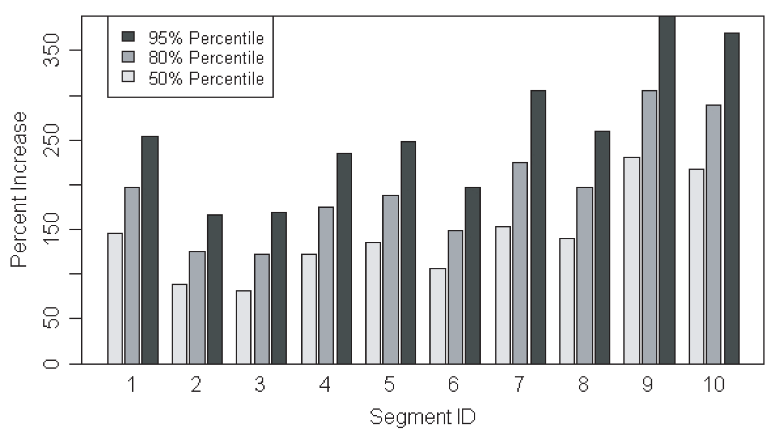


FIGURE 8 Percent increase in cost per mile per freight vehicle relative to free-flow costs for travel times at 50th, 80th, and 95th percentiles.

segments, time of day). This paper discussed a methodology that can estimate the travel time distributions across a particular segment of a corridor. More accurate travel time distributions are useful because they can help a carrier meet departure and arrival time constraints.

Long freight corridors comprise segments with potentially different reliability characteristics. This research developed algorithms that use available truck GPS data to identify corridor natural segments or regions (urban centers, Interstate junctions, and rural areas) and to estimate corridorwide impact of travel time unreliability. The method was applied successfully to segments of the I-5 corridor in Oregon. The impact of travel time reliability on operating and travel time costs was estimated with the predicted travel times with 50th, 80th, and 95th percentiles. Higher costs near urban centers are a direct result of an increase in the variability (decrease in reliability) of travel time within these areas, caused by recurring and nonrecurring congestion.

Among the parameters that are needed to filter outliers, the low-speed threshold is the most critical. Lower low-speed thresholds lead to unrealistic travel time distributions, and higher low-speed thresholds increase the risk of filtering out observations that represent real-world congested travel times.

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REFERENCES

1. Harrison, R., and M. Schofield. *Developing Appropriate Freight Performance Measures for Emerging Users.* SWUTC/07/473700-00073-1. Southwest Region University Transportation Center, Texas Transportation Institute, College Station, 2007.
2. Cambridge Systematics, Inc., Dowling Associates, Inc., System Metrics Group, Inc., and Texas Transportation Institute. *NCHRP 618: Cost-Effective Performance Measures for Travel Time Delay, Variation, and Reliability.* Transportation Research Board of the National Academies, Washington, D.C., 2009.
3. Cambridge Systematics, Inc., PB Consult, Inc., and Texas Transportation Institute. *NCHRP 551: Performance Measures and Targets for Transportation Asset Management.* Transportation Research Board of the National Academies, Washington, D.C., 2006.
4. McCormack, E., X. Ma, C. Klowcow, A. Currarei, and D. Wright. *Developing a GPS-Based Truck Freight Performance Measure Platform.* Transportation Northwest Regional Center X, Washington State Transportation Center, Washington State Department of Transportation, Olympia, 2010.
5. Quiroga, C., and D. Bullock. Travel Time Studies with Global Positioning and Geographic Information Systems: An Integrated Methodology. *Transportation Research Part C,* Vol. 6, No. 1–2, 1998, pp. 101–127.
6. Bertini, R. L., S. Hansen, A. Byrd, and T. Yin. Experience Implementing a User Service for Archived Intelligent Transportation Systems Data. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1917,* Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 90–99.
7. Wieczorek, J., L. Huan, R. Fernandez-Moctezuma, and R. Bertini. Integrating an Automated Bottleneck Detection Tool into an Online Freeway Data Archive. Presented at 88th Annual Meeting of the Transportation Research Board, Washington, D.C., 2009.
8. Nihan, N. L., X. Zhang, Y. Wang, and P. Briglia. *Evaluation of Dual-Loop Data Accuracy Using Video Ground Truth Data.* T1803.38. Washington State Transportation Commission, Olympia, 2002.
9. Wang, Y., N. Nihan, R. Avery, and G. Zhang. *Improving Truck and Speed Data Using Paired Video and Single-Loop Sensors.* T2695.61. Washington State Transportation Commission, Olympia, 2006.
10. Monsere, C., M. Wolfe, H. Alawakiel, and M. Stephens. *Developing Corridor Level Truck Travel Time Estimates and Other Freight Performance Measures from Archived ITS Data.* Oregon Transportation Research and Education Consortium, Oregon Department of Transportation, Salem, 2009.
11. Greaves, S. P., and M. A. Figliozzi. Collecting Commercial Vehicle Tour Data with Passive Global Positioning System Technology: Issues and Potential Applications. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2049,* Transportation Research Board of the National Academies, Washington, D.C., 2008, pp. 158–166.
12. *Highway Capacity Manual 2010.* Transportation Research Board of the National Academies, Washington, D.C., 2010.
13. Figliozzi, M., and M. Saberi. *Travel Time Estimations on Congested Freeways with Stochastic Capacity.* Portland State University, Portland, Ore.
14. Wheeler, N., and M. Figliozzi. Multicriteria Freeway Performance Measures for Trucking in Congested Corridors. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2224,* Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 82–93.
15. Trego, T. G., and D. Murray. Analysis of the Operational Costs of Trucking. Presented at 89th Annual Meeting of the Transportation Research Board, Washington, D.C., 2010.
16. *The Value of Travel Time: Estimates for the Hourly Value of Time for Vehicles in Oregon 2005.* Economics and Policy Analysis Unit, Oregon Department of Transportation, Salem, 2006.

Any errors or omissions are the responsibility of the authors.

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