Title
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Journal
Transportation Research Record: Journal of the Transportation Research Board, 2610(1)

ISSN
0361-1981 2169-4052

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Publication Date
2017

DOI
10.3141/2610-11

Peer reviewed

Truck Activity Monitoring System for Freight Transportation Analysis

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Understanding truck activity is an essential component of strategic freight planning and programming. However, recent studies have revealed a significant void in the availability of detailed truck activity data. Although some existing detectors are capable of providing truck counts by axle configuration, higher-resolution data that indicate truck body configuration, industry served, and commodity carried cannot be obtained from existing sensors. This paper presents the newly developed Truck Activity Monitoring System, which leverages existing in-pavement traffic sensors to provide truck activity data in California. Existing inductive loop detector sites were updated with inductive signature technology and advanced truck classification models were implemented to provide detailed truck count data with more than 40 truck body configurations. The system has been deployed to more than 90 detector locations in California to provide coverage at state borders, regional cordons, and significant metropolitan truck corridors. An interactive geographic information system website provides users with advanced visual analytics and access to archived data across all deployed locations. The case studies presented in this paper demonstrate the potential of the data obtained from this system in analyzing and understanding current and historical industry-specific truck activity.

Trucks are largely responsible for transporting freight. In addition to long-haul shipments, trucks also provide the critical first- and last-mile links in the multimodal freight transportation network. Hence, understanding truck activity is an essential component to ensure that strategic plans and policies for transportation infrastructure investment can effectively support the projected growth of freight movements over the planning horizon.

Recent studies have revealed a significant void in the availability of detailed truck activity data necessary to understand truck movement along major transportation corridors. Although current technologies such as truck GPS data can provide truck travel pattern data, they rarely provide data on vehicle characteristics to link travel patterns to industry served or commodity carried. Moreover, commonly used national truck GPS data sets can provide biased samples of the truck population because not all truck fleets submit GPS data to the national database. Even through GPS data sets can be very large, studies show that there is an overrepresentation of larger corporate fleets (*1*). Existing traffic detector infrastructure, including weigh in motion (WIM) detectors and automatic vehicle classifiers, however, are capable of measuring some physical attributes of trucks, such as vehicle length, gross vehicle weight, number of axles, and axle spacing. These attributes can be used to provide detailed truck count data by axle configuration according to the FHWA scheme of 13 vehicle categories (14 in California) (*2*). However, axle-based classification does not provide the necessary details that are needed for freight modeling, emissions estimation, and other freight- or truck-related studies. Truck activity patterns, emissions, industries served, and commodities carried are highly associated with trucks' body configurations and not their axle count. However, very few data sources provide truck body configuration data to practitioners and researchers. A number of surveys have been undertaken to collect data on truck distribution by body type, such as the national Vehicle Inventory and Use Survey conducted by the U.S. Census Bureau, and other regional and statewide surveys (*3, 4*). However, these survey-based approaches provide aggregated levels of truck body configuration distributions that are obtained from sample populations; the approaches result in significant sampling bias and limited details on spatial and temporal variations of truck activity.

Although a source for high-resolution truck data with wide geographic coverage and comprehensive data on truck characteristics is needed for data-driven freight transportation planning, infrastructure investment, and emissions analysis, it is evident that none of the existing methods for collecting truck data have the capability to effectively capture temporally continuous and detailed, industry-specific truck characteristics or activity patterns. Of all the truck data collection platforms, the detector-based approach is the most ideally suited for reporting temporally continuous real-time traffic for the full population of trucks traversing a given location. In California, more than 100 WIM sites and 8,000 traffic monitoring sites—most of which are instrumented with inductive loop detectors (ILDs)—provide continuous vehicle counts. This paper presents a new high-resolution truck data collection system that leverages the existing ILD infrastructure through the implementation of recently developed truck body classification models by Hernandez et al. (*5*). This solution, the Truck Activity Monitoring System (TAMS), represents excellent stewardship of invested detector systems and produces a new paradigm of detailed truck activity data with marginal costs through the use of cutting-edge classification models (*6*). Compared with conventional FHWA classifications, the models developed in TAMS are able to distinguish 47 and 63 truck configurations from ILD and WIM sites, respectively, by using inductive signature data

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Transportation Research Record: Journal of the Transportation Research Board, No. 2610, 2017, pp. 97–107.
http://dx.doi.org/10.3141/2610-11

from traffic detector sites enhanced with inductive signature technology. The robust and detailed truck classification scheme used by TAMS distinguishes commodity- and industry-specific body configurations, such as agriculture, logging, and livestock trucks; distinguishing these configurations can help researchers to understand the unique temporal and spatial travel patterns of the industries. The near-real-time truck data provided in TAMS are easily accessible through a web interface that incorporates geographic information system mapping functionality. Some of the diverse applications of TAMS include validation and calibration of freight models such as the California statewide freight forecasting model (*7*); development of time of day, day of week, and seasonal factors; and spatial analysis of truck activity patterns.

This paper introduces the technology and classification models, user interface, and products of TAMS. Four case studies are presented to demonstrate some unique applications of TAMS: truck corridor analysis, spatial truck travel pattern, industry-specific truck monitoring, and time of day truck travel pattern analysis.

TAMS SYSTEM DESIGN

Inductive Signature Technology and Truck Body Class Models Used in TAMS

Conventional ILDs produce binary outputs, zero or one, typically at 30 samples per second, as shown in Figure 1. In California, the Performance Measurement System collects data from more than 8,000 traffic monitoring sites—most of which use ILDs—to provide data on traffic volumes, speeds, and congestion measures (*8*). Advanced inductive signature technology produces a waveform signature for each vehicle at up to 1,200 samples per second. The resulting detailed inductive signatures can be subsequently used to determine vehicle body configuration through the use of advanced classification models. Updating an existing ILD site with signature capability is straightforward, requiring only installation of in-cabinet hardware, with no alterations to existing in-pavement sensors required. The conversion is relatively straightforward and cost-effective because lane closures are not required and existing traffic operations—such as traffic monitoring, ramp metering, and census counts—are not compromised.

