Multicriteria Freeway Performance Measures for Trucking in Congested Corridors

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Research was undertaken to develop multicriteria tools for measuring and analyzing the impact of recurring and nonrecurring congestion on freight. Unlike previous studies, this work used several distinct data sources to analyze the effects of congestion on I-5 in the Portland, Oregon, metropolitan area: Global Positioning System data from commercial trucks, Oregon Department of Transportation corridor travel time loop data, and incident data. A new methodology and algorithms combine these data sources and estimate the impact of recurrent and nonrecurrent congestion on reliability and delays, costs, and emissions of freight movements. The results suggest that traditional traffic sensor data tend to underestimate the impact of congestion on travel times and variability of commercial vehicles. Congestion is detrimental not only for carriers' and shippers' costs but also for the planet because of increases in greenhouse gas emissions and for the local community because of increases in oxides of nitrogen, particulate matter, and other harmful pollutants. The developed methodology can provide useful freight operation and performance data for the freight community, transportation decision makers, and other transportation stakeholders.

Because of its geographic location, the Oregon economy is highly dependent on reliable freight transportation. Recent studies indicate that projected growth in freight and passenger traffic will significantly increase congestion and travel time delays. It is predicted that congestion may result in the loss of value-added generation of as much as $1.7 billion per year by 2025 in Oregon and a "loss of 16,000 ongoing jobs" (*1, 2*). For the freight industry, delay and congestion not only negatively affect the businesses that rely on efficient and timely deliveries but also increase emission levels and the cost of transporting goods. To improve the functionality of transportation networks and make efficient use of funds, public agencies must develop the right tools for assessing transportation system performance.

Performance measures allow planners and engineers to monitor and evaluate the operation of transportation facilities. Performance measures can include travel time, speed, and travel time reliability, plus others derived from these basic measures. Early in the adoption process of performance-based metrics, passenger vehicles were the main focus, but freight traffic was not incorporated independently (*3, 4*). Therefore, freight-specific performance measures (FPMs) are not in wide use by public agencies. It is increasingly important to continue development of a system of performance measures that will capture the impact of congestion on various modes, the environment, and people living near a transportation network.

A body of research has emerged that uses new methods for collecting and analyzing data from commercial vehicles for developing FPMs. This research is showing promise for providing consideration of freight in the planning process. This paper develops tools for measuring and analyzing the effect of recurring and nonrecurring congestion on freight corridors in the Portland, Oregon, metropolitan area. The FPMs are then monetized with standard methods and are used to estimate emissions through an urban freeway corridor.

BACKGROUND

Developing Congestion and Mobility Performance Measures

Roadway loop sensors, weigh in motion (WIM) data, and Global Positioning System (GPS) data can be used to obtain travel time and speed information for freight trucks. However, for each data source, there are advantages and challenges in using the data to derive FPMs for congestion and mobility.

Loop Sensors

Archived loop sensor data has been used to estimate freeway performance (e.g., travel time, speed, and vehicle count). Loop sensors can be used to study recurring and nonrecurring congestion and to identify and study bottlenecks within regions (*5, 6*). However, loop sensors are limited in their ability to differentiate vehicle types to provide disaggregate data by mode. 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 congestion (*7–9*).

WIM and Truck Transponder Data

Initial work at the University of Washington investigated the use of truck transponder data in providing link travel time information (*10*). McCormack et al. later found that both GPS and truck transponder

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technologies can estimate travel times; however, these technologies may require a large number of vehicle observations and must incorporate methods for determining whether trucks have stopped for deliveries, resting, or refueling (*11*).

Recent work at Portland State University investigated the use of transponder-equipped trucks to make travel time estimations between weigh stations in rural Oregon (*12*). This research successfully developed nonmobility or congestion measures of performance by quantifying overweight vehicles, ton miles on corridors, empty vehicles, the penetration of trucks with truck transponders, origin–destination (O-D) estimations, and seasonal variability in various measures, as well as travel time estimations (*12*).

Commercial GPS Data

FHWA, in partnership with the American Trucking Research Institute (ATRI), has methods that use GPS technology to determine travel time reliability in freight corridors (*13*) and to identify freight bottlenecks (*14*). FHWA and ATRI released an online freight performance measure tool, FPMweb, that gives users access to aggregated operational truck speed data using GPS data from several hundred thousand unique trucks (*15*). Harrison and Schofield examined limitations associated with the approach of the earlier work (*3*). They observed two main problems: (*a*) the accuracy of the GPS coordinates, which may be in error of up to 0.25 mi; and (*b*) the low number of observations in areas with low traffic volume. A greater limitation is that the data do not differentiate between vehicle stops for congestion and stops for refueling or mandatory driver rest periods. This presents a bias in the data set in which slow speeds may be representing local trips rather than congestion on the network.

Researchers at the University of Washington used GPS data from commercial trucks to estimate link travel time, develop FPMs, and study before-and-after conditions in improvement areas (*11, 16, 17*). Although the data were cleaned to remove erroneous data, the researchers found a benefit of freeway improvement projects by studying GPS data on a small scale before, after, and during construction. An O-D algorithm was developed to separate trucks; this method identified travel patterns of truck traffic between transportation analysis zones (*16, 17*). Further investigation incorporated spot speeds to estimate measures of mobility and then compared these to loop sensor data and space mean speed of consecutive GPS readings (*18*). This study found that spot speeds compare well with space mean speeds and loop sensor data across segments of analysis.

Similarly, researchers in Kansas have developed a method for collecting freight trajectory data by integrating cellular phone data and geographic information systems (*19*). The research is the first to attempt to identify freight-specific cellular data from data in which multiple user types exist and has shown potential for use of trajectory data to study and understand freight movements and geographic extents.

Monetary Performance Measures

Projects may be ranked by system performance, but performance measures may also be monetized and ranked to show benefit and impact of a proposed project. Without accurate information about the operating costs or value of time for the freight industry, the benefit of a given project may be underestimated or the benefit of financing strategies like congestion pricing may be overestimated (*20*).

Variations in Value of Time for Freight Vehicles

Research has shown great variation in freight value of time across regions, roadway conditions, and carrier types.

