Multi-Criteria Trucking Freeway Performance Measures in Congested Corridors

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ABSTRACT

This research focuses on the development of multi-criteria tools for measuring and analyzing the impacts of recurring and non-recurring congestion on freight. Unlike previous studies, this work employs several distinct data sources to analyze the impacts of congestion on interstate 5 (I-5) in the Portland Metropolitan Area: global positioning system (GPS) data from commercial trucks, Oregon DOT corridor travel time loop data and incident data. A new methodology and algorithms are developed to combine these data sources and to estimate the impacts of recurrent and non-recurrent congestion on freight movements' reliability and delays, costs, and emissions. The results suggest that traditional traffic sensor data tend to underestimate the impacts of congestion on commercial vehicles travel times and variability. This research shows that congestion is not only detrimental for carriers and shippers costs but also for the planet due to increases in greenhouse gas emissions, and for the local community due to increases in oxides of nitrogen, particulate matter, and other harmful pollutants. The methodology developed throughout this work has the potential to provide useful freight operation and performance data for the freight community, transportation decision makers, and other transportation stakeholders.

Keywords: commercial vehicles, congestion, GPS, traffic data, incidents, performance measures, emissions, GHG, costs

INTRODUCTION

Due to its geographic location, Oregon's 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. Further, it is predicted that congestion may result in 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 impact the businesses that rely on efficient and timely deliveries, but also increase emission levels and the cost of transporting goods. In order to improve the functionality of transportation networks and make efficient use of funds, it is crucial that public agencies develop the proper tools to assess 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, travel time reliability and others derived from these basic measures. Early on in the adoption process of performance-based metrics, passenger vehicles were the main focus, while freight traffic was not incorporated independently (*3*, *4*). Therefore, freight specific performance measures (FPMs) are not in wide use by public agencies. It is becoming increasingly important to continue to develop a system of performance measures that will capture the impact of congestion on different modes, the environment, and people living near a transportation network.

Recently, a body of research has emerged which employs new methods for collecting and analyzing data from commercial vehicles in order to develop freight performance measures. This research is showing great promise for providing consideration of freight in the planning process. This paper focuses on the development of tools for measuring and analyzing the impacts of recurring and non-recurring congestion on freight corridors in the Portland Metropolitan Area. The FPMs are then monetized using standard methods and used to estimate emissions through an urban freeway corridor.

BACKGOUND

This section provides a review of the development of FPMs related to the trucking industry. Here, the reader will find a description of data sources and methods used to determine congestion and mobility performance measures, methods for monetizing these measures, and guidance for quantifying and monitoring the impact of congestion on the environment and public health.

Developing Congestion and Mobility Performance Measures

Roadway loop sensors, weigh-in-motion data, and GPS data can be used to obtain travel time and speed information for freight trucks. However, with each data source there are advantages and challenges in using the data for the purpose of deriving FPMs for congestion and mobility.

Loop Sensors

The use of archived loop sensor data has shown success in estimating freeway performance (e.g., travel time, speed, and vehicle count). Loop sensors can be used to study recurring and non-recurring congestion, and to identify and study bottlenecks within regions (*5*, *6*). However, loop sensors are limited in their ability to differentiate between vehicle types to provide disaggregate data by mode. Findings show that there is 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*).

Weigh-In-Motion (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*). Following this work, the researchers found that both GPS and truck transponder technologies have the potential to estimate travel times; however, they may require a large number of vehicle observations and must incorporate methods for determining which 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 was successful in developing non-mobility/congestion measures of performance by quantifying overweight vehicles, ton-miles on corridors, empty vehicles, the penetration of trucks with truck transponders, origin-destination estimations, and seasonal variability in various measures as well as travel time estimations (*12*).

Commercial Global Positioning System (GPS) Data
At the national level, the Federal Highway Administration (FHWA) in partnership with the American Trucking Research Institute (ATRI) has looked at methodologies to utilize GPS technology to determine travel time reliability in freight corridors (*13*) and to identify freight bottlenecks (*14*). Most recently, FHWA and ATRI released an online freight performance measure tool, FPMweb, giving users access to aggregated operational truck speed data using GPS data from several hundred thousand unique trucks (*15*). Limitations associated with the approach of the earlier work, (*13*), were carefully examined by Schofield and Harrison (*3*). The main problems they observed were: (a) the accuracy of the GPS coordinates which in some cases may have an error of up to ¼ of a mile and (b) the low number of observations in areas with low traffic volume. In addition, a more severe limitation is that the data do not differentiate between vehicle stops due to congestion and stops due to refueling or mandatory driver rest periods. This presents a bias in the data set, where slow speeds may be representing local trips rather than congestion on the network.

Researchers at the University of Washington acquired GPS data from commercial trucks and have used the data to estimate link travel time, develop FPMs and study before/after conditions in improvement areas (*11*, *16*, *17*). Although a significant amount of data cleaning was employed to remove erroneous data, the team was successful in showing benefit of a 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 (a) loop sensor data, and (b) 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.

Similar to GPS data studies, 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 in using the 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 in order to show benefit and impact of a proposed project. Without

accurate information regarding the operating costs or value of time for the freight industry, it is possible to underestimate the benefit of a given project or overestimate the benefit of financing strategies like congestion pricing (*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.

The NCHRP 431 report investigated variations in value of time for passenger vehicles and freight trucks under 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, based on research conducted by Minnesota, the Oregon DOT, and a national urban area average provided by Texas Transportation Institute (TTI) (*22-24*). Kawamura (2000) investigated differences in value of time among operators and trucking industry segments. Findings from Kawamura show that not only do freight carriers have a higher value of time than passenger vehicles but that there is also significant heterogeneity among carriers (*25*).