The advanced inductive signature technology allows for highly detailed data on truck characteristics to be obtained from ILDs. Examples of inductive signatures from trucks with different trailer configurations are shown in Figure 2. Although all these trucks are classified as FHWA Class 9, five-axle tractor pulling a single trailer, the inductive signatures associated with these trailer examples are clearly distinct, affirming the use of inductive signatures as an effective platform for distinguishing trucks and trailers by body configuration. The use of axle configuration data from a WIM sensor or binary outputs from a conventional ILD would not reveal the industry-specific body types that can be distinguished with inductive signatures.

Two classification models were developed and tested using inductive signatures to provide detailed truck body classification: a stand-alone signature model and a combined WIM–signature model for implementation at existing ILD and WIM sites, respectively (*4, 9*).

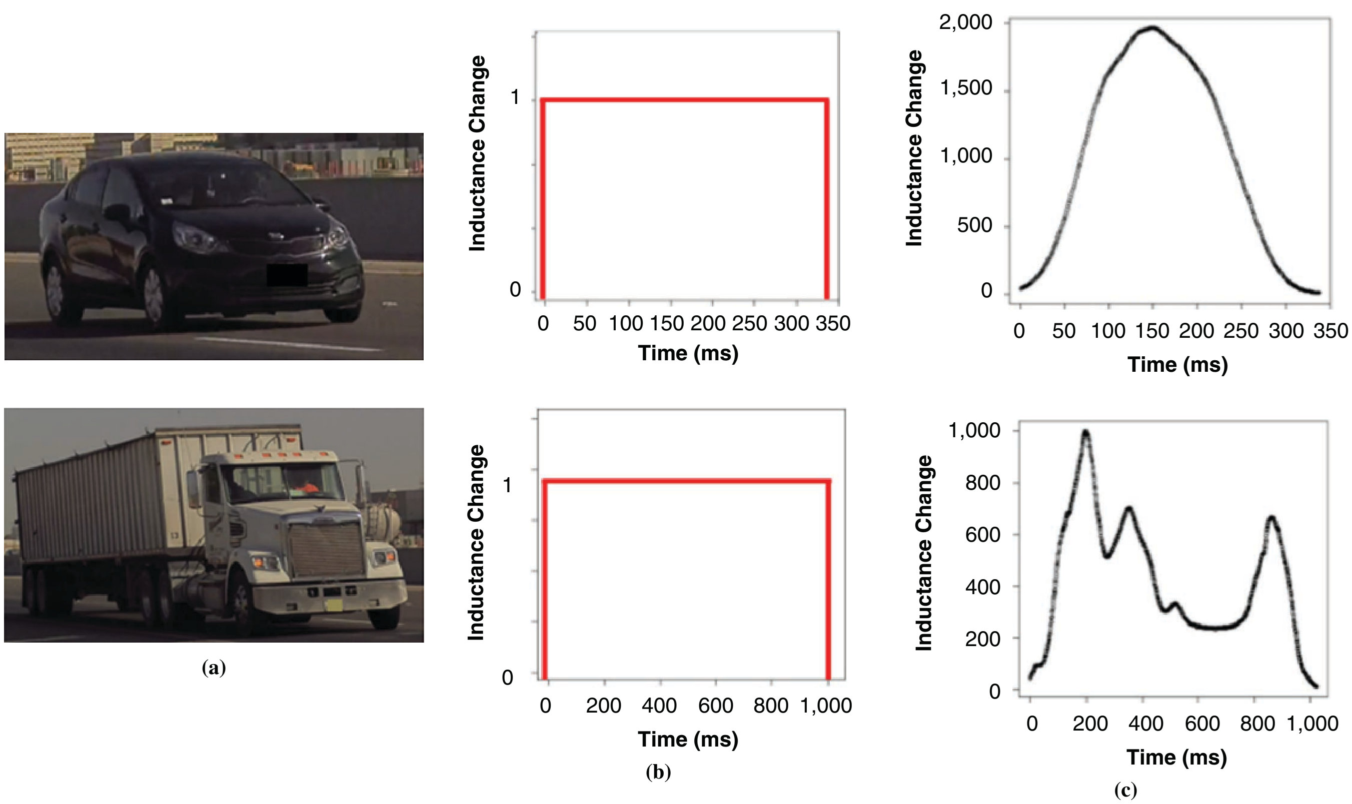


FIGURE 1 Inductive signature technology: (*a*) vehicle type, (*b*) conventional measurement, and (*c*) advanced measurement for sedan (*top*) and semi (*bottom*).