NCHRP 431 investigated variations in value of time for passenger vehicles and freight trucks in hypothetical congested roadway scenarios. For both freight and passenger vehicles, time losses during congestion were valued at more than twice the value of time savings during uncongested conditions. The report recommends the use of travel time values for congested periods that are 2.5 times the value of time estimates during uncongested periods (*21*). Variations in freight value of time are also found by region. Value of time estimates can vary over a wide range, according to research conducted by Minnesota and the Oregon Department of Transportation (Oregon DOT) and to a national urban area average provided by the Texas Transportation Institute (TTI) (*22–24*). Kawamura investigated differences in value of time among operators and trucking industry segments. Findings showed that not only do freight carriers have a higher value of time than passenger vehicles, but there is also significant heterogeneity among carriers (*25*).

Using Value of Time to Monetize Travel Time and Delay

By using the value of time derived from the work of Kawamura (*25*), it is possible to monetize measures of travel time and delay. TTI's Urban Mobility Report evaluates procedures, processes, and data used for developing estimations of the cost of congestion (*24*). Equation 1 is the TTI formula for determining the annual cost of congestion for freight vehicles (*24*):

$$\begin{matrix}\text{annual}\\\text{commercial}\\\text{vehicle}\\\text{cost}\end{matrix} = \begin{matrix}\text{daily}\\\text{vehicle}\\\text{hours}\\\text{of delay}\end{matrix} \times \begin{matrix}\text{commercial}\\\text{vehicles }\%\end{matrix} \times \begin{matrix}\text{commercial}\\\text{vehicle}\\\text{time value}\\(\$/\text{h})\end{matrix} \times \begin{matrix}\text{250}\\\text{working}\\\text{days}\\\text{per year}\end{matrix} \quad (1)$$

Incorporating Travel Time Reliability in Travel Cost Calculations

In addition to travel time and delay, travel time reliability (or variability) can be incorporated into travel cost calculations. Reliability of travel time is particularly important to time-sensitive shippers and time-definite delivery carriers. One of the simplest approaches to quantifying traveler cost takes the form given in Equation 2 (*26*):

$$U_c = a_1 \times T + a_2 \times V(T) + a_3 \times M \quad (2)$$

where

U_c = traveler cost,
T = trip travel time,
$V(T)$ = trip travel time variability,
M = cost of traveling, and
a_1, a_2, a_3 = parameters representing the dislike of travel time, variability, and travel cost, respectively.

Cohen and Southworth used a low-end and a high-end range for a_2 of 0.3 and 1.3 (*26*). Research has shown that by improving reliability during congested peak periods, there is great potential to significantly reduce the cost of travel during congestion.

Using Operational Cost to Monetize Travel Time and Delay

Although the value of time has been widely incorporated into cost–benefit analysis, by examining marginal operating costs one can gain insight into decisions made by carriers and how the freight industry is affected by the performance of the transportation system.

In a recent study, ATRI found the average marginal operating cost for the freight industry to be $1.78 per mile and $83.68 per hour; cost per hour was based on the respondents' hourly wage (*20*). ATRI also found that specialized carrier types had the highest cost per mile, followed by less-than-truckload and truckload carrier types. Fuel, driver wages, and truck or trailer lease or purchase were among the top cost items. As shown by value-of-time studies, there are major differences among trucking industry sectors. ATRI also used a three-step method to apply average cost values to investigate the annual cost impact of a bottleneck on the trucking industry (*27*).

Environmental and Health Performance Measures

Freeway performance measures can be used to quantify environmental and health performance measures related to tailpipe emissions and to provide transportation agencies the tools to link transportation performance to environmental and societal goals. To do this, planners and engineers often use a sequential three-step model process in which outputs from one step are the input for the next. This process generally consists of the following models: (*a*) transportation demand traffic models, (*b*) emissions rate models, and (*c*) pollution dispersion models.

A variety of models can be used to estimate tailpipe vehicle emission rates. The MOVES2010 model can be used to estimate national, state, county, and project-level emissions for greenhouse gases (GHG), select mobile source air toxics (MSAT), and criterion pollutants. Among models, there is some variation in the specific vehicle and roadway factors and assumptions. Several studies have used emissions models to investigate the impact of freight vehicle characteristics (e.g., speed, acceleration, weight) and the impact of roadway characteristics (e.g., grade, classification) on emission rates. In general, speeds outside the range of 30 to 60 mph, heavy vehicle loads, and increases in grade (*28–33*) lead to major increases in emission rates.

RESEARCH CONTRIBUTION

Distinct from other studies, this work uses GPS data from commercial trucks, corridor travel time loop data (from Oregon DOT sensors), and incident data to develop FPMs. Integrating the loop sensor data with the GPS data allows for validation between the two data sets and improves the filtering process to identify trucks that have experienced congested freeway conditions. Unlike the loop sensor data, which may underestimate the impact of congestion on trucks, the GPS data more accurately portray the roadway conditions experienced by a truck.

A methodology has been developed to combine these data sources and estimate the impact of recurrent and nonrecurrent congestion on freight movement speed, travel time, and travel time reliability. The study seeks to distinguish trucks moving along a freeway network from those making local movements (such as for deliveries, rest, or refueling) to study freight performance with unbiased measures. In addition, this paper uses multiple criteria for evaluating freight performance.

The research demonstrates how FPMs can be monetized and used to estimate emissions through an urban corridor with standard methods. Focus of multicriteria performance measures will center on mobility congestion and briefly cover cost and emissions; however, criteria could extend beyond these three basic categories. A more expansive discussion regarding the cost and emissions estimations is available elsewhere (*34*). Analysis of the GPS commercial truck data is a significant step toward understanding not only the behavior of freight transit throughout the day but also the impact of recurring congestion and incidents on trucks traveling along the corridor.

DESCRIPTION OF AVAILABLE DATA

Loop Sensor Data

Portland State University has direct access to corridor loop data from Oregon DOT sensors. These sensors collect the count and speed of vehicles in the Portland region. The Portland Oregon Regional Transportation Archive Listing (PORTAL) offers traffic data, performance measures, and analytical tools in a user-friendly interface (*34*).

Incident Data

In addition to the loop sensor data, PORTAL has integrated incident data from the Oregon DOT Advanced Transportation Management System. This gives the user more information with which to discern whether the traffic behavior was recurring or nonrecurring (caused by an incident, weather event, or roadside construction). The incident database includes information on the type of incident, severity, approximate start and end time, and approximate location of the incident, in addition to several other fields.

Truck GPS Data

This work incorporates GPS data from a sample of commercial trucks along the I-5 corridor. GPS truck data were provided by the ATRI as part of a research contract between FHWA and Portland State University. The GPS devices onboard the trucks report a unique truck identification number (truck ID), date, time, and position (latitude and longitude) for each truck reading. Some truck IDs in the data set report readings more frequently than others, meaning there is no common gap time between readings.