Monetizing Travel Time and Delay Using Value of Time

Utilizing the value of time derived from (*25*) it is possible to monetize measures of travel time and delay. TTI publishes the Urban Mobility Report, which evaluates procedures, processes, and data used for developing estimations of the cost of congestion (*24*). The following expression (Eq. 1) is the TTI formula to determine the annual cost of congestion for freight vehicles (*24*).

$$\text{Annual Commercial Vehicle Cost} = \text{Daily Vehicle-Hours of Delay} \times \text{Commercial Vehicles \%} \times \text{Commercial Vehicle Time Value (\$/hr)} \times \text{250 Working Days Per Year} \qquad \text{(Eq. 1)}$$

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 following form shown in (Eq. 2) (*26*):

$$U_c = a_1 \times T + a_2 \times V(T) + a_3 \times M \qquad \text{(Eq. 2)}$$

where:

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

Cohen uses a low- and 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.

Monetizing Travel Time and Delay Using Operational Cost

Although the value of time has been widely incorporated into cost-benefit analysis, by examining marginal operating costs we can gain insight into decisions made by carriers and how the freight industry is impacted 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/trailer lease or purchase, were among the top cost items. As revealed in value of time studies, there are major differences among trucking industry sectors. ATRI also applied average cost values to investigate the annual cost impact of a bottleneck on the trucking industry, using a three-step methodology (*27*).

Environmental and Health Performance Measures

Utilizing freeway performance measures, it is possible 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. In order to do this, planners and engineers often use a sequential three-step model process where 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.

There are a variety of models that 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 criteria 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 30 to 60 mph range, heavy vehicle loads, and increases in grade (*28-33*) lead to major increases in emission rates.

RESEARCH CONTRIBUTION

Distinct from other studies, this work employs 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 impacts 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 impacts of recurrent and non-recurrent 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, rests or refueling) in order to study freight performance with unbiased measures. In addition, this paper seeks to use multiple criteria for evaluating freight performance.

The research demonstrates how the FPMs can be monetized and used to estimate emissions through an urban corridor using standard methods. Focus of multi-criteria performance measures will center on mobility congestion, and briefly cover cost and emissions; however, it should be understood that criteria could extend beyond these three basic categories. For a more expansive discussion regarding the cost and emissions estimations, please see reference (*34*). The analysis of the GPS commercial truck data is a significant step not only in understanding the behavior of freight transit throughout the day, but also the impacts caused by recurring congestion and incidents truck 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), see http://portal.its.pdx.edu, offers traffic data, performance measures, and analytical tools in a user-friendly interface.

Incident Data

In addition to the loop sensor data, PORTAL has also integrated incident data from the ODOT Advanced Transportation Management System (ATMS). This provides the user with more information to discern whether the traffic behavior was recurring or non-recurring (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

Most significantly, this work incorporates GPS data from a sample of commercial trucks along the I-5 corridor. GPS truck data were provided by the American Trucking Research Association (ATRI) as part of a research contract between Federal Highway Administration and Portland State University. The GPS devices are onboard the trucks and report a unique truck identification (truck ID) number, date, time, and position (latitude/longitude) for each truck reading. Some truck ID’s in the data set report readings more frequently than others, meaning there is no common gap time between readings.

The trucks present in the data set can be 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, or partial through/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 in close proximity to the interstate. Because of the close 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 the concerns discussed above, a research methodology was developed to identify through trucks to estimate the impact of congestion on freight movements throughout the day, and reduce bias from trucks that have deviated from the freeway or traveling on the local network.

METHODOLOGY TO IDENTIFY THROUGH TRUCKS

This section discusses the procedure to identify through trucks. Two main filtering processes were implemented: 1) truck ID matching process to identify all potential through trucks and 2) comparison of GPS speeds to loop sensor average travel time by time period.

Filter Process 1: Truck ID Matching

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

Start buffer = m_s +/- r,

End buffer = m_e +/- r,

where:

r = 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 have made one or more local stops through the corridor. This parameter is set liberally to ensure that vehicles traveling 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. Because of this, the matching process must also incorporate rules to distinguish between multiple through trips made by the same truck ID. The logic for identifying potential through trucks is summarized in Figure 1.

Filter Process 2: Comparison to Loop Sensor Average Travel Time
In the second step to identifying through trucks, the corridor travel times from each potential through truck are sorted by the "start" reading timestamp into time bins of 15 minute intervals. These times are then compared to the loop sensor average travel time at a 15 minute resolution for the time period of interest. A *deviation index* is calculated using the loop sensor data 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 minute 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 minute time bin t let,
T_k = the 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 it 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/refuel purposes, and therefore can be classified as a through truck. Because loop detection has the potential to underestimate the impact of congestion on the freight trucks (as shown in a later section), it is expected that in general loop sensor average travel times may be shorter than truck travel times. Therefore, this important fact must be taken into account when setting the value of parameter m in order to exclude only trucks making stops.

Methodology for Non-Recurring Congestion
The incident analysis requires only minor modifications to the procedure discussed above in order to identify through-incident trucks. Instead of examining the entire corridor, attention 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 are resulting from the incident itself.

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

The recurring congestion analysis presented in this paper focused on weekdays during 2007. The non-recurring congestion analysis studied trucks passing through a 5 mile segment of roadway south of an incident on northbound I-5. The incident took place at milepost 304 on December 12th, 2008 was designated as a "crash" type lasting from 12:02-12:46 PM, and affecting 2 lanes of traffic; there was a small amount of rain through the afternoon but no adverse weather.