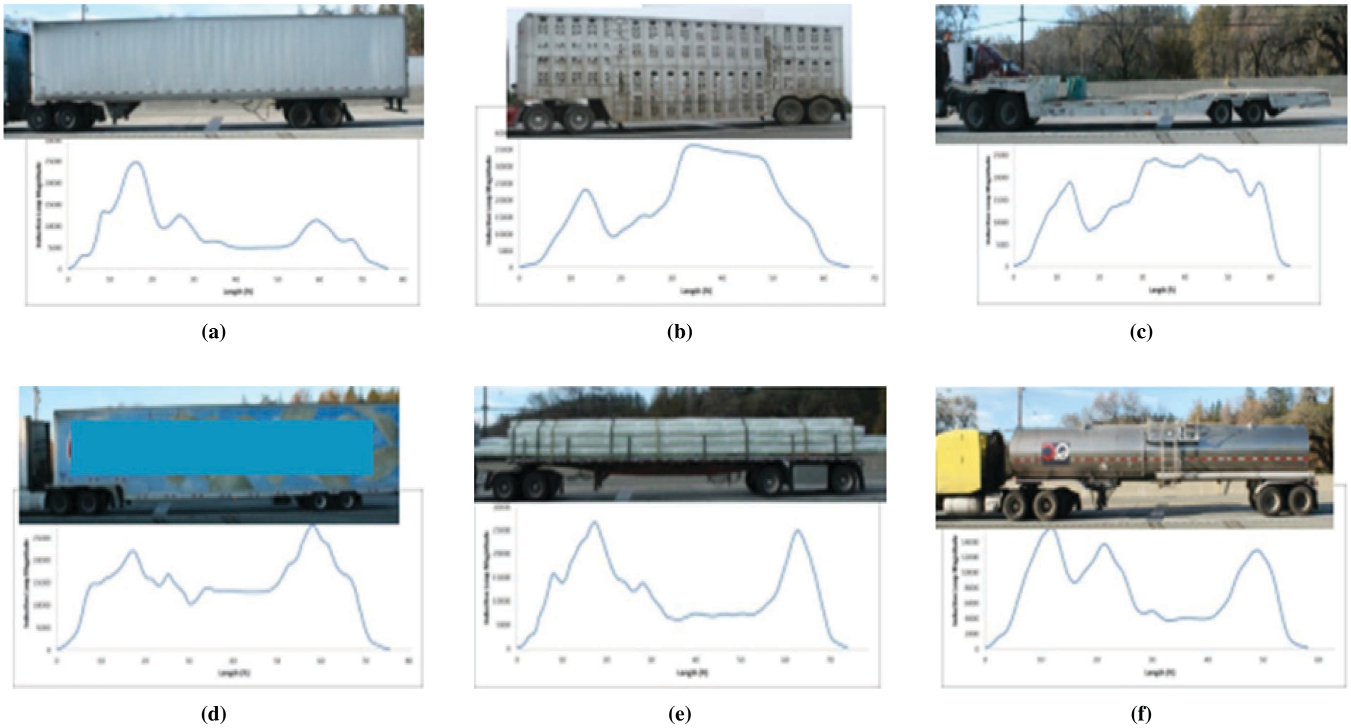


FIGURE 2 TAMS classifications for FHWA Class 9 vehicle category: (*a*) enclosed van, (*b*) livestock, (*c*) lowboy platform, (*d*) drop-frame van, (*e*) basic platform, and (*f*) tank.

The stand-alone signature model is stratified into three tiers of submodels: the first tier distinguishes single units from multiunits, the second tier predicts five general body configurations, and the third tier predicts detailed body configurations across 45 truck classes, as shown in Table 1. The WIM–signature model integrates axle data with inductive signatures and produces body classifications stratified by axle configuration. Sixty-three distinct truck body configurations can be classified at WIM sites.

A total of 20,957 vehicle signature records, including passenger vehicles with corresponding still images, were collected from four locations in California for model development and validation (*9*). The models with three tiers were developed with 6,362 truck records and tested with 8,940 trucks records that were not used for the model development. Because of the limited number of WIM sites deployed, the focus of this study is on results obtained from the stand-alone signature model.

Two performance measures were used to evaluate the performance of the model:

1. Classification accuracy, which represents the percentage of correctly classified vehicles within a truck class, and
2. Volume error, which is defined as the absolute difference between the numbers of observed and predicted vehicles divided by the observed number, expressed as a percentage.

Classification accuracy is an important indicator of model performance for individual body classification results, and volume error measures the accuracy of counts over an aggregated interval, such as hourly and daily volume estimates.

Within each general body configuration (i.e., second tier), the average classification accuracy of detailed truck body configurations ranges from 72% to 94%, with aggregated volume errors ranging from 7% to 15%, as shown in Table 2. The third tier's results show that 34 truck body classes have accuracies above 70% and 19 classes were predicted with a volume error of within 10%. Table 3 summarizes the performance of the five most common vehicle classes from each model, together with container and logging trailers, which are used in the case studies presented in this paper. Among tractors pulling a single semitrailer, the model predicted enclosed van trailers, typically the most frequently observed on highways, with an accuracy of 74.6% and volume error of 10.8%. For 20- and 40-ft container trailers, which are highly associated with intermodal facilities, the model achieved an accuracy of 77.8% and volume error of 8.0%. A more in-depth description of the WIM–signature model used in TAMS and further validation results of both models is described in work by Hernandez et al. (*5*) and the California Air Resources Board (*9*).

Data Collection Sites Used in TAMS

As shown in Figure 3, TAMS has more than 90 data collection sites, most of which are deployed at ILD sites. Eight of these ILD sites were selected for case studies to demonstrate potential uses of TAMS data.

Hardware Components and Communication Architecture of TAMS

Figure 4 summarizes the hardware components and communication architecture of TAMS. The hardware components are installed

TABLE 1 Stand-Alone Signature Model Truck Classification Scheme (*9*)

Tier 2 Class	Detailed Body Class
Passenger vehicle	
Single-unit (straight) trucks with no trailer	Conventional van/platform Cab over van/platform 30-ft bus 20-ft bus Multistop van/RV Utility/service Concrete Dumpster transport Garbage Bobtail Dump triple rear Street sweeper Dump/tank
Single-unit (straight) trucks with trailer	Small trailer Dump–dump RV with towed vehicle Concrete with lift axle Tank–tank Platform–platform Tow truck with vehicle Dump with lift axle
Tractors pulling single semitrailer	Enclosed van (FHWA 9) Enclosed van reefer (FHWA 9) Enclosed van (FHWA 8) Enclosed van reefer 53-ft container 40-ft container 40-ft container reefer 20-ft container Platform Tank Open-top van Auto Lowboy platform Drop-frame van Dump Logging Livestock Agriculture Beverage Platform/tank
Tractors pulling multiple trailers	Pneumatic tank Hopper Agricultural van Low-chassis van

NOTE: RV = recreational vehicle; reefer = refrigerated.

TABLE 2 Validation Results for Inductive Signature Only Model (*9*)

Model	Number of Classes	Number of Testing Samples	Accuracy (%)	Volume Error (%)
Single-unit (straight) trucks with no trailer	13	1,476	72.3	15.4
Single-unit (straight) trucks with trailer	8	746	94.2	8.2
Tractors pulling single semitrailer	19	6,113	74.2	11.3
Tractors pulling multiple trailers	7	605	90.4	7.0

within existing ILD and WIM traffic cabinets. The collected data (e.g., ILD signatures, WIM data records, or both) are transmitted in real time to a central PostgreSQL database through a Secure Shell tunnel. The data are then processed nightly to yield detailed classification results and aggregated summaries. Queries to the database produce classification results that are displayed on the TAMS web interface.