The trucks in the data set are categorized into four groups: through, partial through, partial local, and local. A through truck makes no stops on the freeway corridor and has at least one reading before and after the start and end of the corridor. A truck that has only one reading on one end of the corridor is defined as a partial through truck. Partial local and local trucks contain some or all readings on the local network; these trucks may represent local or arterial street conditions rather than congested freeway conditions.

It is crucial to separate truck types because of the potential distorting effect of including local, partial through, or partial local truck GPS data in the aggregation of travel time and speed estimates along freeway corridors. The distorting effect may arise, for example, where an Interstate is elevated, with local streets directly beneath the Interstates or close to it. Because of the proximity of the local network to the Interstate network and the accuracy of GPS units, it is possible for readings on the local network to be improperly assigned to the freeway network, presenting a bias of slower speeds in the data set. In addition, where two Interstates meet at a junction, it is possible to create bias by mixing freeway reads, as one freeway can be uncongested while the other is highly congested.

To address these concerns, a research methodology was developed that identifies through trucks so the impact of congestion on freight movements throughout the day can be estimated and bias from trucks that have deviated from the freeway or are traveling on the local network can be reduced.

METHODOLOGY FOR IDENTIFYING THROUGH TRUCKS

Two main filtering processes were implemented in the procedure to identify through trucks: (*a*) truck ID matching process to identify all potential through trucks and (*b*) comparison of GPS speeds with loop sensor average travel time by period.

Filter Process 1. Truck ID Matching

Figure 1 is a diagram of parameters for identifying through trucks. The extremities of the corridor are defined in Figure 1 as start mile m_s and end mile m_e. Because it is unlikely that readings will occur exactly at mile m_s or m_e, a buffer region surrounding the start and the end mile is created:

$$\text{start buffer} = m_s \pm r$$

$$\text{end buffer} = m_e \pm r$$

where r is the buffer radius in miles.

A time window t_c is defined as the maximum threshold for a vehicle to clear the extremities of the corridor plus the buffer region. This assumes that one trip must be completed within time window t_c; otherwise, it is assumed that the truck has made one or more local stops through the corridor. This parameter is set liberally to ensure that vehicles traveling at less than free-flow speed during congested periods are captured as potential through trucks. Similarly, time window t_b is defined as the maximum threshold for a vehicle to clear the buffer region surrounding m_s or m_e.

Many of the trucks found in the data set have made multiple trips through the corridor, either on the same day or on another day in a given month. Thus, the matching process must incorporate rules to distinguish between multiple through trips made by the same truck ID. The logic for identifying potential through trucks is as follows:

1. Use the ArcGIS linear referencing tool (locate features along routes) to obtain milepost measures along an Interstate for each GPS truck reading using latitude and longitude data.
2. Determine the corridor extremities (m_s and m_e).
3. Create a record of each reading falling within the start and end buffer ranges.

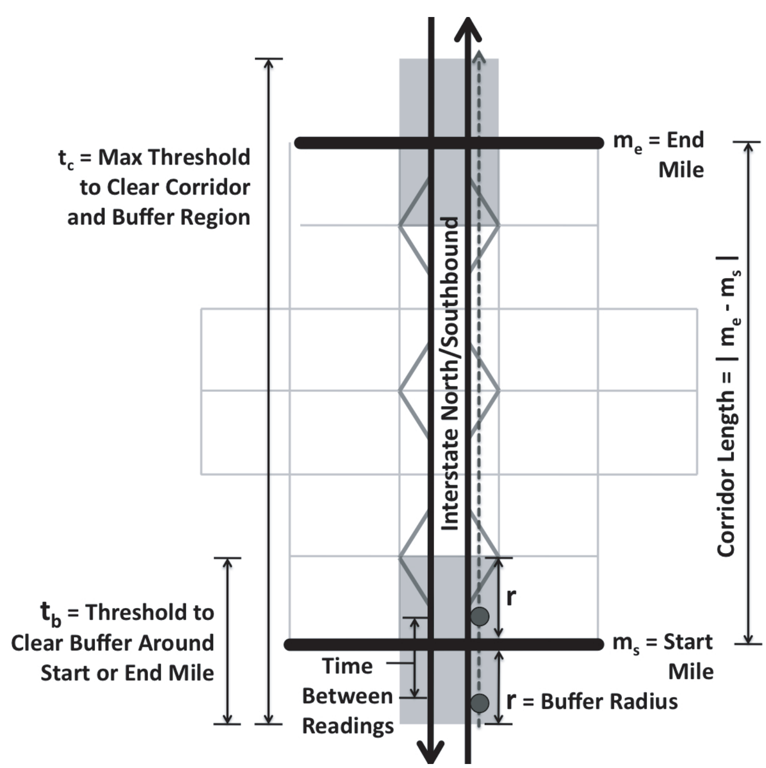


FIGURE 1 Diagram of user-defined parameters for Filtering Process 1 and truck ID matching to find potential through trucks.

4. For all readings that fall within the buffer ranges, use time thresholds to distinguish individual trips by each truck, and identify the start and end points of each trip.

5. For each truck ID, match all start readings to a downstream end reading that occurs within a time t_c and record as a single trip.

6. Search the entire data set to find all intermediate readings for a truck ID that fall between the trip start and end readings (use time stamp and milepost data) to create a complete trip through the corridor.

7. Use speeds obtained from the next closest reading to adjust the start and end reading time stamp and milepost to begin at m_s and m_e.

8. For each truck ID and trip, use adjusted start and end reading time stamps to obtain the travel time and speed through the corridor, and use milepost data to identify trip direction of travel.

Filter Process 2. Comparison with Loop Sensor Average Travel Time

In the second step for identifying through trucks, the corridor travel times from each potential through truck are sorted by the start reading time stamp into time bins of 15-min intervals. These times are then compared with the loop sensor average travel time at a 15-min resolution for the period of interest. The loop sensor data are used to calculate a deviation index to determine if the through truck values deviate too greatly from the expected average given by loop sensors. The deviation index is calculated as follows:

For a 15-min time bin t let

a_t = loop sensor average travel time at time bin t

σ_t = loop sensor day-to-day standard deviation in travel time at time bin t

For each truck trip k in 15-min time bin t let

T_k = corridor average travel time for truck trip k

Then the deviation index g_k is defined as

$$g_k = |a_t - T_k| / \sigma_t$$

Any $g_k > m \times \sigma$ for all time bins is assumed to be too far from the expected average and is excluded from subsequent analysis; m is a user-defined parameter.

