Ancillary Functions for Smartphone Weight–Mile Tax Truck Data

Evaluation of Data on Smartphone Weight–Mile Tax for Trucks for Supporting Freight Modeling, Performance Measures, and Planning

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Oregon is one of the few states that currently charge a weight–mile tax (WMT) on commercial trucks. This research evaluated ancillary applications for a system developed by the Oregon Department of Transportation (DOT) to simplify WMT collection. The data collection system developed by Oregon DOT—truck road use electronics (TRUE)—includes a smartphone application with a Global Positioning System (GPS) device and microprocessor. The TRUE data have enormous advantages over the GPS data used in previous research because of TRUE's level of disaggregation and potential to differentiate between vehicle and commodity types. This research evaluated the accuracy of the TRUE data and demonstrated the successful application of the data to develop trip generation rates for a variety of truck types and land use categories. This research confirms the value of the TRUE data to enhance existing Oregon DOT transportation planning models and performance measures.

Reliable freight transportation is particularly important to Oregon because of its geographic location. According to the Oregon Freight Plan (*1*), Oregon is the ninth most trade-dependent state in the nation and is expected to see significant increases in freight flows in the future. This trade dependency comes with unwanted side effects, such as congestion, travel unreliability, environmental and health concerns, and increased transport costs (*2, 3*). For these reasons, recent research has stressed the importance of freight performance measures and associated data management processes in sustaining an effective transportation planning system (*4, 5*).

Freight data that might be used for such performance measures are usually incomplete, scarce, and expensive to collect. However, a unique and highly promising data source is available through a system recently developed by the Oregon Department of Transportation (DOT) to simplify its weight–mile tax (WMT) collection. Oregon is one of the few states that currently charge a commercial truck WMT; Oregon's WMT applies to trucks operating at weights of more than 26,000 lb.

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In February 2010, the Oregon DOT Motor Carrier Transportation Division implemented a pilot project for the use of truck road use electronics [TRUE (*6*)]. The TRUE system provides an automated process for WMT collection that reduces the administrative burden on trucking firms and Oregon DOT while also reducing reporting errors and tax avoidance. The system includes a smartphone application with a Global Positioning System (GPS) device and microprocessor. The application can be uploaded to the phones of truck drivers to track the number of miles traveled; the data are then sent electronically to Oregon DOT to produce the company's WMT invoice, which can be paid online.

This research serves to evaluate ancillary applications for the TRUE data; applications that address Oregon DOT needs for freight modeling, performance measures, and planning are explored. Previous research on the use of freight GPS data provides a valuable starting point for this research. However, because of its level of disaggregation and its potential to differentiate between vehicle and commodity types, the TRUE data set has many unique characteristics and enormous advantages over the truck GPS data used in past research. Data collected through TRUE provide not only commercial truck origin–destination, space–time coordinates, and trajectories but also weight class, truck type, and commodity codes. Such information can be used to understand the intricacies of freight transportation and to better inform decision makers.

This paper provides a review of relevant past research and associated applications, as well as an evaluation of the applications that will be possible for Oregon, given the unique characteristics of the TRUE WMT GPS data.

LITERATURE REVIEW

Table 1 provides a summary of past academic research that explored applications for commercial truck GPS data. The work reviewed in Table 1 is not intended to be an exhaustive list but, rather, a representation of research relevant to this project.

One of the earlier, successful urban-scale examples of the use of commercial truck GPS data for transportation engineering applications was performed in Australia (*12*); in that research, a trip identification algorithm was developed to determine the location of trip ends. The algorithm provided a means to differentiate between genuine stops and false-positive stops (those associated with congestion, signals, etc.). Perhaps one of the more progressive uses of

TABLE 1 Research Categories

Research	Performance Measures: Mobility	System Condition	Environment	Safety	Connectivity	Oregon	Data Processing and Integration	Planning and Modeling
Greaves and Figliozzi, 2008 (*12*)	X						X	
Sharman and Roorda, 2010 (*7*)	X		X				X	X
Holguin-Veras et al., 2011 (*13*)	X		X		X		X	X
Wheeler and Figliozzi, 2011 (*2*)	X		X			X		
Figliozzi et al., 2011 (*3*)	X		X			X	X	
McCormack et al., 2011 (*9–11*)	X		X		X		X	X
You and Ritchie, 2012 (*26*)	X		X		X		X	
FHWA, 2013 (*8*)	X							
Park et al., 2012 (*32*)	X		X					

Note: X = category addressed; blank cell = not addressed.

GPS data was associated with research on traffic in the New York City metropolitan area (*13*). Holguin-Veras et al. used commercial truck GPS data to evaluate the use of financial incentives to shift truck traffic to off-peak hours (*13*).

In 2011, Wheeler and Figliozzi researched the potential to develop multicriteria (mobility, cost, and emissions) performance measures through the use of truck GPS data (*2*). They showed that loop sensor data may underestimate the impact of congestion on freight travel time reliability. Those researchers subsequently developed a new methodology and algorithms for combining freight GPS data with loop sensor data to model congestion and emissions more accurately. In later research, corridor-level travel time reliability algorithms and programming logic were successfully applied to segment corridors and to estimate travel times for each segment identified (*3*). Considerable research with commercial truck data from private GPS vendors has also been completed in the state of Washington to develop transportation metrics (*9–11, 14*).

In general, applications of truck GPS data are limited because the data typically do not differentiate between different truck or commodity types. Furthermore, use of truck GPS data often involves an ongoing cost, as it is typically purchased from an outside provider or third party. As a result, researchers have had limited success in developing trip generation rates with truck GPS data. It has also been determined that improvements in the data used for previous research would be needed before they could be used for freight transportation modeling (*14*).

The freight performance measure categories included in Table 1 are those that have been receiving increasing attention at both the national and state levels. In 2011, the National Cooperative Freight Research Program (NCFRP) released *NCFRP Report 10: Performance Measures for Freight Transportation* (*5*). That report proposes a balanced scorecard framework for a freight system report card with 29 performance measures in six categories. The report suggested that, given the ability to disaggregate freight data, the balanced scorecard framework proposed could be used to analyze the performance of individual links or bridges at the state or local level. The authors also noted that a major challenge to such efforts would be the availability of useful data. At the state level, a report completed for the Oregon DOT in May 2010 provided recommendations for Oregon freight performance measures (*4*). Most of the measures suggested for Oregon overlap those suggested by NCFRP (Table 2).