User Interface of TAMS

The TAMS web interface (http://freight.its.uci.edu/tams) was developed to provide access to on-demand summary truck classification reports using a combination of Java, JavaScript, and JavaServer Pages. Figure 5 shows an example of truck classification data provided by TAMS. The TAMS interface allows the user to query data within various spatial regions, including 12 Caltrans districts, nine major metropolitan planning organizations, and eight air basins in California. An interactive interface based on OpenStreetMap allows users to intuitively search truck classification results by vehicle category and location. All historical data are accessible to facilitate access to archived truck count data. Each site initially provides the breakdown of daily volumes by lane and aggregated by vehicle class categories (see Box A in Figure 5). A detailed breakdown of hourly volume counts by detailed truck classes can be obtained by clicking on the individual daily volume entries (see Box B in Figure 5). With the hourly volume table, a cell color scheme is implemented to represent variations of the daily hourly volume patterns. This feature facilitates a quick assessment of the predominant truck volumes at each location and the peak hourly volumes corresponding to each truck configuration.

CASE STUDIES

The four case studies in this section illustrate how the data obtained from TAMS can be used to analyze truck activity along major corridors by industry, time of day, and day of week. Each focuses on a unique application of TAMS data that can be used by researchers and practitioners to better understand truck activity patterns. As mentioned, TAMS provides two-levels of truck counts, aggregated daily volume categories and hourly volume by detailed truck class, to facilitate various levels of analysis. In this paper, the volume difference between single-unit truck and tractor pulling trailer(s) was compared through an aggregated truck corridor analysis. For the detailed level of analysis, spatial truck travel pattern, industry-specific truck monitoring, and time of day truck travel pattern analysis were performed using selected truck classes, such as intermodal container trailers, logging trailers, and enclosed van trailers, each of which serve dissimilar industries with distinct operational characteristics.

Truck Corridor Analysis

Compared with passenger vehicles, which have diverse route choice options, trucks have distinct travel patterns that are constrained by the locations and operations of industries and facilities they serve. The first case study focuses on distinguishing truck corridors. Truck corridor analysis allows agencies to understand the spatial distribution of truck travel patterns to facilitate freight facility investment planning and pavement maintenance.

TABLE 3 Truck Body Class Model Results for Selected Truck Body Classes (*9*)

Model	Body Classes	Number of Testing Samples	Accuracy (%)	Volume Error (%)
Single-unit (straight) trucks with no trailer	Conventional van/platform	333	74.5	12.9
	Utility/service	312	68.9	0.3
	Cab over van/platform	209	68.4	9.6
	30-ft bus	114	89.5	4.4
	Bobtail	107	89.7	2.8
Single-unit (straight) trucks with trailer	Small trailer	515	96.3	2.5
	Dump–dump	87	100	4.6
	RV with towed vehicle	49	85.7	8.2
	Concrete with lift axle	34	100	2.9
	Tank–tank	30	76.7	13.3
Tractors pulling single semitrailer	Enclosed van (FHWA 9)	2,343	74.6	10.8
	Enclosed van reefer (FHWA 9)	1,624	74.3	3.7
	Platform	796	77.5	11.2
	Tank	283	70.7	6.0
	Open-top van	185	60.5	18.9
	53-ft container	124	57.3	12.9
	20-ft and 40-ft container	150	77.8	8.0
	Logging	15	80.0	13.3
Tractors pulling multiple trailers	Enclosed van	253	92.9	2
	Dump	126	90.5	6.3
	Platform/tank	121	90.1	2.5
	Hopper	46	91.3	23.9
	Pneumatic tank	36	75.0	22.2

Six TAMS sites (Sites C through H in Figure 3) located on SR-210, I-10, and SR-60 in Southern California were chosen because these corridors serve as parallel routes connecting San Bernardino County and Los Angeles County. To compare truck volume along the select corridors, daily truck count data on Tuesdays and Wednesdays in June 2016 were extracted from TAMS. About 1.5 million single-unit and tractor pulling trailer(s) trucks were observed and were used for this analysis. In Figure 6, corridor geometries were created to represent each data collection site, and average daily volumes for single-unit and tractor pulling trailer(s) trucks were compared for the six corridors. Results show that single-unit trucks showed similar volume at all six sites, whereas volumes for tractor pulling trailer(s) trucks were quite distinct. Because single-unit trucks are mostly associated with local service, their volumes were expected to be more evenly distributed in a metropolitan area. However, much higher volumes of tractor pulling trailer(s) trucks were observed at Sites C, E, G, and F, which is likely explained by the sites' close proximity to facilities such as warehouses and intermodal rail facilities.