Filter Process 2 is necessary to ensure that the identified potential through trucks from Filter Process 1 have not stopped for rest or refueling and therefore can be classified as a through truck. Because loop detection can underestimate the impact of congestion on the freight trucks (as shown in a later section), it is expected that loop sensor average travel times may be shorter than truck travel times. This must be taken into account when the value of parameter m is set to exclude only trucks making stops.

Methodology for Nonrecurring Congestion

The incident analysis requires only minor modifications to the previously discussed procedure to identify through-incident trucks. Instead of examining the entire corridor, the analysis is restricted to a small roadway segment preceding an incident. The incident data helps to pinpoint the incident along the corridor, narrow the analysis period, and validate that slower truck speeds through an incident area around the time of the incident result from the incident itself.

CASE STUDY

The presented case study investigates a 31.75-mi segment of northbound I-5 from Milepost 283.93 in Multnomah County, Oregon, through Milepost 7.3 in Clark County, Washington. Because horizontal and vertical curves of a roadway typically affect the speed of trucks more than the speed of passenger vehicles, the segment investigated in the case study offers some control for this effect, as it is fairly flat with few curves.

The recurring congestion analysis presented in this paper focused on weekdays during 2007. The nonrecurring congestion analysis studied trucks passing through a 5-mi segment of roadway south of an incident on northbound I-5. The incident took place at Milepost 304 on December 12, 2008, was designated as a crash type lasting from 12:02 to 12:46 p.m., and affected two lanes of traffic. A small amount of rain fell through the afternoon, but there was no adverse weather.

The methodology for recurring congestion was applied to study nonrecurring congestion. Trucks passing through the 5-mi segment without stopping were considered through-incident trucks. Additionally, trucks making partial local, partial through, and through-incident movements over the incident segment were investigated at the incident area so the bias of including these non-through movements could be estimated.

RESULTS

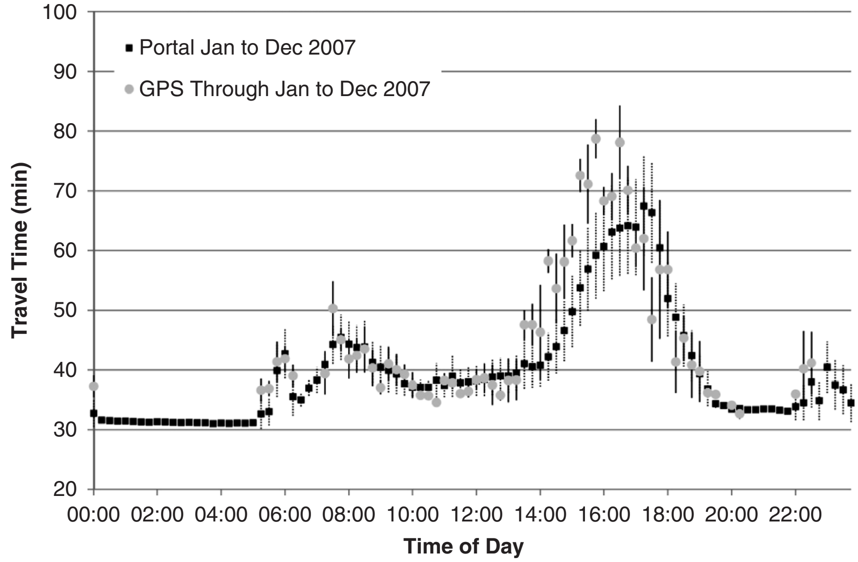
Recurring Congestion Results

Figure 2*a* presents the aggregated average weekday travel times for the through truck corridor for 2007. The results show that in the evening peak, from 3:00 to 6:00 p.m., the travel time for through trucks is consistently greater than the travel time based on loop sensor data, which suggests that in the evening peak period, loop sensor data may underestimate the impact of congestion for freight vehicles.

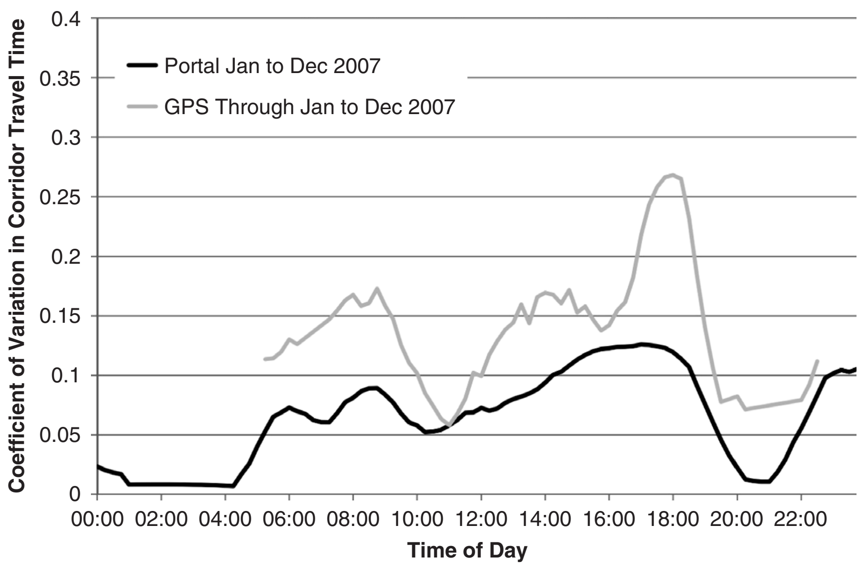
Figure 2*a* also presents the standard deviation of the mean loop sensor data and standard error for through truck averages. The standard error of the mean for through truck averages indicates less-reliable travel time during the congested evening peak of 3:00 to 6:00 p.m., as shown by greater standard error values. This means that in addition to longer travel time during congested periods, there is a high degree of unpredictability in day-to-day corridor travel time. Figure 2*b* presents the coefficient of variation in travel time for the through trucks and loop sensor data; data were smoothed with a moving average over three time bins. This figure confirms increased variability during congested periods for both loop sensor and through truck data. However, variability of through truck data is considerably higher. It is clear that loop sensor data underestimate the impact of freight travel time variability.