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

RESULTS

Recurring Congestion Results

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

Figure 2a 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 congested PM peak hours from 3-6 PM, as evident by greater standard error values. This means that in addition to longer travel time experienced during congested periods, there is a high degree of unpredictability in day-to-day corridor travel time. Figure 2b presents the coefficient of variation in travel time for the through trucks and loop sensor data; data were smoothed using a moving average over three time bins. This figure confirms increased variability during congested periods for both loop sensor and through truck data. However, through truck data variability is considerably higher. It is clear that loop sensor data underestimate the impact of freight travel time variability.

Non-Recurring Congestion Results

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

As shown in Figure 3a, there are obvious differences in the loop sensor data for the two 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 other periods of slower speeds in comparison to the non-incident day. For this reason, all incidents happening downstream of incident “A” were considered as a potential cause; they are labeled along the x-axis in Figure 3a to show the time and duration of the incidents (downstream incidents are labeled “d”). It is clearly shown that the downstream incidents also impact speeds through the incident area throughout the day.

Similar to the non-recurring through-incident truck analysis, Figure 3b 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/local truck data varies more so 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 there is likely to be some bias. Partial local trucks may underestimate speeds, while partial through trucks may not have traveled completely through the incident area (or corridor) and therefore avoided part or all 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.

Congestion Cost Estimation Results

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

In general there were three formulations for the cost estimates, which are summarized in Figure 4. 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 using 0.3 as a factor for dislike on variability (*26*), while formulation C uses 1.3 as 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 formulations, 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 22-31% relative to free-flow costs. Additionally, during the PM peak, costs increase by 95% without considering variability and up to 120% when variability is considered. These results point to the importance of travel time reliability on the cost of freight operation.

Different value of time and operating cost figures were applied to each formulation type described above to provide a range of cost per mile—these are referred to as cost scenarios. Figure 5b presents a description of the cost scenarios, and parameters used to calculate daily cost per mile for the corridor analyzed. Values of time from the literature review were adjusted for consumer price index (CPI) 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 the northbound I-5—these results are presented in Figure 5a. For cost scenarios 2-10, the daily cost was also calculated for all trucks traveling northbound I-5 using 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 5a. 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 looking at costs by operator type) to $2,551 per mile (when considering regional value of time for Oregon with a 2.5 congestion markup, and incorporating the effect of variability). The wide range of cost results shows the importance of taking into account the distinct types of carrier operations, and also the accuracy of value of time and operating cost per hour parameters to provide realistic industry cost estimates.

Values of time used in cost calculations should also 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, as this has shown to have a heavy impact on travel cost and is particularly valuable to the freight industry. Because of lack of good count data on the breakdown of carrier characteristics, it is not recommended to separate costs by operator or service type. However, it is understood that there are documented differences between carriers. If reliable data become available in the future, 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 impact on emission rates during peak hour. By linking mobility performance measures with emissions analysis tools like 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 using the EPA's MOVES2010 model, and hourly travel time and speed distributions obtained from the recurring congestion analysis. Figure 6b presents the increase in freight vehicle emission rates (grams/mile) during congestion relative to emissions rates during 52.05 mph free-flow conditions—an additional graph (Figure 6a) shows the percent increase in freight vehicle-hours per mile through the day. As shown, there is an 80-120% increase in freight vehicle emission rates (per mile) during the PM peak period which corresponds to an 85-95% increase in freight vehicle-hours per mile; i.e. congestion and delay during peak hours are highly correlated to increased emissions.

Environmental concerns are largely centered on carbon dioxide (CO_2), as it is the prominent GHG. Figure 6b shows that on a daily basis, an additional 24,099 grams per mile are emitted from freight vehicles as the result of congestion (a nearly 50% increase on emissions with respect to free-flow conditions).

Other gases, such as oxides of nitrogen (NO_x), present concerns for public health as 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. Due to recurrent congestion, a daily increase of 65% in NO_x emissions, 13% of PM emissions, and 49% of SO_2 emissions was found on the northbound I-5 corridor.

When providing emission estimations, it is important to estimate different pollutants (as shown in Figure 6). This is because the relationship between vehicle speed and emissions is non-linear, and emission rates are not the same for all pollutant types. Investigating different emission types provides insight into the impacts regarding the environment (e.g., GHG emissions), and public health (e.g., MSAT, and criteria pollutants).

PRACTICAL APPLICATION

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

This research could also help inform decisions made regarding congestion management strategies, infrastructure improvements, and incident response strategies. Understanding the monetary and environmental impacts of non-recurring congestion may motivate the need for system wide improvements by showing the benefit of technologies (such as variable message signs) in communicating the occurrence of an incident, or in justifying the need for increased incident response.

From a freight industry perspective, multi-criteria performance measures will allow carriers to improve routing and scheduling logistics. By modifying scheduling and routing based on a region wide system of freeways, carriers would be able 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 to study multi-criteria trucking performance measures. The integration of diverse data sources has validated the accuracy of the raw GPS data and allowed for a new methodology to identify through trucks using a two-step flittering process. The first process finds all potential through trucks, while the second process integrates loop sensor data in order to eliminate any remaining through trucks that may have stopped midway through the corridor. It is 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 in general, the GPS truck data have greater travel times than the expected loop sensor average in the PM 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 not only detrimental for carriers costs and shippers just-in-time operations but also for the planet due to major increases in GHG emissions and for the local community due to increases in NO_x, PM, and other harmful pollutants. This work is a significant step in studying and 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 as well as other stakeholders that can benefit from lower emissions or the reduction of economic inefficiencies such as congestion costs.