Spatial Truck Travel Pattern Analysis

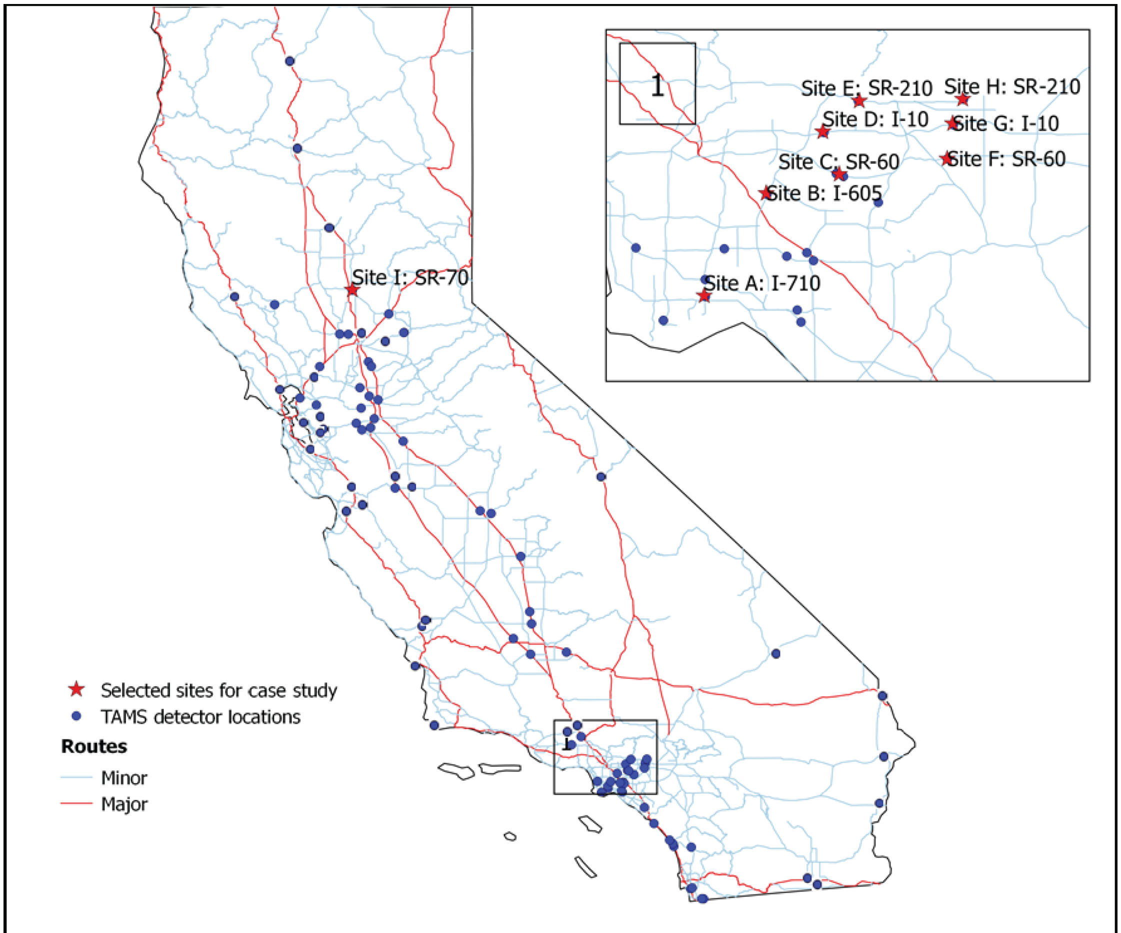
The Los Angeles and Long Beach port complex in California is the busiest in the United States, moving $180 billion per year in cargo between the United States and Asia (*10*). Consequently, there is a substantial volume of trucks transporting goods in intermodal containers from the ports to adjacent cities where freight transfer facilities and distributions centers are located. In particular, 20- and 40-ft intermodal containers—referred to as port container trailers—are seen in heavy numbers along the corridors that serve the ports and inland cities. Commodities carried from the port in 20- and 40-ft intermodal containers are commonly repackaged in 53-ft containers at inland distribution centers or at near-dock rail yards before being shipped to their final destination (*11*). Thus, 53-ft container trailers—referred to as domestic container trailers—are rarely observed near seaports because 53-ft containers cannot be loaded on cargo ships.

In this case study, travel patterns of two types of container trailers (i.e., port trucks and domestic container trailers) were compared across cities adjacent to ports. Five sites in Southern California (Sites A through E in Figure 3) were selected to show the spatial distribution of container trailers. The I-710 corridor connects to port entry and exit gates, and the other four sites represent major routes within the influence of the ports. Data were obtained from Tuesdays through Thursdays in June 2016 to represent typical weekday truck traffic patterns. The data were aggregated to daily volumes, and the average daily volumes for port and domestic container trailers are compared in Figure 7.

As expected, data from TAMS revealed that a substantial volume of port containers were observed at Site A, located on I-710. The overall route distribution at the five study sites showed a distinct trend in 20- and 40-ft container trailer counts close to the Port of Long Beach, whereas trucks hauling 53-ft containers were more likely traveling along inland corridors for domestic freight movement. A large number of port trucks was observed traveling through the site located along SR-60 instead of the site on SR-210 and the site on I-10. Thus, SR-60 can be identified as a major corridor for port container trailers. The volumes of domestic container trailers were more significant on SR-210 and I-10 compared with port container trailer movements; SR-60 was a key corridor for domestic container trailers as well. The reason is that there is an intermodal rail facility along the routes. This observation confirms that the travel patterns of the two types of container movements are highly related to their affiliated industrial facilities.

Industry-Specific Truck Monitoring

In most industries, directional truck volumes by configuration are fairly equal. However, logging trucks are an exception because they



Site Name	Description	Site Name	Description
Site A: I-710	I-710 at Willow Street	Site E: SR-210	I-210 at Pasadena Avenue
Site B: I-605	I-605 at Slauson Avenue	Site F: SR-60	SR-60 at East End Avenue
Site C: SR-60	SR-60 at Slauson Avenue	Site G: I-10	I-10 at Mills Avenue
Site D: I-10	I-10 at Francisquito Avenue	Site H: SR-210	I-210 at Baseline Road

FIGURE 3 Data collection sites in TAMS.