Nonrecurring Congestion Results

In general, the through-incident average truck speeds closely followed the loop sensor data in proximity to the incident location. Figure 3*a* presents the results for through-incident truck speeds crossing the 5-mi



(a)



(b)

FIGURE 2 Results following Filter Process 2: (*a*) average corridor travel time, aggregated PORTAL loop sensor and through trucks for 1 year (standard error of mean noted for multiple readings in time bin), and (*b*) coefficient of variation in travel time, data smoothed by moving average of three time bins.

area south of Incident A. Loop sensor speeds south of Incident A are also shown on the day of the incident and on a day when no incident occurred (December 9, 2008).

Figure 3*a* shows obvious differences in the loop sensor data for the 2 days, with major drops in speed around the time of the incident of interest. The through-incident truck average corridor speeds appear to closely follow the average loop sensor data on the day of the incident. In addition to slower speeds around the time of Incident A, there were periods of slower speeds in comparison with the non-incident day. Thus, all incidents happening downstream of Incident A were considered a potential cause; they are labeled along the *x*-axis in Figure 3*a* to show the time and duration of the incidents (downstream incidents are labeled *d*). It is clearly shown that the downstream incidents also affect speeds through the incident area throughout the day.

Similar to the nonrecurring through-incident truck analysis, Figure 3*b* presents results when only partial through and partial local incident trucks were included in the average. For the aggregated data in time bins with multiple readings, it can be seen that the standard error of the mean for partial through and local truck data varies more than when only through-incident trucks were averaged. This finding points to the effectiveness of through-only trucks serving as the best indicator of performance estimations.

When trucks making partial through or partial local movements are included in the estimation, some bias is likely. Partial local trucks may underestimate speeds, while partial through trucks may not