As cell phone technology has evolved, so too have efforts to use these devices in a variety of roles in the transportation sector. A common goal of cell phone applications is the estimation of travel times. A report for the Florida DOT evaluated travel time measurements that were estimated by five companies using cell phone technology (*15*). Estimates were evaluated on the basis of the methodology, data filtering and aggregation, reliability of the data, and other key measures. The study observed good results under free-flow or fast traffic conditions; the study was unable to conclude whether the estimates obtained in heavy traffic were accurate. In 2000, Zhao reviewed the three most common location-detecting technologies: stand-alone (dead reckoning), satellite-based (GPS), and land-based (navigation system, cell network) technologies (*16*). Zhao concluded that the cell phone identification-based method had the worst positional accuracy and that assisted GPS had the best (*16*). In 2008, Barbeau et al. addressed the trade-off between data accuracy and battery life, data transmission costs, and the burden on the server (*17*). The researchers introduced two algorithms, a critical point algorithm and a location-aware state machine algorithm, intended to ensure that the GPS devices did not waste battery power obtaining point fixes that would not enhance the quality of the data. Newer uses that involve smartphones can provide emissions estimates to the user and suggestions to improve driving (*18–20*).

Of the proprietary uses of commercial truck GPS data, a private company, INRIX, anonymously collects GPS data from probe vehicles, in part through agreements with fleet operators who have GPS

TABLE 2 Comparison of Freight Performance Measure Categories

NCFRP Report 10 (*5*)	Oregon DOT Report (*4*)
Demand Efficiency	Mobility, congestion, and reliability
System condition	Maintenance and preservation
Environmental impact	Environmental
Safety	Safety
Adequacy of investment	—
—	Accessibility and connectivity

Note: — = category was not listed.

devices in their trucks, but also from personal vehicles (individuals who have downloaded the INRIX application to their smartphone) and taxis (*21*). The data are compiled into average speed profiles for freeways, highways, and arterials. INRIX uses the results to provide travel information to a variety of users, including individual travelers, commercial fleets, and the public sector. Customers from commercial fleets are provided services such as dispatch services, traffic map overlays, fastest routes, next-day planning, and congestion pricing (*22*). In addition, INRIX provides the majority of the data used to produce the *Texas A&M Transportation Institute's 2011 Urban Mobility Report Powered by INRIX Traffic Data* (*21*). INRIX also offers a mobile application developer kit for smartphone application developers wishing to use INRIX data.

A technology with applications similar to those of the Oregon DOT TRUE system is Xata Turnpike (*23*). Xata Turnpike is a fleet management and optimization technology that provides real-time information to commercial trucking companies. Xata charges users a subscription price per vehicle per month. Xata's electronic onboard recorder tracks hours of service, data for International Fuel Tax Association and state mileage forms, the actual route driven (with online mapping), auto arrival and departure times, engine diagnostics, speed, revolutions per minute, hard braking, idle time, and fuel efficiency. In 2009, a company named Eroad Limited used a similar device to implement an autonomous global navigation satellite system and cellular network tolling system for commercial trucks in New Zealand (*24*). Eroad uses a secure onboard unit to collect road charges on the basis of vehicle distance traveled, location, mass, time, and emissions. Eroad has a web application that monitors logistical information for clients, including tracking of driver compliance, fuel efficiency, messaging, and maintenance.

DATA DESCRIPTION AND PRELIMINARY ANALYSIS

Data available for this research consisted of 172,385 records from the TRUE pilot study for the entire year of 2011. Seventeen trucks subject to Oregon's WMT were equipped with a TRUE device for the pilot study. These trucks were from three carriers. The TRUE devices were configured to collect the latitude and longitude locations of each vehicle every 5 min. The travel of the pilot study vehicles was tracked through seven U.S. states and three regions in Canada; however, the geographic limitations of future data collection will depend on the degree of partnership with the private sector. Furthermore, because trucks making through trips on Oregon's highway network are required to pay WMT, data for those trucks may be included in future data sets if companies adopt the system.

The intention of the pilot project was to test the TRUE system, potential applications, and associated data processes rather than to provide data that are representative of the entire population of trucks in Oregon. Likewise, regardless of the sample rate of this pilot study, the methodologies proposed could be applied to the statewide implementation of the TRUE system.

According to the GPS_ACCURACY field of the data, the accuracy of the GPS readings ranged from 3 to 840 ft. Figure 1 provides a histogram of the cumulative distribution of the values from the GPS_ACCURACY field for readings of up to 80 ft (data for the small number of records with accuracies worse than 80 ft are not included in Figure 1). An accuracy within 10 ft was recorded for more than 50% of the GPS records, an accuracy within 20 ft was recorded for more than 75%, an accuracy of within 53 ft was recorded for more than 95%, and an accuracy of within 79 ft was recorded for more than 98%.

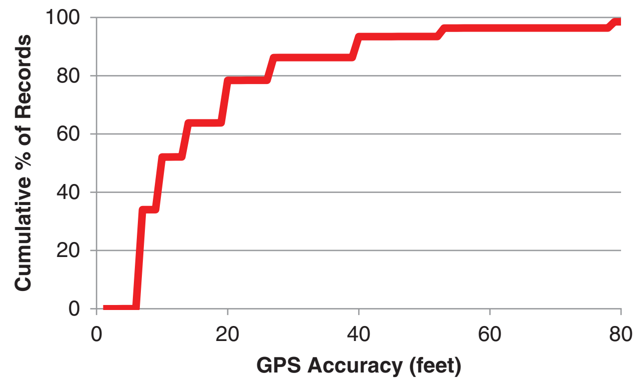

FIGURE 1 Distribution of GPS accuracies.

In addition to the GPS records, the data set available for this research included corresponding weigh-in-motion (WIM) station records for vehicles participating in the pilot project. Figure 2 provides a schematic showing data fields available through the TRUE and the WIM data sets. Through the use of the DEVICE_ID, BASE_PLATE, WAYPOINT_TIME, and WEI_PSTDATETIME fields, a TRUE record can be found for each WIM record that is (*a*) from the same truck as the WIM record and (*b*) closest in time to the WIM record. This process can be completed through the use of the RStudio program.