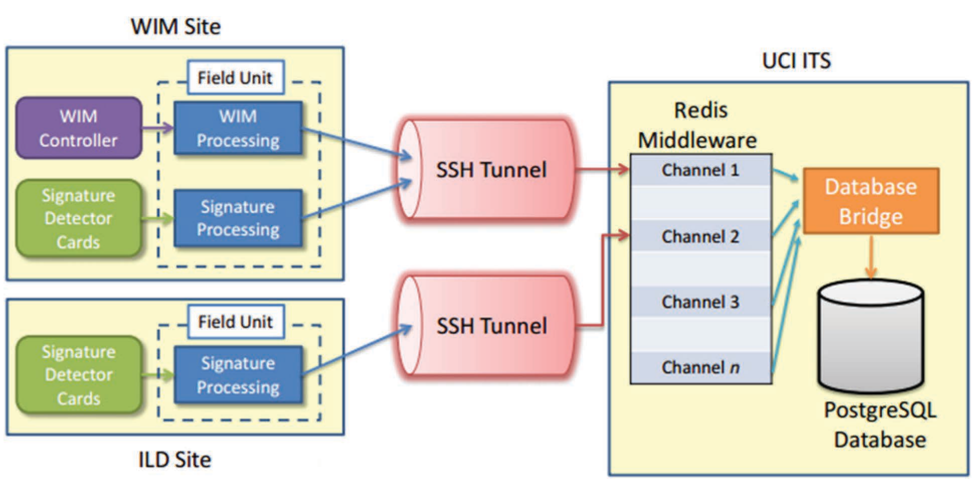
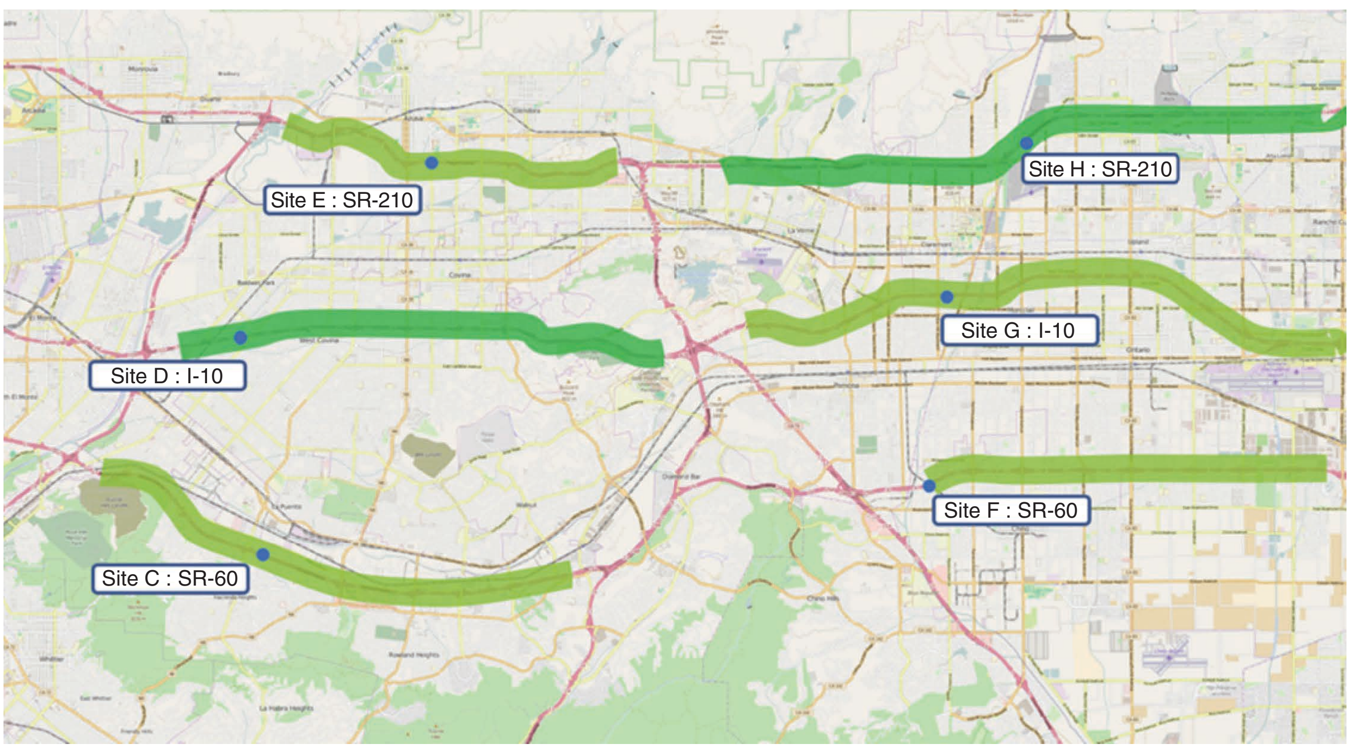


FIGURE 4 Data flow architecture of TAMS (SSH = Secure Shell; UCI ITS = University of California, Irvine, Institute of Transportation Studies).

FIGURE 5 TAMS user interface.



(a)