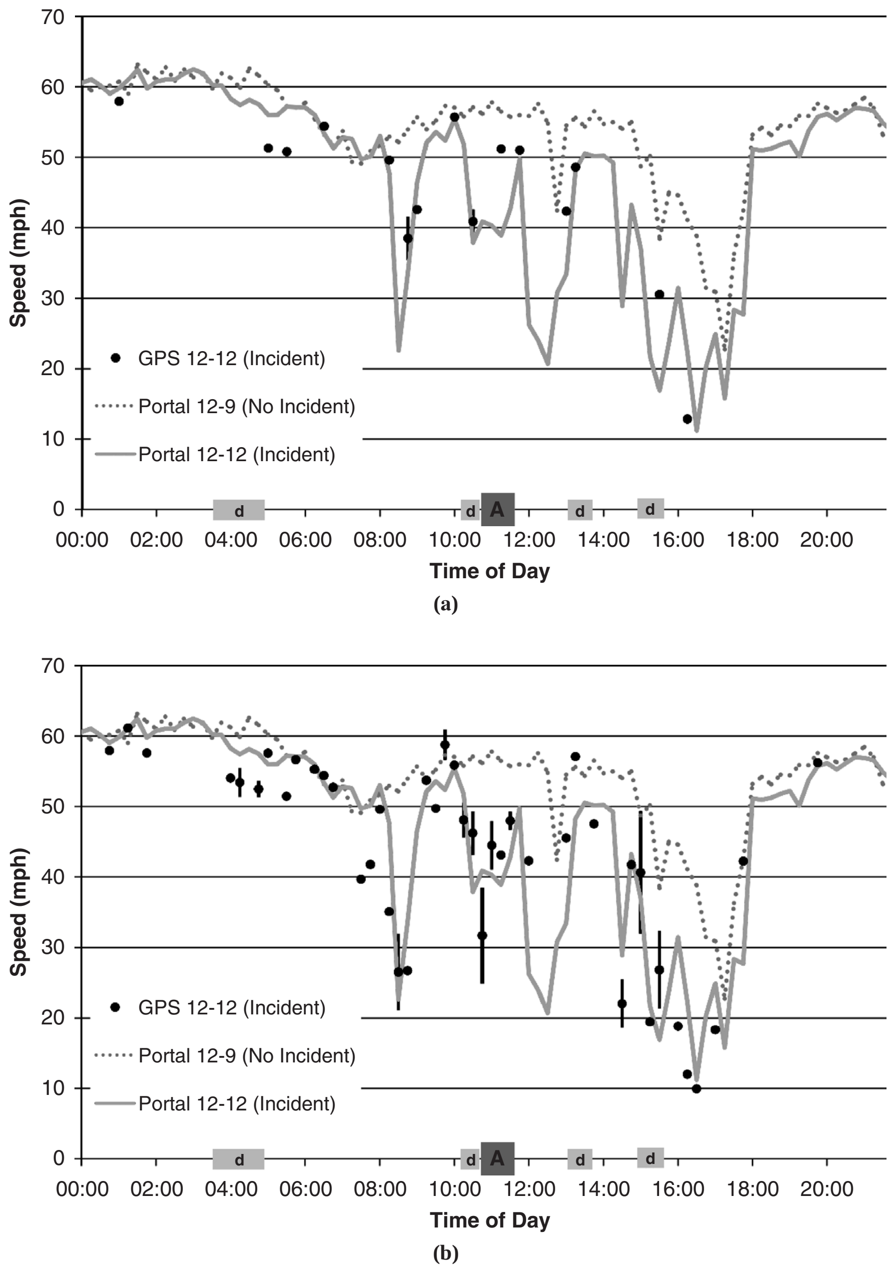


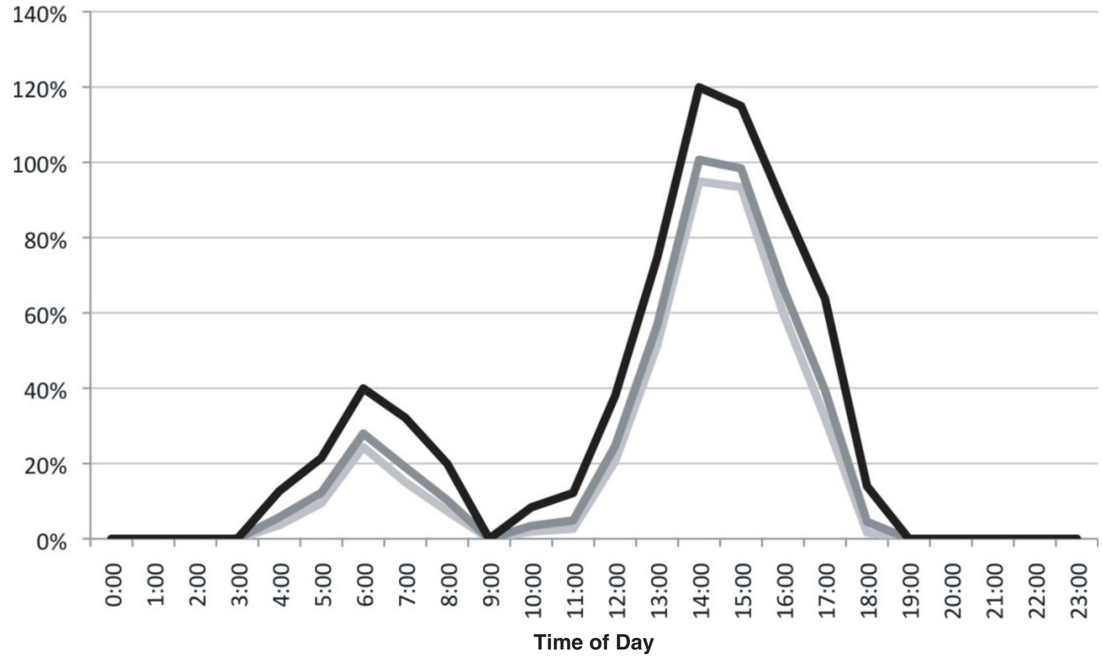
FIGURE 3 Nonrecurring results following Filter Process 2: (*a*) aggregated through-incident truck corridor average speeds (standard error of mean noted for multiple readings in time bin) and (*b*) aggregated partial through and partial local incident truck corridor average speeds (with standard error of mean noted for multiple readings in time bin).

have traveled completely through the incident area (or corridor) and therefore avoided part or all of the congestion. Alternatively, through-incident vehicles provide the best estimation of performance measures because they must travel the length of the incident area (or corridor) and fully experience incident congestion.

Results of Congestion Cost Estimation

Hourly travel time and speed distributions obtained from the recurring congestion analysis were used to calculate the cost of congestion for freight vehicles traveling the northbound I-5 corridor. The free-flow speed was assumed to be the accepted industry average operating speed, 52.05 mph, a conservative speed for cost calculations when compared with posted freeway speed limits (*20, 27*). An hourly truck count distribution was estimated from 2006 Port of Portland disaggregated vehicle counts (*35*).

Figure 4 summarizes the three formulations for the cost estimates. Formulation A multiplies the travel time (or delay) per mile by operating cost or value of time figures. Formulation B incorporates a term for travel time variability by using 0.3 as a factor for dislike on variability (*26*), whereas Formulation C uses 1.3 as



(a)

General Formulation of Cost Calculation		Percent Increase in Daily Cost of Freight Vehicle-Hours of Delay Per Mile Relative to 52.05 mph Free-Flow Travel Time
A	Multiplies delay by operating CPH or VOT to obtain costs. Reflects percent increases in travel time by hour and daily travel time per mile, relative to Free-Flow conditions.	19%
B	Incorporates Reliability (low-end).	22%
C	Incorporates Reliability (high-end).	31%

(b)

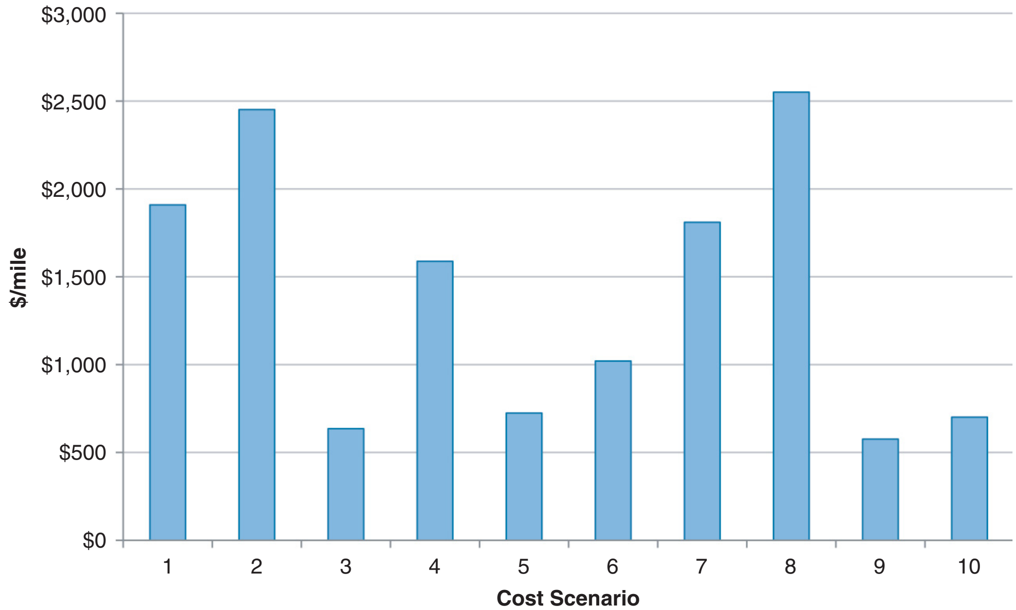
FIGURE 4 Northbound I-5: (*a*) increase in freight vehicle cost of delay for three types of cost formulation and (*b*) summary of types of cost formulation (CPH = cost per hour, VOT = value of time).

a factor for dislike on variability (*26*). These approaches provide low- and high-end estimates for the effect of variability on travel cost. For each cost formulation, Figure 4 presents the percent increase (relative to free-flow conditions) in travel cost per mile for freight vehicles by time of day and provides a summary of the daily cost per mile for freight vehicles traveling the northbound I-5 corridor. The daily cost of delay for freight vehicles is 19% higher than free-flow cost; if variability is considered, costs increase by 22% to 31% relative to free-flow costs. Additionally, during the evening peak, costs increase by 95% without consideration of variability and up to 120% when variability is considered. These results indicate the importance of travel time reliability on the cost of freight operations.

Different values of time and operating cost figures were applied to each formulation type to provide a range of cost per mile; these are referred to as cost scenarios. Figure 5*b* describes the cost scenarios and the parameters used to calculate daily cost per mile for the analyzed corridor. Values of time from the literature review were adjusted for consumer price index inflation to reflect 2010 values (*36*).