A preliminary review of the TRUE records and corresponding WIM data indicated that the TRUE records from the pilot project represented vehicles of nine weight classes (ranging from 46,000 to 105,500 lb) with four to eight axles and three commodity codes (empty, machinery, and other). The linkage of these two data sets provides the ability to cross-check the WIM system data with TRUE data and vice versa. Further applications available through the linkage of these two data sets are described in later sections of this paper.

Each of the applications explored in this paper requires some degree of data processing; however, the TRUE data in their raw form provide values for the fields listed in the top and middle sections of Figure 2, including latitude and longitude coordinates with corresponding time stamps, the weight class and axle count of each vehicle, and GPS record accuracy. The initial data-processing steps consisted of formatting, including conversion of time stamp values to a database-readable time format. The data processing required for specific applications are discussed in later sections of this paper.

POINT- AND LOCATION-BASED APPLICATIONS

Previous work on the use of freight GPS data provided a valuable starting point for this research. The balanced scorecard methodology proposed by NCFRP Report 10 (*5*) and the suggestions from the *Freight Performance Measures: Approach Analysis* prepared for the Oregon DOT (*4*) represent a useful framework with which to develop ancillary applications for the Oregon WMT GPS data. Table 3 provides a list of potential applications, along with the data fields required to provide accurate results for each. All of the data fields listed in Table 3 are provided by the TRUE system.

TRUE GPS RECORDS	FIELD	DESCRIPTION
	ROW_ID	System-generated row id
	DEVICE_ID	Unique identifier for each smartphone
	LATITUDE	Latitude of device
	LONGITUDE	Longitude of device
	WAYPOINT_TIME	Time stamp of GPS record
	WEIGHT_CLASS	Weight class of vehicle
	AXLES	Axle count of vehicle
	RECEIVED_TIME	Time stamp waypoint was received by server
	LOCATION_NAME	General location name
	PERMIT_NO	Permit number vehicle is operating under
	GPS_ACCURACY	Accuracy of the GPS fix in meters
	ODOMETER	Most recent odometer entry by driver

DEVICE / TRUCK	FIELD	DESCRIPTION
	DEVICE_ID	Unique identifier for each smartphone
	ACCT_NO	Oregon taxpayer id
	CARRIER_UNIT_ID	Unit number of vehicle assigned by carrier
	PHONE_NO	Phone number of mobile device
	BASE_PLATE	Base plate of vehicle
	BASE_ST	Base state of vehicle
	ASSIGNED_DATE	Time stamp mobile device was assigned to carrier

WEIGH-IN-MOTION RECORDS	FIELD	DESCRIPTION
	WEI_ID	System-generated row id
	WEI_AUTHNO	Oregon taxpayer id
	WEI_BASEPLATE	Base plate of vehicle
	WEI_BASESTATE	Base state of vehicle
	WEI_PSTDATETIME	Time stamp of event in PST
	WEI_SCALENO	Scale number
	WEI_LOCATION	Location
	WEI_CARRIERNAME	Carrier name
	WEI_VTID	Vehicle class id (VEHTYPE)
	WEI_VCID	Vehicle type id (VEHCLASS)
	WEI_AXLES	Vehicle axle count
	WEI_COMMODITY	Commodity code of what vehicle is hauling
	WEI_GROSS	Gross weight
	WEI_WGT	Weight at each axle
	WEI_DIRECTION	Direction of lane
	WEI_VEHICLE	Calculated value, based on class and type ids

FIGURE 2 Data fields (id = identifier; PST = Pacific standard time).

The ability to disaggregate the TRUE GPS data by vehicle type provides an opportunity for development of trip generation rates that has not been available with previous truck GPS data sets. Such rates could allow planners and modelers to relate the number of truck trips from different categories of trucks to the land use (i.e., commercial, industrial, and residential) that generated the trip. For example, the number of trips relative to the following vehicle categories could be determined through the use of the integrated TRUE and WIM data: weight class, number of axles, vehicle type, vehicle class, commodity code, gross weight, and calculated value of vehicle.

In addition to truck trips associated with particular land uses, a similar analysis could be completed by consideration of areas of different population densities, employment levels, parcel sizes, counties, or other traffic analysis zones (TAZs). As an example, an analysis was performed in the ArcGIS program to determine the proportion of GPS records from the TRUE pilot project that were within different land use categories in the Portland, Oregon, metropolitan area. A 2010 land use geographic information system (GIS) file from Portland Metro's Regional Land Information System (*25*) was used for this analysis. The results (provided in Figure 3) not only demonstrate the relative proportion of records within different land use categories (i.e., trucks generally traveled in mixed-use residential areas more than in rural areas) but also the relative proportion of records from different weight classes for each land use category (i.e., trucks over 98,000 lb traveled in rural areas more than in mixed-use residential areas).

The GIS plot in Figure 4 provides a second example of the disaggregation of this data set, which is by truck type category. The plot in Figure 4 provides a visual analysis of the spatial distribution of the pilot project GPS records for trucks in the 1030 weight class (103,000 lb). The number of GPS records for various segments of Interstate, U.S., and state highways in Oregon is shown for this weight class. Similar disaggregations by other vehicle type categories (i.e., commodity type, gross weight, and axle weight) are also possible.

As demonstrated by Figures 3 and 4, the TRUE GPS data provide the level of detail needed to determine the location of truck travel at the TAZ level and, thus, to develop truck trip generation rates with a level of accuracy that has not been possible with previous truck

TABLE 3 Applications Framework

Category	Performance Measure or Application	Data Fields: Latitude and Longitude	Time Stamp	Weight Class	Axle Count	Accuracy of GPS	Vehicle Class	Vehicle Type	Commodity Code	Gross Weight	Axle Weight
Mobility	Travel time	X				X					
	Travel time reliability	X				X					
	Travel time index	X				X					
	Planning time index	X				X					
	Volume to capacity ratio	X				X					
	Percentage of congested miles	X				X					
	Interstate MC VMT	X				X					
	Freight tonnage by commodity	X				X			X		
System condition	Estimate pavement condition	X	X	X	X	X	X	X		X	X
	Scope pavement condition surveys	X	X	X	X	X	X	X		X	X
	Pavement forensics	X	X	X	X	X	X	X		X	X
	Bridge weight limit violations	X	X	X	X	X	X	X		X	X
Environment	GHG emissions estimations	X	X	X	X	X	X	X		X	X
	Other emissions estimations	X	X	X	X	X	X	X		X	X
	GreenSTEP integration	X	X	X	X	X	X	X	X	X	X
Safety	Miscellaneous	X	X			X					
Accessibility and connectivity	LCV network access	X	X			X					
	Truck turnaround time at terminals	X	X			X					
Planning and modeling	Trip generation rates	X	X	X	X	X	X	X	X	X	X
	SWIM2 integration	X	X	X	X	X	X	X	X	X	X
	Visual analysis (i.e., GIS)	X	X	X	X	X	X	X	X	X	X
	Partner with regional projects	X	X	X	X	X	X	X	X	X	X
	Route choice	X	X	X	X	X	X	X	X	X	X
	Vehicle choice	X	X	X	X	X	X	X	X	X	X
	Freight activity modeling	X	X	X	X	X	X	X	X	X	X
	Mode choice	X	X	X	X	X	X	X	X	X	X