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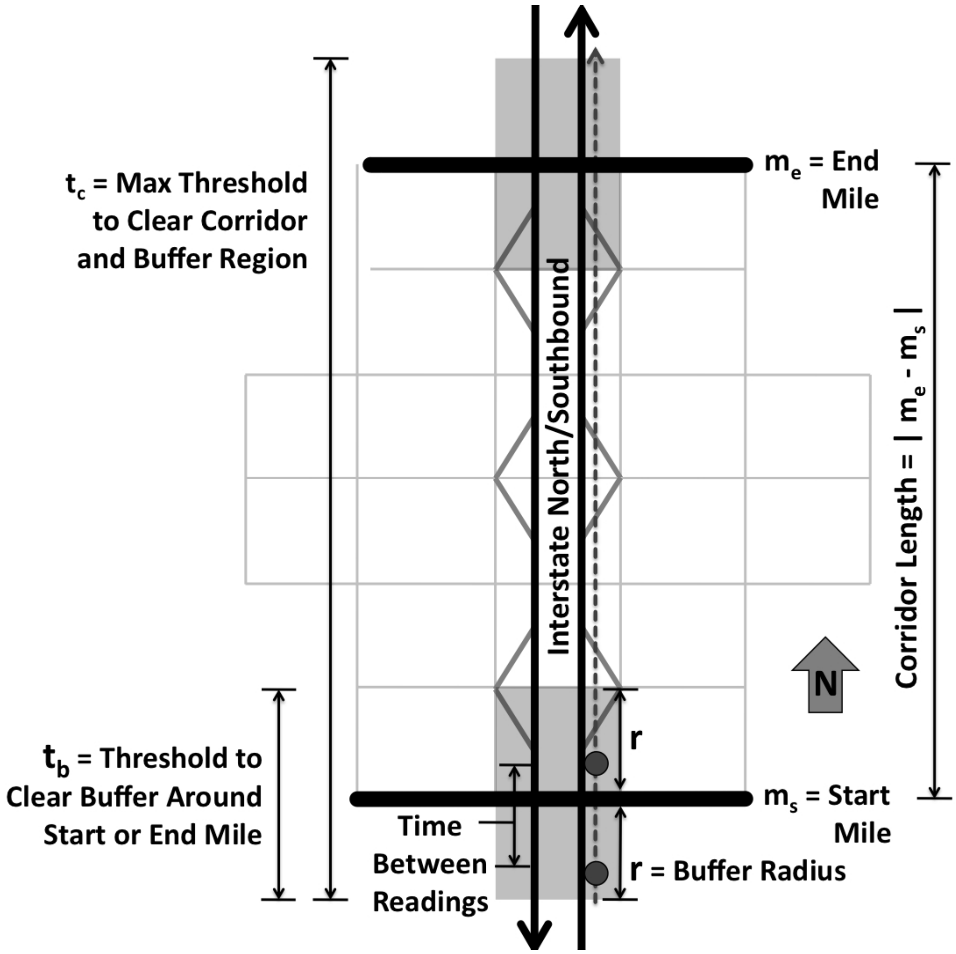
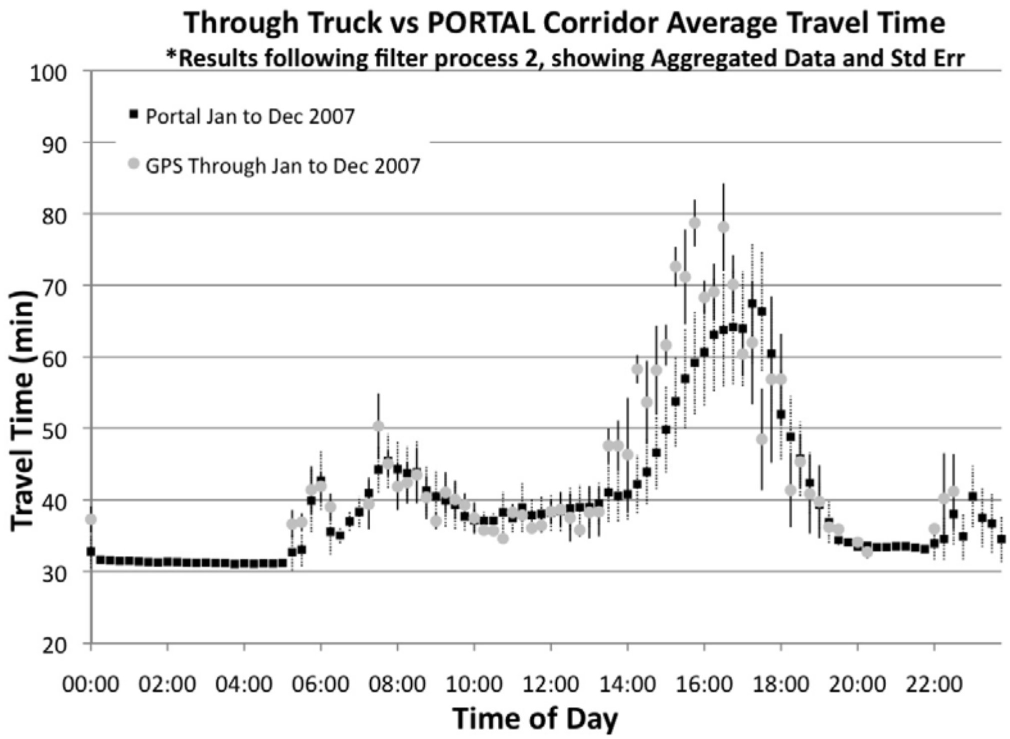
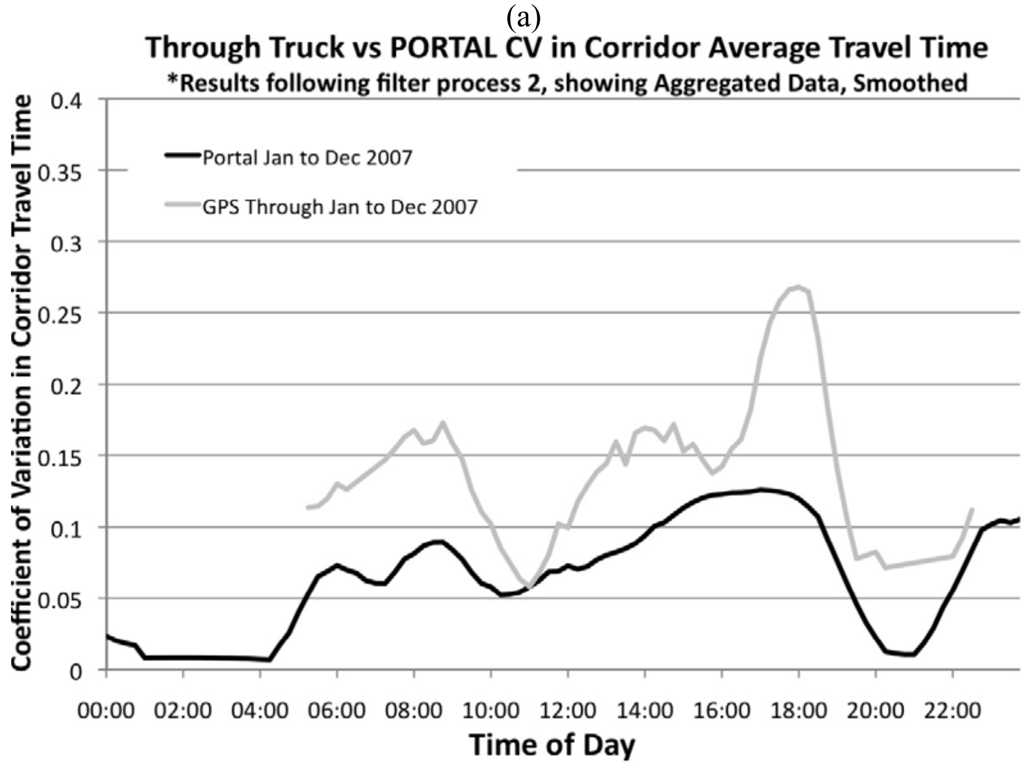