Cost Scenario 1 applies the methods outlined by ATRI (*20, 27*) and shows a daily marginal operating cost of $1,909 per mile for all trucks traveling northbound on I-5; these results are presented in Figure 5*a*. For Cost Scenarios 2 through 10, the daily cost was calculated for all trucks traveling northbound I-5 with a range of value-of-time figures for freight vehicles (*21, 23–25*). The cost scenarios were intended to incorporate combinations of regional characteristics, the effect of congestion on value of time, and the effect of reliability on the cost to travel the corridor; these results are presented in Figure 5*a*. Additionally, values of time reflecting differences in operator and service type were incorporated in two scenarios (9 and 10).

Daily cost per mile for the northbound I-5 corridor was found to range from $576 per mile (when costs by operator type are considered) to $2,551 per mile (when regional value of time for Oregon with a 2.5 congestion markup is considered and the effect of variability is incorporated). The wide range of cost results shows the importance of taking into account the distinct types of carrier operations and the accuracy of the parameters value of time and operating cost per hour to provide realistic industry cost estimates.



(a)

Cost Scenario	General Formulation of Cost Calculation	Factors/Parameters Represented	Cost Source for Operating Cost Per Hour (CPH) or Value of Time (VOT)	Freight CPH	Factor of dislike for variability
1	A : ATRI, 2010	Marginal Operating Cost	ATRI, 2010	$ 83.26	
				***Freight VOT ($/hr)**	
2	A : TTI, 2009	National/Urban	TTI, 2009	$ 107.46	
3	A : TTI, 2009	Regional	ODOT, 2005 Avg Truck	$ 27.85	
4	A : TTI, 2009	Regional + Congestion	ODOT, 2005 Avg Truck X 2.5 (NCHRP)	$ 69.61	
5	B : TTI, 2009 + Cohen, 1999	Regional + Reliabilty	ODOT, 2005 Avg Truck	$ 27.85	0.3 (low-end)
6	C : TTI, 2009 + Cohen, 1999	Regional + Reliabilty	ODOT, 2005 Avg Truck	$ 27.85	1.3 (high-end)
7	B : TTI, 2009 + Cohen, 1999	Regional + Congestion + Reliability	ODOT, 2005 Avg Truck X 2.5 (NCHRP)	$ 69.61	0.3 (low-end)
8	C : TTI, 2009 + Cohen, 1999	Regional + Congestion + Reliability	ODOT, 2005 Avg Truck X 2.5 (NCHRP)	$ 69.61	1.3 (high-end)
9	A : TTI, 2009	Difference in Operator Type	Kawamura, 2000 Private Carriers	$ 23.05	
9	A : TTI, 2009	Difference in Operator Type	Kawamura, 2000 For-Hire Carriers	$ 36.67	
10	A : TTI, 2009	Difference in Service Type	Kawamura, 2000 Avg All Carriers	$ 30.64	
10	A : TTI, 2009	Difference in Service Type	Kawamura, 2000 Truck Load	$ 32.74	
10	A : TTI, 2009	Difference in Service Type	Kawamura, 2000 Less-Than Truck Load	$ 29.60	

(b)

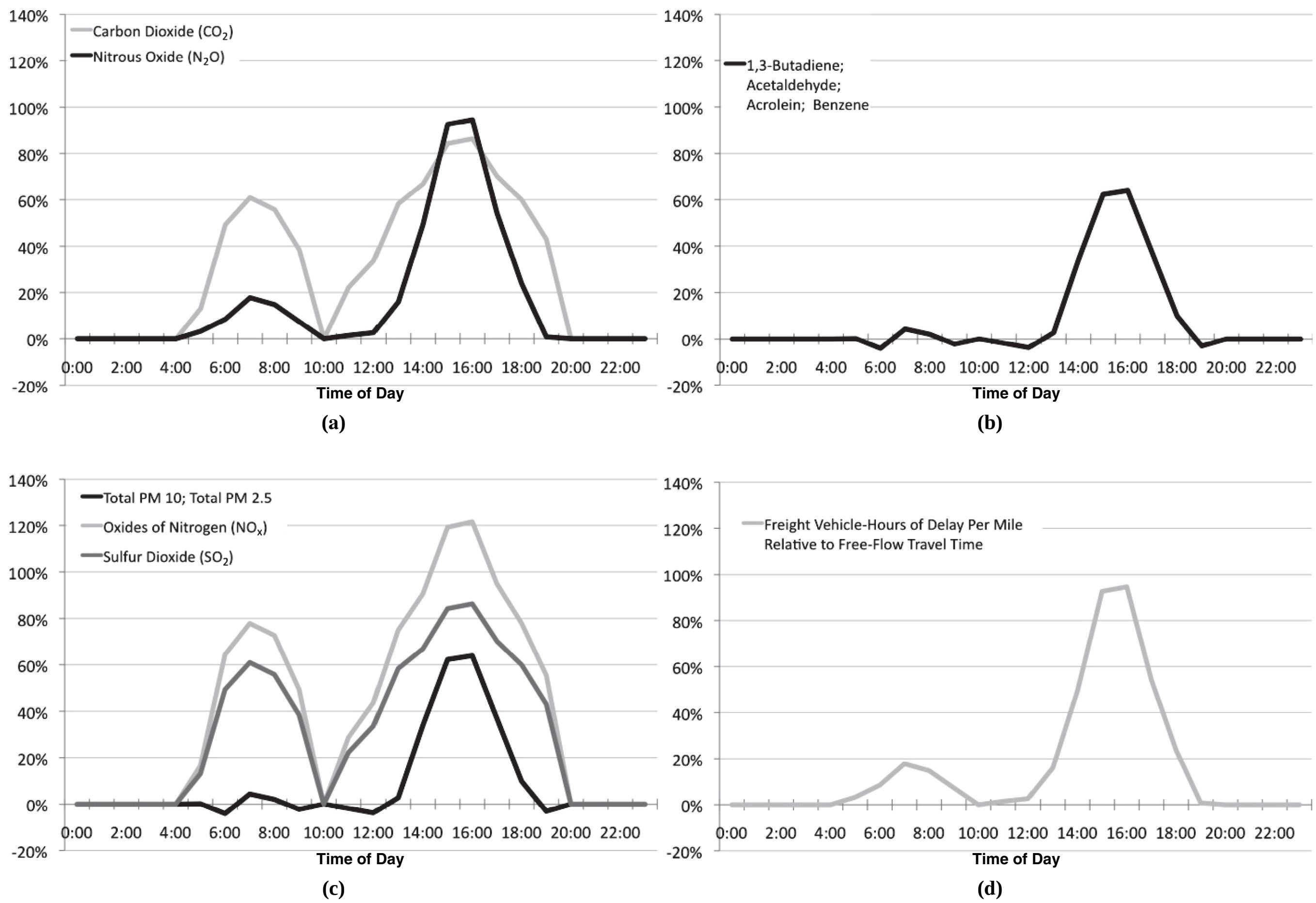
FIGURE 5 Cost of delay on northbound I-5: (*a*) cost per mile for freight vehicles and (*b*) cost scenarios, parameters, and formulations. Freight VOT was adjusted for inflation and reflects 2010 prices. Formulation A uses CPH or VOT to obtain costs; Formulation B incorporates reliability low-end estimation; and Formulation C incorporates reliability high-end estimation (ODOT = Oregon DOT).