NOTE: X = required for each performance measure or application; blank cell = not required; MC = motor carrier; VMT = vehicle miles traveled; GHG = greenhouse gas; LCV = longer combination vehicles; SWIM2 = Second-Generation Statewide Integrated Model.

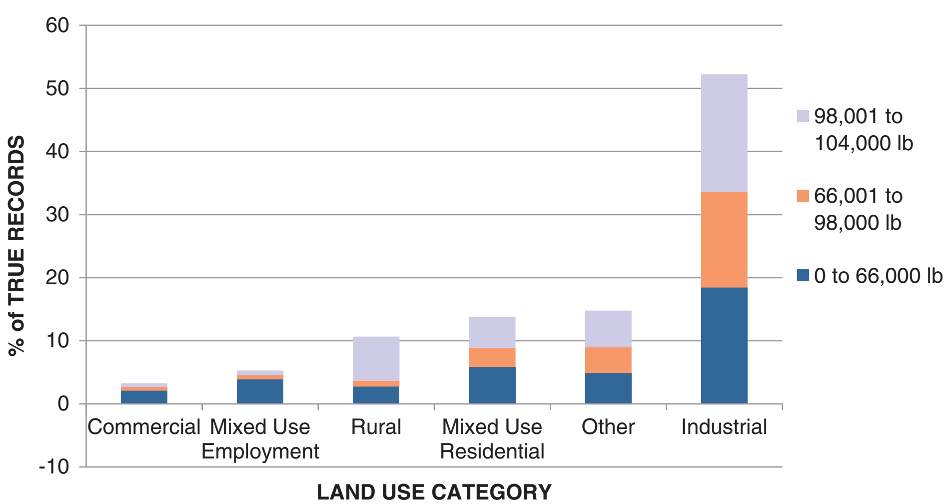

FIGURE 3 Density of GPS records by weight class and land use in Portland metropolitan area.

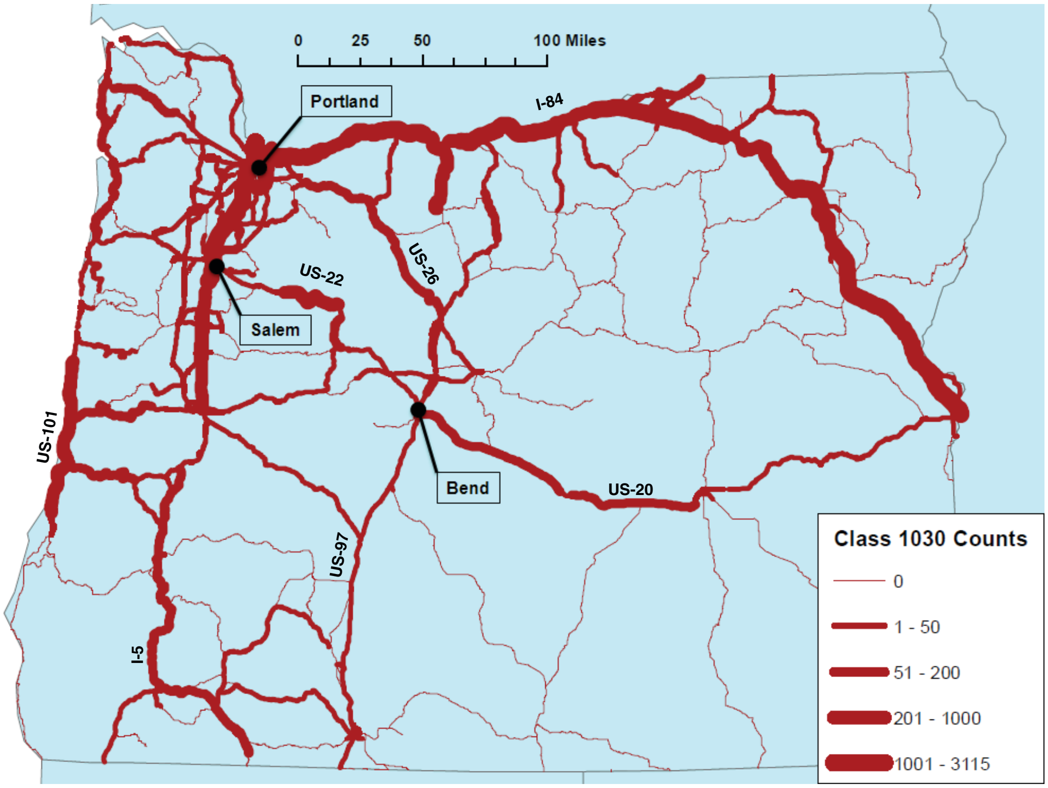

FIGURE 4 GPS record counts for 1030 weight class.

GPS data. However, the accuracy of such trip generation rates could be further enhanced by identification of TRUE GPS records that represent trip ends (origin and destination locations); for example, a methodology to identify trip origins and destinations through the use of GPS data has been presented previously (*12*). Subsequently, if the TRUE system was implemented statewide, the resulting data could be used to develop highly accurate trip generation rates that could be used as an alternative to or to complement less accurate employment- or production-based trip generation rates. Furthermore, results from TRUE analyses could be compared with those obtained through the use of other regional analysis tools, such as the Commodity Flow Survey of the Bureau of Transportation Statistics or the Freight Analysis Framework of FHWA. Such resources provide aggregated commodity flow data that could be calibrated or disaggregated through the use of TRUE data.