FIGURE 6 Average daily volume by vehicle type: (a) single-unit trucks.
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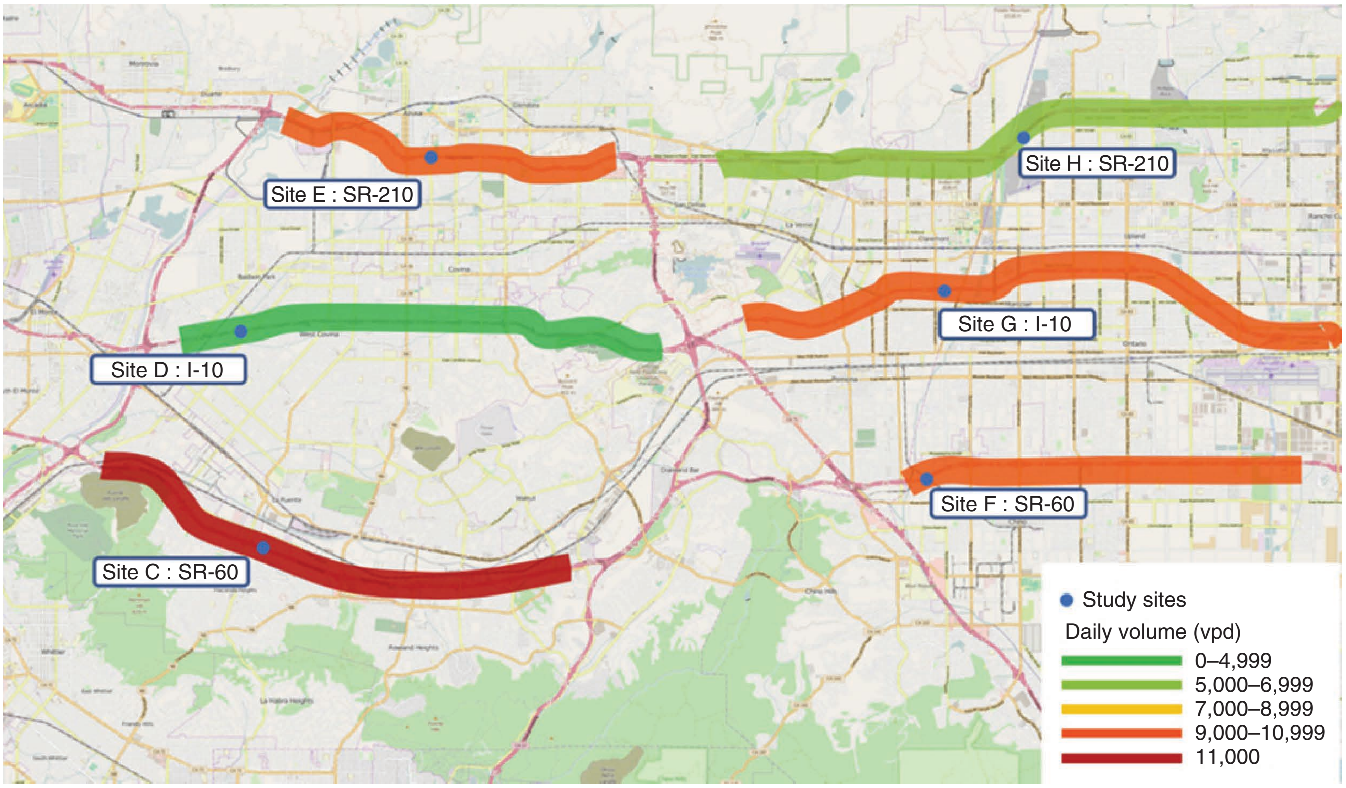
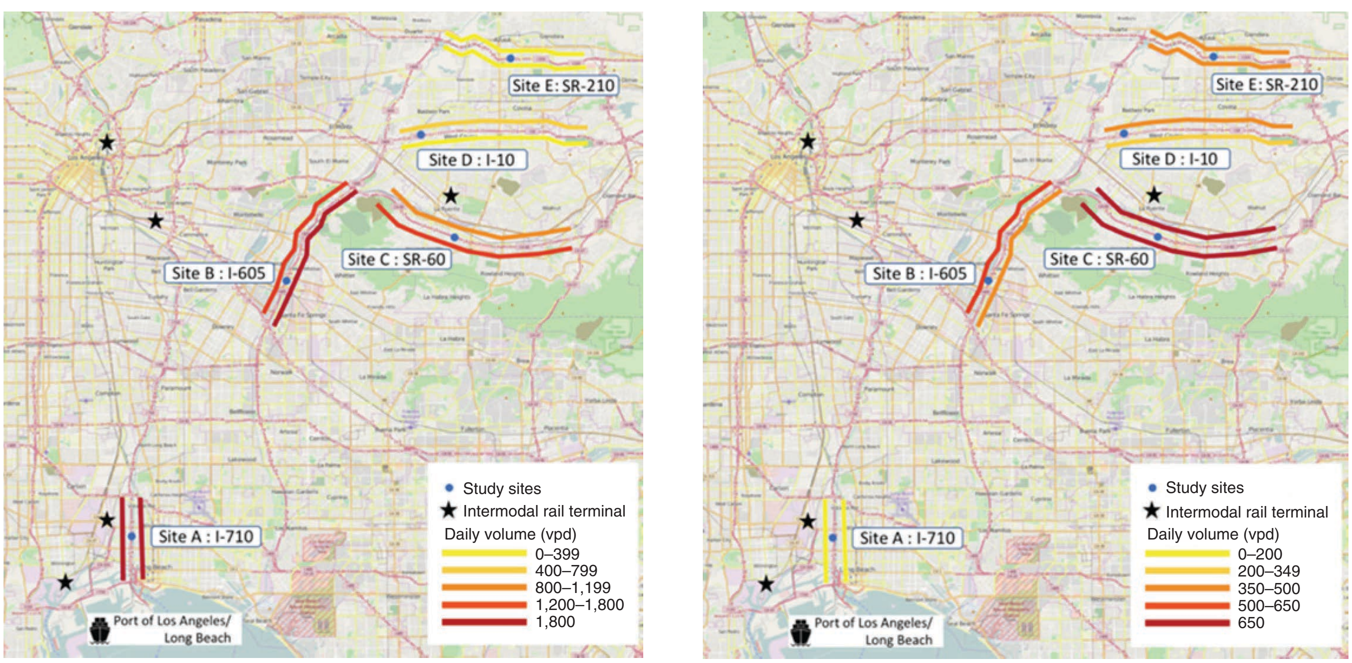


(b)

FIGURE 6 *(continued)* Average daily volume by vehicle type: (*b*) tractor-pulling trailer(s).



(a) (b)

FIGURE 7 Average daily volume of container trailers: (*a*) port container trailers (20 and 40 ft) and (*b*) domestic container trailers (53 ft).

(a)

(b)

FIGURE 8 Logging trucks: (*a*) loaded and (*b*) empty (*12*).

are specially designed with increased load capacity to handle the unique dimensional commodity of logs. The platform bed on which logs are loaded has an adjustable length to allow for the most efficient use of loading space. Once a load is delivered, logging trucks typically carry their trailers in a piggyback configuration in which the collapsible empty trailer is carried on the bed of the tractor, as shown in Figure 8. Hence, analysis of logging truck volumes can reveal their directional operational patterns, which are highly related to the location of logging and processing facilities.

For this case study, the TAMS station at SR-70 near Beale Road in Yuba County, California, (Site I in Figure 3) was selected because the site is located in a timber-producing area. About 3,000 logging trucks were observed on weekdays in June 2016. Figure 9 compares the average daily volume from Monday through Friday by directional flow.

The directional flow shows distinct differences in volume. Whereas the eastbound direction experienced an average of 100 logging trucks a day, only 30 trucks on average were observed in the westbound direction. Logging trucks in the empty piggyback configuration were observed primarily in the westbound direction. This result indicates that the timber-producing facility is located west of the data collection site.

Truck Travel Pattern Analysis by Time of Day

Site A, located on northbound I-710 was selected for analysis of truck travel patterns by time of day. The volumes of port container trailers and enclosed van trailers were compared. About 59,000 port container trailers and 8,300 enclosed van trailers were observed from Tuesday through Thursday in June 2016. To capture the time of day pattern, a normalization process was implemented to average hourly volumes; total average daily volume of each body type was used as a denominator in the normalization process. The average daily volumes of 4,922 for port trucks and 698 for enclosed van trailers were used in this analysis. Figure 10 presents the time of day pattern with the normalized hourly average volume.