Values of time used in cost calculations should represent regional characteristics as much as possible and should reflect the impact of congestion on the value of time. This work incorporated Oregon specific value of time and, for several cost scenarios, used value of time with a 2.5 congestion markup to reflect congested value of time. Additionally, the effect of variability on total travel cost should be considered within the cost formulation, because this has been shown to have a large impact on travel cost and is particularly valuable to the freight industry. Because of a lack of good count data on the breakdown of carrier characteristics, separation of costs by operator or service type is not recommended. However, it is understood that there are documented differences between carriers. If reliable data become available, a breakdown of annual costs by operator or service type may provide valuable information.

Emission Estimation Results

Fluctuations in speed during congestion, as well as reduction of speed, have a strong effect on emission rates during peak periods. By linking mobility performance measures with emissions analysis tools such as MOVE2010, planners and engineers can evaluate the impact of the transportation system on the environment and the people that live there.

The average daily freight vehicle emissions per mile along the northbound I-5 corridor were estimated with the U.S. Environmental Protection Agency MOVES2010 model and hourly travel time and speed distributions obtained from the recurring congestion analysis. Figure 6*b* presents the increase in freight vehicle emission rates (grams/mile) during congestion relative to emissions rates during



Pollutant		Daily Freight Vehicle Emission Rates (g/mile)	Daily Percent Increase in Total Freight Vehicle Emission Rates (g/mile)
GHG	Carbon Dioxide (CO_2)	24,099.96	49.49%
	Nitrous Oxide (N_2O)	0.03	25.80%
MSAT	1,3-Butadiene Acetaldehyde Acrolein Benzene	0.02	13.43%
CP	PM_{10} - Total $PM_{2.5}$ - Total	3.78	13.43%
	Oxides of Nitrogen (NO_x)	138.55	65.75%
	Sulfur Dioxide (SO_2)	0.64	49.51%

(e)

FIGURE 6 Increases in freight vehicle emissions (g/mi) and delay in congestion relative to 52.05-mph free-flow emission rates: (*a*) increased GHG emissions, (*b*) increased MSAT emissions, (*c*) increased criterion pollutant emissions, (*d*) increased vehicle hours of delay per mile, and (*e*) summary.

52.05-mph free-flow conditions. Figure 6*a* shows the percent increase in freight vehicle hours per mile through the day. As shown, there is an 80% to 120% increase in freight vehicle emission rates (per mile) during the evening peak period, which corresponds to an 855 to 95% increase in freight vehicle hours per mile; that is, congestion and delay during peak hours are highly correlated to increased emissions.

Environmental concerns are largely centered on carbon dioxide, because it is the prominent GHG. Figure 6*b* shows that on a daily basis, an additional 24,099 g/mi are emitted from freight vehicles because of congestion (a nearly 50% increase on emissions compared with free-flow conditions).

Other gases, such as oxides of nitrogen (NO_x), present public health concerns because they are linked to respiratory problems. Particulate matter (PM_{10}) and ultrafine particulate matter ($PM_{2.5}$) are linked to ailments such as cancer and heart problems. Because of recurrent congestion, a daily increase of 65% in NO_x emissions, 13% of PM emissions, and 49% of sulfur dioxide emissions was found on the northbound I-5 corridor.

When estimations of emission are made, it is important to estimate the various pollutants (as shown in Figure 6) because the relationship between vehicle speed and emissions is nonlinear, and emission rates are not the same for all pollutant types. Investigating different emission types provides insight into environmental impact (e.g., GHG emissions) and public health (e.g., MSAT, criterion pollutants).

PRACTICAL APPLICATION

The methodology developed in this work can provide useful freight operation and performance data so decision makers can incorporate FPMs into the planning process. The methodology can be modified to identify and study bottlenecks and to prioritize areas in need of improvement. Quantifying the impact of congestion on freight vehicles in a variety of terms (mobility and congestion, cost, and emissions) creates transparency in the planning process, holding agencies accountable to the public for the decisions they make.

This research could also help inform decisions about congestion management strategies, infrastructure improvements, and incident response strategies. The monetary and environmental impacts of nonrecurring congestion may motivate systemwide improvements by showing that technologies (such as variable message signs) can be used to communicate the occurrence of an incident or by justifying the need for increased incident response.

From a freight industry perspective, multicriteria performance measures will allow carriers to improve routing and scheduling logistics. By modifying scheduling and routing based on a regionwide system of freeways, carriers could to identify the optimal routing that would reduce costs and emissions, improve reliability, and allow carriers to more easily adhere to strict scheduling.

CONCLUSIONS

A unique contribution of this research is the integration of GPS with loop sensor and incident data for the study of multicriteria trucking performance measures. The integration of diverse data sources validates the accuracy of raw GPS data and allows for a new methodology that can identify through trucks by using a two-step filtering process. The first process finds all potential through trucks, and the second process integrates loop sensor data to eliminate any remaining through trucks that may have stopped midway through the corridor. It was shown that the separation of through trucks from partial through, partial local, and local trips removes bias from the estimation of performance measures.

Findings show that GPS truck data have greater travel times than the expected loop sensor average in the evening peak period. The GPS data more accurately portray the roadway conditions experienced by a truck, and the comparison with loop sensor data indicates that traditional loop detector congestion estimates tend to underestimate increases in both truck travel time and travel time variability.

This research also shows that congestion is detrimental not only for carriers costs and shipper just-in-time operations but also for the planet, because of major increases in GHG emissions, and for the local community, because of increases in NO_x, PM, and other harmful pollutants. This work is a significant step in addressing the needs of all users of the transportation system, as current freeway performance measures are not freight specific. Freight performance measures should get the attention of the freight community and other stakeholders that can benefit from lower emissions or the reduction of economic inefficiencies such as congestion costs.

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Any errors or omissions are the responsibility of the authors.

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