The *Freight Performance Measures: Approach Analysis* report for the Oregon DOT suggests that the ratio of the total cost of freight loss and damage from accidents to the total freight vehicle miles traveled is the ideal safety freight performance measure for both statewide analysis and specific highway segments (*4*). The total cost of freight loss includes (*a*) the cost of lost and damaged equipment, (*b*) the value of lost and damaged cargo, and (*c*) delays imposed to other freight carriers on the same highway corridor. The vehicle type, class, weight, and commodity data available through TRUE data (in combination with WIM data) would assist with the estimation of such costs. The 2010 report also suggests that motor carrier crash rate and triple-trailer crash rate are worthwhile performance measurements for Oregon (*4*). If a system such as TRUE was implemented on a statewide level, it could be combined with Oregon's existing data sources for safety performance measures to assist with the determination of more accurate estimates for these performance measures.

Accessibility and connectivity performance measures are particularly relevant to Oregon because of the multimodal nature of freight transport in the state (i.e., ports, airports, and highways). McMullen and Monsere suggest that the percentage of freight originating or terminating within a certain number of miles of corridors with longer combination vehicles is a potential measure of accessibility (*4*). The expansion of the network for longer combination vehicles was frozen by the Intermodal Surface Transportation Efficiency Act in 1991. McMullen and Monsere also note that shipment origin or destination data do not contain the level of specificity needed to make such a measurement (*4*); however, as demonstrated in Figures 3 and 4, the TRUE data have the potential to provide such detail. Truck turnaround time at terminals (ports), as measured in research by You and Ritchie (*26*), is another potential performance measure available to Oregon through the TRUE data.

Maintenance and preservation efforts by state DOTs typically focus on highway bridge and pavement management (*4*). Bridge wear is primarily a function of gross vehicle weight; pavement wear is primarily a function of axle weights. As such, the capability of TRUE data (in combination with WIM data) to provide estimates of both the gross vehicle weight and the axle spacing of vehicles traveling on virtually any segment of state highway could be useful to determine user impacts. According to *Infrastructure Costs Attributable to Commercial Vehicles,* DOTs typically allocate 40% or more of their annual budgets to pavement maintenance and rehabilitation projects (*27*). Furthermore, the relationship between axle loads and consequent pavement damage is known to be exponential (*28*). For these reasons, it is pertinent to consider applications of detailed truck GPS data within the field of pavement management. The TRUE GPS data could be applied to (*a*) pavement forensics, (*b*) determination of more accurate estimates for highway design equivalent single-axle loads, and (*c*) decrease the frequency of pavement condition surveys for highway segments receiving minimal truck traffic. The integrated TRUE and WIM data could also provide route information for trucks of various gross vehicle weights to determine weight limit violations on bridges.

The Oregon DOT recently developed the Oregon Freight Plan to consider infrastructure investment and policy options for freight (*1*). To account for the current economic uncertainty, the Oregon Freight Plan analyzed various alternative scenarios for the future. The Oregon DOT Second-Generation Statewide Integrated Model (SWIM2) was used to complete this analysis. SWIM2 is a spatial economic modeling system that represents transportation, economics, and land use, as well as the interactions between them (*29*). In 2010, short-, mid-, and long-term improvements were proposed to the commercial truck module of SWIM2 (*30*). It was noted that SWIM2 provides a comprehensive approach to household travel activity but that the commercial truck module was in need of enhancements to forecast freight movements and the impacts of energy price changes more adequately and to provide sound policy analysis of greenhouse gas (GHG) emissions, taxes, and tolling. According to the researchers, applications for the commercial truck module are limited to "a subset of freight policy problems that can be appropriately modeled with simple behavior rules and limited data" (*30*). The TRUE data provide an excellent opportunity to produce more accurate results in SWIM2 and for the Oregon Freight Plan analysis in particular. Given the disaggregated nature of the TRUE data, it would be an asset when SWIM2 analysis is performed at a regional level in Oregon and for implementation of the suggested improvements to the commercial truck module.

In summary, given the accuracy of the data (Figure 1) and the associated analysis capabilities (Figures 3 and 4), several applications ranging from trip generation and commodity and land use planning to infrastructure management would greatly benefit from the statewide use of the TRUE data set.

SPEED-BASED APPLICATIONS

Of the freight performance measures listed in Tables 1 and 2, those associated with mobility have probably received the most attention on a national level, specifically in relation to travel time reliability and congestion at bottlenecks (*4*). As demonstrated in Table 1, all of the research on freight GPS data from the literature review for this project explored applications in this area. The following are some commonly used mobility performance measures for which the TRUE data could provide estimates:

- Travel time, which is the time taken by a driver to travel between an origin and a destination (*3*);
- Travel time reliability, for which NCHRP Report 618 recommends that the 90th and 95th percentile travel times (reflecting travel delays that can occur during heavy congestion) be used as indicators of travel time reliability (*31*);
- Travel time index, which is the ratio of the average speed for a given highway segment at a particular time of day to the functional free-flow speed of the same segment of highway (*32*); and
- Planning time index, which is the ratio of the average travel speed for a given highway segment at a particular time of day in a worst-case scenario to the functional free-flow speed of the same segment of highway (*32*).

To estimate space mean speeds by use of the data in the TRUE data set, highway mileages between GPS records rather than straight-line or great-circle distances were used. The distances between GPS records in the TRUE data set are typically on the order of 5 mi. As such, significant error would result if straight-line or great-circle distances were used along curved highway segments. The use of highway mileages reduces such error and is thus a more accurate measure of traveled distance. The highway mileages of the GPS records were determined through interpolation by comparison of latitude and longitude measurements of the GPS records with those of known mileposts. The source of the highway milepost locations was an ArcGIS file from Portland Metro's Regional Land Information System (*25*). The interpolation process was completed with the RStudio program. An automated process was subsequently developed in RStudio to determine the speeds between GPS records. To assess the accuracy of the space mean speeds calculated from the GPS data, the calculated space mean speeds were compared with the speeds from the Portland, Oregon, Regional Archive Listing (PORTAL), the official archived data user service for the Portland metropolitan area. Speed measurements available through PORTAL are based on inductive-loop detector data from nearly 600 sensors located throughout the Portland metropolitan area on I-5, I-205, I-405, I-84, OR-207, and US-26 (*33*).