1. Use ArcGIS linear referencing tool (Locate Features Along Routes) to obtain milepost measures along an interstate for each GPS truck reading using latitude/longitude data
2. Determine the corridor extremities (m_s and m_e)
3. Create a record of each reading falling within the start and end buffer ranges
4. For all readings which fall within the buffer ranges, distinguish individual trips by each truck using time thresholds 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 (using timestamp and milepost data) to create a complete trip through the corridor
7. Adjust the "start" and "end" reading timestamp and milepost to begin at m_s and m_e using speeds obtained from the next closest reading
8. For each truck ID and trip, use adjusted "start" and "end" reading timestamp to obtain the travel time and speed through the corridor, and identify trip direction of travel using milepost data

FIGURE 1 Diagram showing user-defined parameters for filtering process 1 (truck ID matching to find potential through trucks), and corresponding algorithm logic.

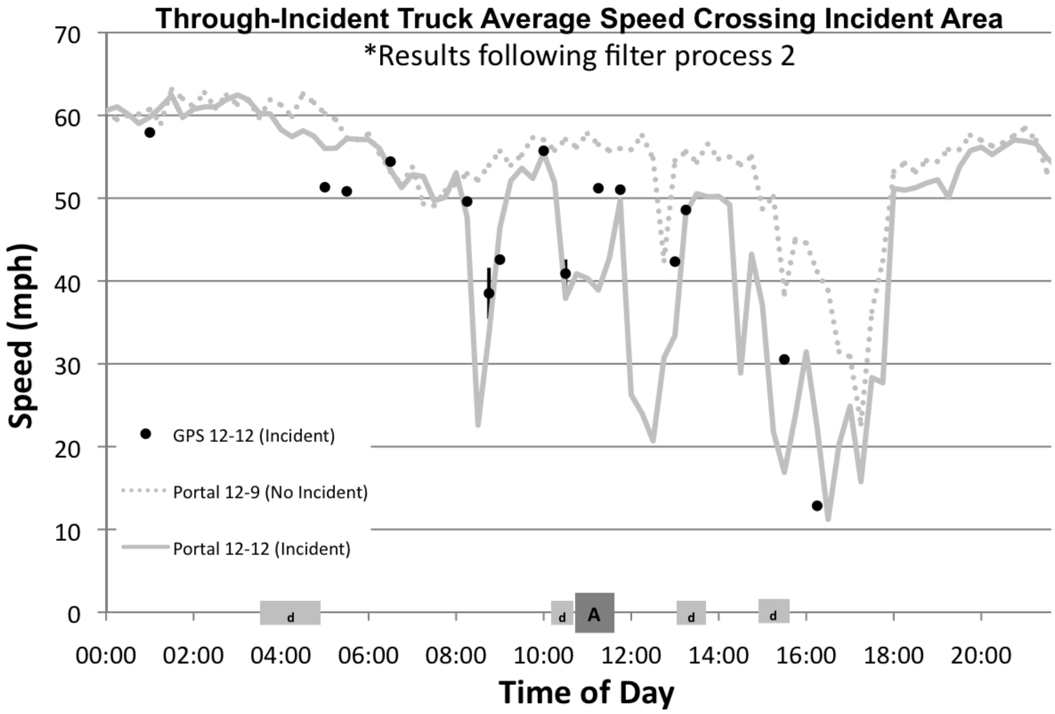


(a)