The time of day distributions of port trucks and enclosed van trailers have unique and distinct patterns. Whereas enclosed van trailers have high peak volumes between 7 a.m. and 5 p.m., port

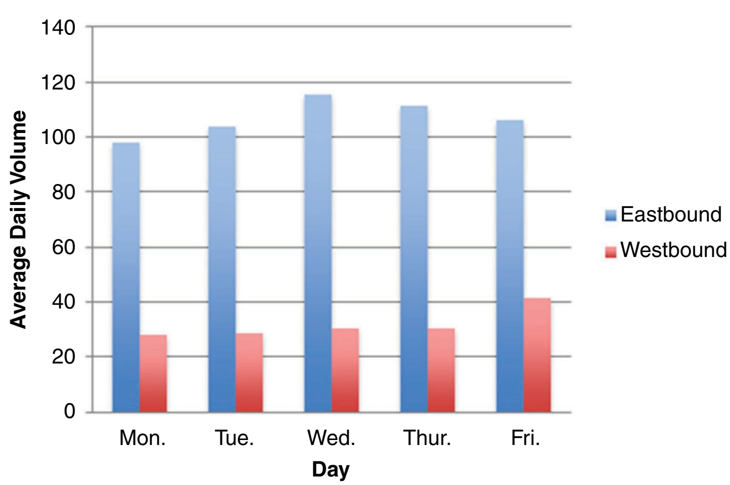


FIGURE 9 Weekly volume summary of logging trucks.

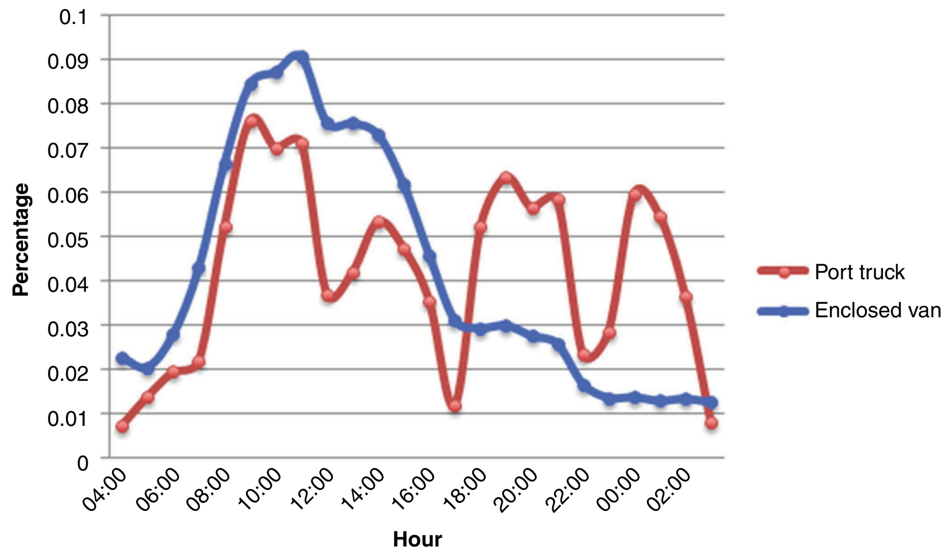


FIGURE 10 Time of day distributions for port truck and enclosed van trailers.

trucks have several peak hours throughout the day. Three dip points were observed in the distribution for port trucks. These points are assumed to be explained by a break time for lunch and dinner or drivers' work shifts. Volume for the port trucks could be influenced by the PierPass program from the Port of Long Beach and the Port of Los Angeles. As an incentive program, PierPass encourages trucks to use port facilities during the non–peak hours of 6 p.m. through 3 a.m. on weekdays (*13*).

This temporal truck movement analysis showed that even though trucks may have an identical axle-based class (enclosed van trailers and port trucks are associated with FHWA Class 9), the time of day travel pattern of trucks differed significantly by body type. This result confirms that the availability of detailed truck configuration data provides valuable insight into the temporal travel behavior and industrial activity of trucks.

CONCLUSIONS AND FUTURE WORK

TAMS was developed as a data source for truck activity, with the capability of providing detailed truck classification data along major truck corridors in California; the data have the potential to be linked with commodity groups and industries served by trucks. TAMS was designed to be publicly accessible via an interactive web-based interface and to archive data continuously. The data from TAMS can assist planning agencies and other users in gaining further insight of truck activity patterns and behaviors to guide freight planning and infrastructure investment while mitigating negative impacts such as emissions, safety concerns, and traffic congestion.

The primary objective in the development of TAMS was to measure truck activity along major truck corridors for emissions and freight analysis. However, many collateral benefits are expected from this system. First, the TAMS data can be used to monitor truck activities for policy analysis. For example, the system can be used to identify and monitor corridors with a high incidence of lane violations, on which heavy-duty trucks may occasionally travel on prohibited faster inner lanes instead of the outer truck lanes. It can also be used to monitor the effects of truck policies, such as the influence of the PierPass program on the extent of intermodal truck traffic by time of day. In addition, data from TAMS also has the capability to facilitate analysis of temporal and seasonal variations of truck activities by industry; this capability can help in gaining a better understanding of industry impacts on traffic, infrastructure, and emissions and may be a key data source for developing improved estimates of truck vehicle miles traveled. Because trucks have a far more significant impact on pavement service life than passenger vehicles, TAMS can also be used to identify the relationship between truck volumes and pavement deterioration rates. Despite the need to better understand the impacts of trucks in crashes (*14*), this area of research has been lacking because of the unavailability of reliable truck exposure data. This lack can be mitigated by the detailed truck class data provided by TAMS. Furthermore, TAMS is expected to provide valuable data to improve the effectiveness of tax policies associated with truck activities. Finally, TAMS may also be extended to arterial roadways to enhance urban area truck data and provide further insight into last-mile freight movements.

ACKNOWLEDGMENTS

The research reported in this paper was initially developed under the sponsorship of the California Air Resource Board, and has been expanded and enhanced in a follow-up study titled California Truck Data Collection and funded by the California Department of Transportation.

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The Standing Committee on Trucking Industry Research peer-reviewed this paper.