A set of all TRUE GPS records within 2.5 mi of a PORTAL station was created, and a random sample of 30 TRUE records was selected from this set. For each of the 30 TRUE records in the random sample, the next downstream TRUE record was determined to calculate space mean speeds. The PORTAL station closest to each of the sampled TRUE records was subsequently determined to create 60 TRUE–PORTAL pairs (or 30 TRUE–PORTAL groups). PORTAL speed estimates corresponding to the location and time stamp of each of the corresponding TRUE records were then determined. At the time of analysis, speeds were available at PORTAL stations in 5-min increments. As such, PORTAL speed records just before and just after the corresponding TRUE time stamp were selected for each TRUE–PORTAL pair. The PORTAL speeds at the exact times of each corresponding TRUE record were then determined by interpolation. The average speed between PORTAL stations in each TRUE–PORTAL group was then determined for comparison with the calculated space mean speed between the corresponding TRUE records.

PORTAL speed records are available for each individual lane at the location of each PORTAL station. For the purposes of this analysis, it was assumed that trucks from the TRUE data set were always traveling in the right truck lane (the lane the farthest from the median); likewise, PORTAL records from the truck lane were used for comparison with the TRUE space mean speeds. The 5-min time intervals used for this research were considered more appropriate than a smaller time interval because flow rates become unstable as the period of analysis becomes smaller; for example, the *Highway Capacity Manual 2010* recommends 15-min intervals to study peak period flow rates (*34*).

Records representing destinations or origins were identified and removed from the speed comparison process. Destinations or origins usually consist of a cloud of observations that can be consolidated into one observation (representing a trip origin or trip end) to avoid erroneous speed calculations (false low speeds). In addition, Tukey's method to identify outliers was used to determine if the percent difference in speed for any of the 30 TRUE–PORTAL pairs was an outlier (*35*). Outliers were then removed from the analysis, and a randomly selected TRUE record was selected as a replacement. Such outliers were often indicative of a geocoding error in which the ArcView GIS assigned one of the two TRUE GPS records to an incorrect highway segment. Removal of outliers also served to eliminate from the analysis records that represented trucks at rest or slowing down in an auxiliary lane, thus limiting the review to through movements more representative of the general traffic conditions.

As can be seen in Figure 5, more than 50% of the space mean speeds calculated from the TRUE data set were within 8% of the speeds calculated from PORTAL; all of the TRUE speeds were within 25% of the PORTAL speeds. The absolute values of the speed differences averaged 9%; however, the TRUE speeds were, on average, approximately 7% (3.65 mph) less than the PORTAL speeds; the speed differences had a standard deviation of 8% (4.41 mph). Eighty percent of the TRUE speeds were less than the PORTAL speeds. This result likely occurred because PORTAL speeds are an aggregation of speed measurements from a variety of vehicle types (i.e., mostly passenger vehicles, which typically travel faster than trucks). The TRUE speeds ranged from 21% (12.4 mph) less than the PORTAL speeds to 10% (5.6 mph) greater than the PORTAL speeds.

The results of a paired-sample *t*-test indicate that at the .01 significance level the tested sample provides sufficient evidence to conclude that the difference between the PORTAL speeds and the speeds calculated from the TRUE data is significant. This conclusion appears to be consistent with the findings of previous research on the same freeway segments in the Portland region (*2*); previous research results indicated that during the peak p.m. period speeds estimated from loop detectors were generally greater than speeds estimated by truck GPS data provided by the American Transportation Research Institute.

Because of the following limitations of this analysis, further analysis would be required to calculate more precisely the statistical relationship between speeds estimated by TRUE and those estimated by PORTAL: (*a*) PORTAL speed estimates were time mean speeds; TRUE speed estimates were space mean speeds, and differences in the methods used to calculate each type of speed estimate would affect the results, especially when loop detectors are far apart (in the case of the PORTAL system, loop detectors are, on average, separated by approximately 1 mi, and therefore, the error is not likely to be high); (*b*) the analysis had sample size limitations (the analysis included a variety of locations and time periods; the change in the relationship for different locations and time periods was not considered); and (*c*) errors in interpolation could have been made, which could be of particular concern for hours during the transition to peak periods; however, 22 of the 30 TRUE–PORTAL pairs represented time periods well outside peak hours (8 p.m. to 5 a.m. and 11 a.m. to 3 p.m.), likely because commercial trucks typically avoid traveling during more congested, unreliable times.

Emissions rates are highly correlated with travel speeds and traffic conditions (*36*). Therefore, accurate environmental performance measures for emissions are greatly dependent on the availability of detailed mobility performance measures. The performance measures used by state DOTs to measure the success of environmental stewardship include emissions of volatile organic compounds, nitrous oxides, carbon monoxide, ozone, particulate matter, and GHGs. Truck GPS data integrated with WIM data could be input into air quality modeling programs, such as the U.S. Environmental Protection Agency's Motor Vehicle Emission Simulator, to improve the accuracy of model results. The methodology used by Wheeler and Figliozzi could be used and further developed to estimate freight emissions through the use of Oregon DOT's TRUE GPS and WIM data (*2*).

According to NCFRP Report 10, national targets for most types of large and heavy-duty truck emissions are on track, but the industry's GHG emissions continue to rise (*5*). The Oregon DOT recognizes the need to address this concern and has developed the Greenhouse Gas Strategic Transportation Energy Planning (GreenSTEP) model to assess the effects of policies and other factors (i.e., gas prices) on GHG emissions from the transportation sectors (*37*). The model specifically estimates and forecasts vehicle ownership, vehicle travel, fuel consumption, and GHG emissions. As of October 2011, GreenSTEP focused on emissions from household and light-duty