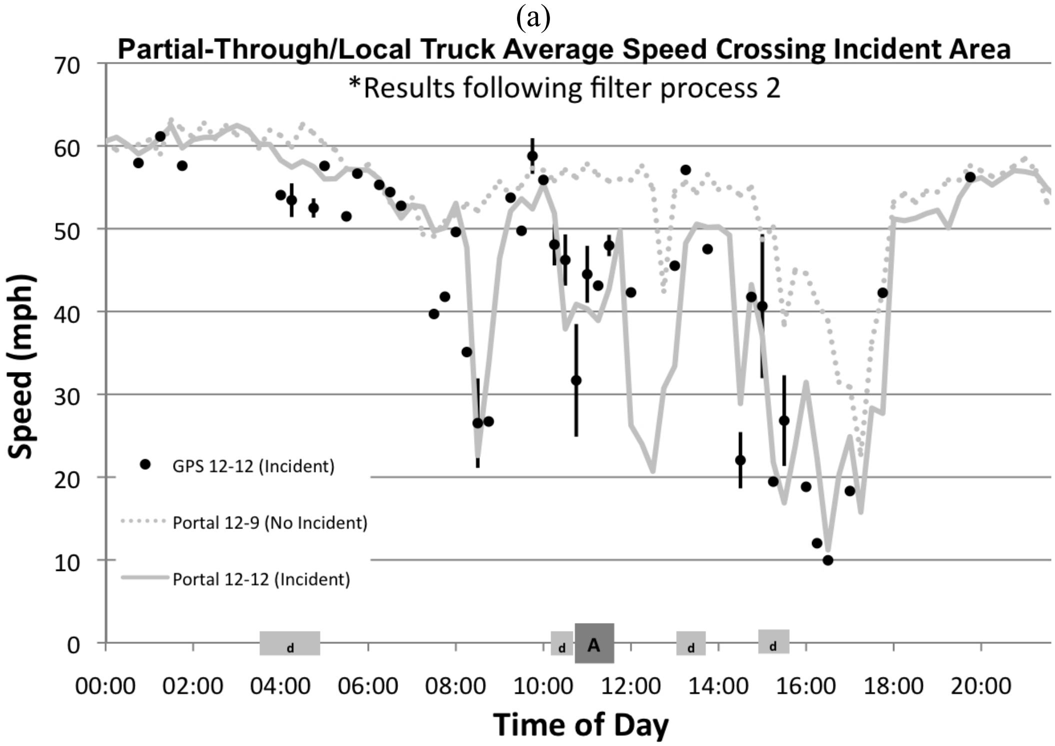


(b)

FIGURE 2 From top to bottom, a) Average corridor travel time results following filter process 2, showing aggregated PORTAL loop sensor and through trucks over one year (with standard error of mean noted for multiple readings in a time bin); b) Coefficient of variation in travel time (smoothed data by moving average of 3 time bins).