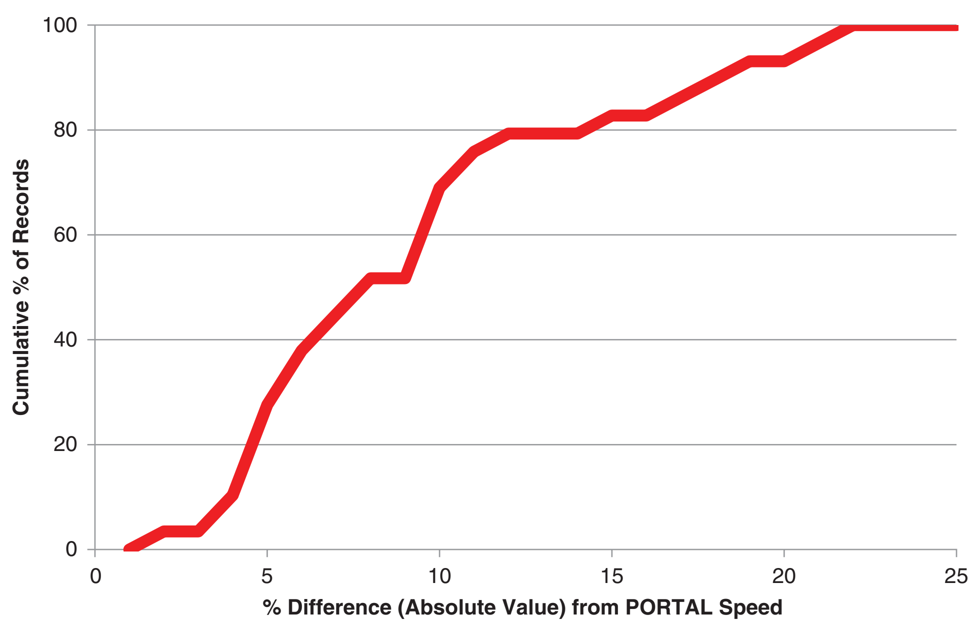

FIGURE 5 TRUE speed measurement accuracy.

commercial vehicles (i.e., autos, SUVs, pickup trucks, and vans); modeling of GHG emissions from freight is still under development. According to Oregon DOT reports (*37*), estimates from GreenSTEP could further be used to assess the relative equity of different policy proposals for different road users. Given that commercial vehicle emissions are greatly dependent on vehicle weight and speed, TRUE data (in combination with WIM data) would be highly valuable for the further development of the freight portion of GreenSTEP in anticipation of the impacts of proposed policies on the freight sector.

CONCLUSIONS AND FUTURE RESEARCH

This research demonstrates the potential to use Oregon DOT's WMT data for a variety of important applications. Highly accurate truck trip generation rates by commodity or vehicle type are possible, given that the accuracy of most TRUE GPS data is within 50 ft; this is an accuracy level that is more than appropriate for determination of the location of truck travel at the TAZ level (TAZ areas are usually several miles wide and long). The accuracy of such trip generation rates could be further enhanced through the identification of TRUE GPS records that represent trip ends (the origin and destination locations of truck tours). If the TRUE system was implemented statewide, the resulting data could be used to develop highly accurate trip generation rates as an alternative to more inaccurate employment- or production-based trip generation rates and to calibrate the outputs of statewide freight models.

Furthermore, TRUE data provide a valuable resource for the development of mobility performance measures specific to freight vehicle type and commodity type. The findings of this research indicate that, in general, space mean speeds calculated from the TRUE GPS data are lower than those estimated from loop detector measurements and that the difference is statistically significant. This finding appears to the consistent with previous research that found that for peak p.m. periods, speeds estimated by truck GPS data were generally less than those measured by loop detectors (*2*).

In addition to applications for the generation of trip generation rates and mobility measures, these data exhibit a strong potential to be used for performance measure categories, such as safety, accessibility and connectivity, system condition, and environmental stewardship. The applications framework developed through this research proposes applications in each of these areas, along with the data fields required to provide accurate results in each. All of the data fields required for the proposed applications are available through the integration of TRUE and WIM data.

Although previous research has had limited success with the use of commercial truck GPS data for planning and modeling purposes, the TRUE data have an advantage in their level of disaggregation and their ability to differentiate between vehicle and commodity types. Previous assumptions about freight behavior made within SWIM2 and the Oregon Freight Plan could be reassessed because they were made in a significantly poorer freight data environment.

The Oregon DOT GreenSTEP model has previously focused on the impact of policies and investments on emissions from household and light-duty commercial vehicles. The TRUE data provide an opportunity to develop the freight portion of this model through the provision of details about vehicle type and travel behavior, as well as the possibility of more accurate weight load, fuel consumption, and speed estimates.

Likewise, the potential to use the TRUE data to obtain emissions estimates from the U.S. Environmental Protection Agency's Motor Vehicle Emission Simulator should be explored. Previous research provides examples of the successful use of truck GPS data in the Motor Vehicle Emission Simulator (*2*); however, the TRUE data (in combination with WIM data) provide an opportunity to enhance the accuracy of such estimates through the incorporation of vehicle weight and speed estimates more representative of actual conditions.

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REFERENCES

1. Cambridge Systematics, Inc., and Oregon Department of Transportation Freight Mobility Unit. *Oregon Freight Plan, An Element of the Oregon Transportation Plan.* Oregon Department of Transportation, Salem, 2011.
2. 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.
3. Figliozzi, M. A., N. Wheeler, E. Albright, L. Walker, S. Sarkar, and D. Rice. Algorithms for Studying the Impact of Travel Time Reliability Along Multisegment Trucking Freight 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. 26–34.
4. McMullen, S. B., and C. Monsere. *Freight Performance Measures: Approach Analysis.* OTREC-RR-10-04. Oregon Department of Transportation/Oregon Transportation Research and Education Consortium, Salem, 2010.
5. Gordon Proctor and Associates, Inc. *NCFRP Report 10: Performance Measures for Freight Transportation.* Transportation Research Board of the National Academies, Washington, D.C., 2011.
6. *Truck Road Use Electronics Pilot Project.* Office of Innovative Partnerships and Alternative Funding, Oregon Department of Transportation, Salem. http://cms.oregon.egov.com/ODOT/HWY/OIPP/Pages/TRUE.aspx. Accessed July 31, 2012.
7. Sharman, B., and M. Roorda. Analysis Tool to Process Passively Collected GPS Data for Commercial Vehicle Demand Modeling Applications. Presented at Innovations in Freight Demand Modeling and Data Symposium, SHRP-2, Transportation Research Board of the National Academies, Washington, D.C., 2010.
8. Performance Measurement. In *Freight Management and Operations,* FHWA, U.S. Department of Transportation, 2013. http://ops.fhwa.dot.gov/freight/freight_analysis/perform_meas/index.htm.
9. McCormack, E. *Developing Transportation Metrics from Commercial GPS Truck Data.* Report TNW2011-12. Transportation Northwest, Department of Civil and Environmental Engineering, University of Washington, Seattle, 2011.
10. Bassok, A., E. D. McCormack, M. L. Outwater, and C. Ta. Use of Truck GPS Data for Freight Forecasting. Presented at 90th Annual Meeting of the Transportation Research Board, Washington, D.C., 2011.
11. Ma, X., E. D. McCormack, and Y. Wang. Processing Commercial Global Positioning System Data to Develop a Web-Based Truck Performance Measures Program. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2246,* Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 92–100.

12. 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.
13. Holguin-Veras, J., K. Ozbay, A. Kornhauser, M. A. Brom, S. Iyer, W. F. Yushimito, S. Ukkusuri, B. Allen, and M. A. Silas. Overall Impacts of Off-Hour Delivery Programs in New York City Metropolitan Area. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2238,* Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 68–76.
14. Zhao, W., A. V. Goodchild, and E. D. McCormack. Evaluating the Accuracy of Spot Speed Data from Global Positioning Systems for Estimating Truck Travel Speed. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2246,* Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 101–110.
15. Wunnava, S., K. Yen, B. Tadeusz, R. Zavaleta, R. Romero, and C. Archilla. *Travel Time Estimation Using Cell Phones for Highways and Roadways.* Florida Department of Transportation, Gainesville, 2007.
16. Zhao, Y. Mobile Phone Location Determination and Its Impact on Intelligent Transportation Systems. *IEEE Transactions,* Vol. 1, No. 1, 2000, pp. 55–64.
17. Barbeau, S., M. A. Labrador, A. Perez, P. Winters, N. Georggi, D. Aguilar, and R. Perez. Dynamic Management of Real-Time Location Data on GPS-Enabled Mobile Phones. UBICOMM 2008. *Proc., Second International Conference on Mobile Ubiquitous Computing, Systems, Services, and Technologies,* 2008, pp. 343–348.
18. Zheng, Y., L. Liu, L. Wang, and X. Xie. Learning Transportation Mode from Raw GPS Data for Geographic Applications on the Web. *Proc., 17th International Conference on World Wide Web,* Beijing, China, Association for Computing Machinery, New York, 2008, pp. 247–256.
19. Manzoni, V., D. Manilo, K. Kloeckl, and C. Ratti. *Transportation Mode Identification and Real-Time CO_2 Emission Estimation Using Smartphones.* SENSEable City Lab, Massachusetts Institute of Technology, Cambridge, 2011.
20. Froehlich, J., T. Dillahunt, P. Klasnja, J. Mankoff, S. Consolvo, B. Harrison, and J. A. Landay. UbiGreen: Investigating a Mobile Tool for Tracking and Supporting Green Transportation Habits. *Proc., 27th International Conference on Human Factors in Computing Systems,* Boston, Mass., Association for Computing Machinery, New York, 2009, pp. 1043–1052.
21. Schrank, D., T. Lomax, and B. Eisele. *Texas A&M Transportation Institute's 2011 Urban Mobility Report Powered by INRIX Traffic Data.* Texas A&M Transportation Institute, Texas A&M University System, College Station, 2011.
22. INRIX, Inc. *INRIX,* 2012. http://inrix.com/. Accessed Feb. 11, 2012.
23. Xata Corporation. Xata Turnpike, 2012. http://www.xata.com/fleet-management-solutions/xata-turnpike-enterprise-fleet-management/. Accessed Feb. 5, 2012.
24. Eroad Limited. *Eroad.* 2011. http://eroad.com/. Accessed Feb. 10, 2012.
25. Portland Metro. RLIS Live, Geographic Information System Data, 2012. http://www.oregonmetro.gov/index.cfm/go/by.web/id=593. Accessed June 4, 2012.
26. You, S. I., and S. G. Ritchie. Tour Behavior of Clean Drayage Trucks in Southern California. Presented at 91st Annual Meeting of the Transportation Research Board, Washington, D.C., 2012.
27. Boile, M., K. Ozbay, and P. Narayanan. *Infrastructure Costs Attributable to Commercial Vehicles.* Final Report FHWA-NJ-2001-030. FHWA, U.S. Department of Transportation, 2001.
28. Equivalent Single Axle Load. In *Pavement Interactive,* 2012. http://www.pavementinteractive.org/article/equivalent-single-axle-load/. Accessed July 31, 2012.
29. Hunt, J. D., T. J. Weidner, R. Knudson, A. O. Bettinardi, and E. Wardell. Applying the SWIM2 Integrated Model in Freight Planning in Oregon. Presented at 90th Annual Meeting of the Transportation Research Board, Washington, D.C., 2011.
30. Figliozzi, M. A., and K. Shabani. *Critical Review and Analysis of Existing CT Module.* Technical memorandum and final report IGA 24620 WOC 4. Portland State University, Portland, Ore., 2010.
31. Cambridge Systematics, Inc., Dowling Associates, Inc., System Metrics Group, Inc., and Texas Transportation Institute. *NCHRP Report 618: Cost-Effective Performance Measures for Travel Time Delay, Variation, and Reliability.* Transportation Research Board of the National Academies, Washington, D.C., 2008.
32. Park, L., D. Pierce, and J. Short. A System for Utilizing Truck GPS Data to Monitor Urban Highway Congestion. Presented at 91st Annual Meeting of the Transportation Research Board, Washington, D.C., 2012.
33. Li, H., and R. L. Bertini. Comparison of Algorithms for Systematic Tracking of Patterns of Traffic Congestion on Freeways in Portland, Oregon. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2178,* Transportation Research Board of the National Academies, Washington, D.C., 2010, pp. 101–110.
34. *Highway Capacity Manual 2010.* Transportation Research Board of the National Academies, Washington, D.C., 2010.
35. Sullivan, M. *Statistics: Informed Decisions Using Data,* 4th ed. Pearson, Boston, Mass., 1967, p. 169.
36. Figliozzi, M. A. The Impacts of Congestion on Time-Definitive Urban Freight Distribution Networks CO_2 Emission Levels. *Transportation Research Part C,* Vol. 19, No. 5, 2011, pp. 766–778.
37. *Greenhouse Gas Strategic Transportation Energy Planning Model.* Oregon Department of Transportation and Department of Land Conservation and Development, Salem, 2011. http://www.oregon.gov/ODOT/TD/OSTI/docs/Media/Model.pdf?ga=t. Accessed Feb. 25, 2012.

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