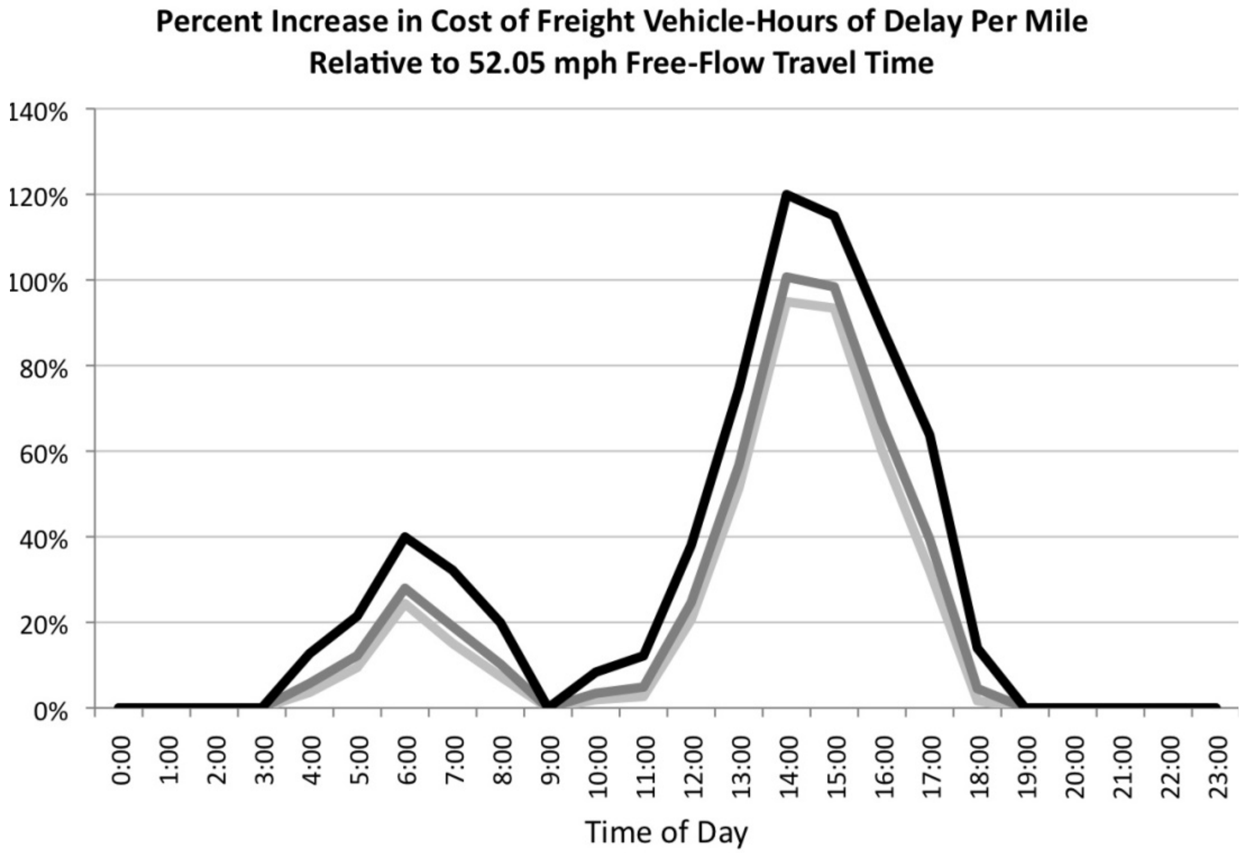


(a)



(b)

FIGURE 3 From top to bottom, a) Non-recurring results following filter process 2, showing aggregated through-incident truck corridor average speeds (with standard error of mean noted for multiple readings in a time bin); b) Non-recurring results following filter process 2, showing aggregated partial through and partial local incident truck corridor average speeds (with standard error of mean noted for multiple readings in a time bin).

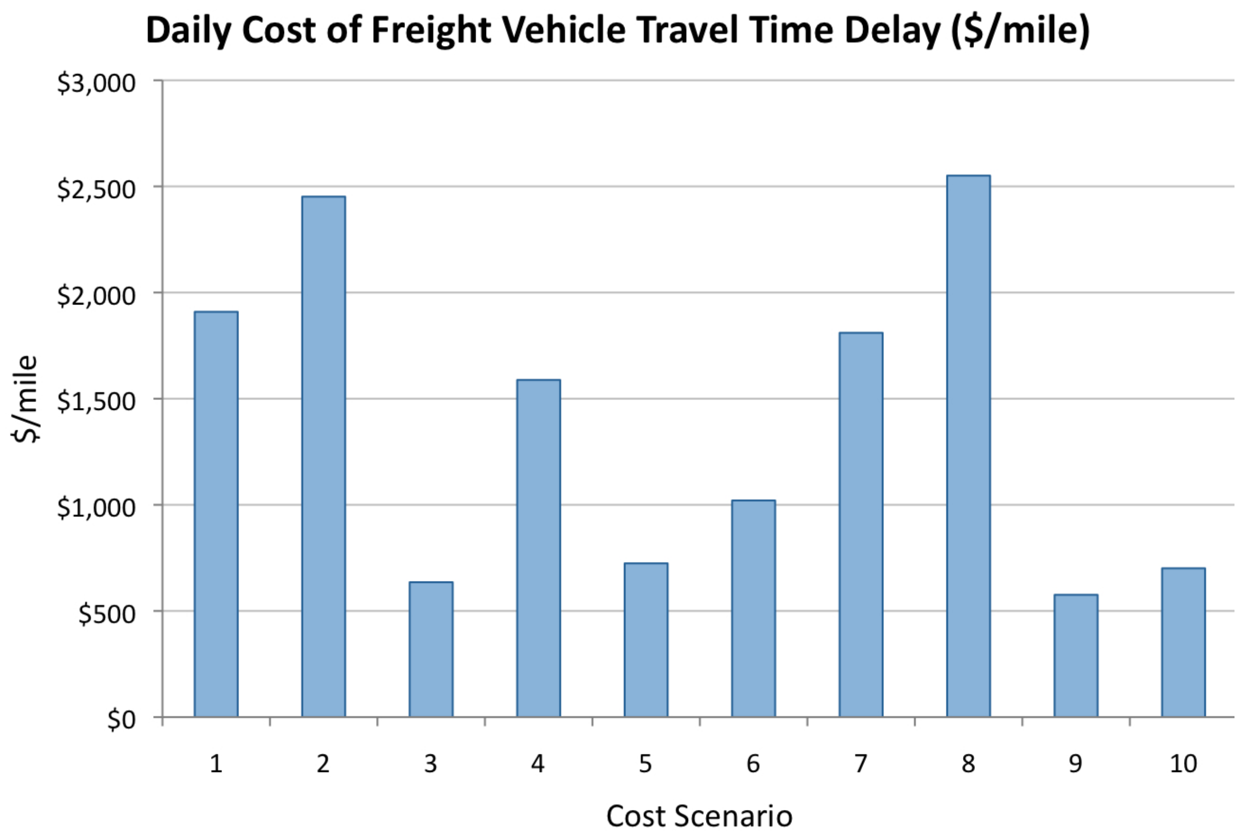


(a)

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 From top to bottom, a) Percent increase in freight vehicle cost of delay for northbound I-5 for three cost formulation types; b) Summary of general cost formulation types and percent increase in daily cost of delay for freight vehicles relative to 52.05 mph free-flow travel time.



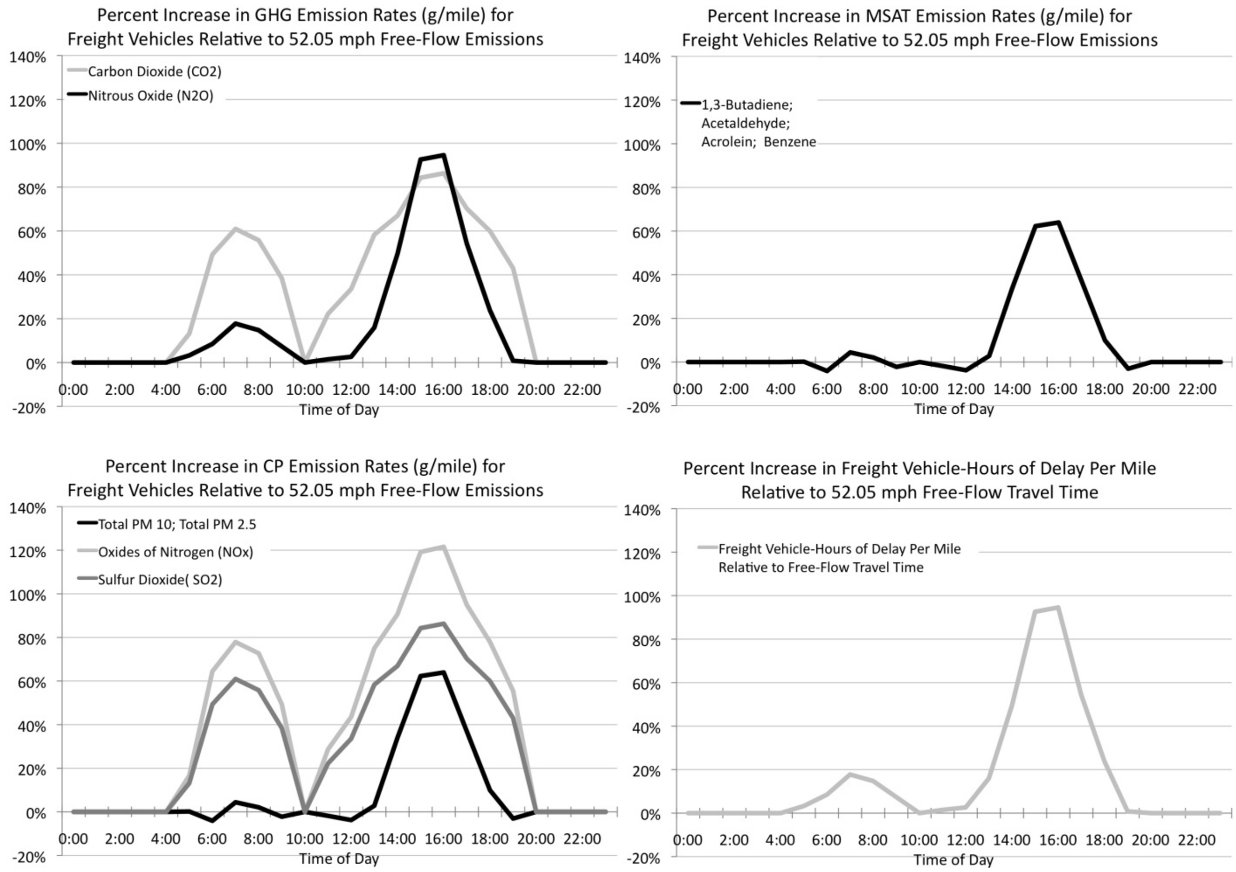
(a)

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	Differnce in Operator Type	Kawamura, 2000 Private Carriers	$ 23.05	
9	A : TTI, 2009	Differnce in Operator Type	Kawamura, 2000 For-Hire Carriers	$ 36.67	
10	A : TTI, 2009	Differnce in Service Type	Kawamura, 2000 Avg All Carriers	$ 30.64	
10	A : TTI, 2009	Differnce in Service Type	Kawamura, 2000 Truck Load	$ 32.74	
10	A : TTI, 2009	Differnce in Service Type	Kawamura, 2000 Less-Than Truck Load	$ 29.60	

*Freight Value of Time (VOT) have been adjusted for inflation and reflect 2010 prices.
A, B, and C refer the general formulation:
A : Uses CPH or VOT to obtain costs
B : Incorporates Reliability (low-end estimation)
C : Incorporates Reliability (high-end estimation)

(b)

FIGURE 5 From top to bottom, a) Daily cost of delay per mile for freight vehicle traveling northbound I-5 for different cost scenarios; b) Cost scenario descriptions, parameters and formulations used.



(a)

Pollutant		Daily Freight Vehicle Emission Rates (g/mile) Above 52.05 mph Free-Flow Emission Rates	Daily Percent Increase in Total Freight Vehicle Emission Rates (g/mile) Relative to 52.05 mph Free-Flow Emission Rates
GHG	Carbon Dioxide (CO_2)	24099.96	49.49%
	Nitrous Oxide (N_2O)	0.03	25.80%
MSAT	1,3-Butadiene Acetaldehyde Acrolein Benzene	0.02	13.43%
CP	PM10 - Total PM2.5 - Total	3.78	13.43%
	Oxides of Nitrogen (NO_x)	138.55	65.75%
	Sulfur Dioxide (SO_2)	0.64	49.51%

(b)

FIGURE 6 Top to bottom: a) Percent increase in freight vehicle Greenhouse Gas (GHG), Mobile Source Air Toxic (MSAT), and Criteria Pollutant (CP) emissions in congestion relative to 52.05 mph free-flow emission rates, and corresponding increases in freight vehicle-hours of delay per mile; b) Summary of daily freight vehicle emission rates above 52.05 mph free-flow emission rates.