Estimation of Average Payloads from Weigh-in-Motion (WIM) Data

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ABSTRACT

Average payloads define the ton-to-truck conversion factors that are critical inputs to commodity-based freight forecasting models. However, average payloads are derived primarily from outdated, unrepresentative truck surveys. With increasing technological and methodological means of concurrently measuring truck configurations, commodity, and weights, there are now viable alternatives to truck surveys. In this paper, a method to derive average payloads by truck body type using weight data from Weigh-In-Motion (WIM) sensors is presented. Average payloads by truck body type are found by subtracting an estimated average empty weight from an estimated average loaded weight. Empty and loaded weights are derived from a Gaussian Mixture Model (GMM) fit to a Gross Vehicle Weight (GVW) distribution. An analysis of truck body type distributions, loaded weights, empty weights, and resulting payloads of five axle tractor trailer (FHWA Class 9 or '3-S2') trucks is presented to compare national and state-level VIUS data to the WIM-based approach. Results show statistically significant differences between the three datasets in each of the comparison categories. A challenge in this analysis is the definition of a correct set of payloads since both the WIM and survey data are subject to their own inherent misrepresentations. WIM data, however, provides a continuous source of measured weight data which overcomes the drawback of using out-of-date surveys. Overall, average payloads from measured weights are lower than both the national or California VIUS estimates.

INTRODUCTION

Truck trip forecasts are needed to analyze freight bottlenecks and to derive freight performance measures to guide informed, data-driven freight planning and programming. Since the number of trucks between freight origins and destinations (OD) is not available from existing data sources, samples of commodity flows from the Commodity Flow Survey (CFS) are used as a surrogate. Ton-to-truck conversion factors are then applied to estimate the number of truck trips from commodity flow forecasts. Average payloads- the amount of commodity carried by a truck- are direct inputs to ton-to-truck conversion factors used in state and national freight forecasting models.

Freight forecasting models like the Freight Analysis Framework (FAF) rely heavily on the Vehicle Inventory and Use Survey (VIUS) *(1)* to estimate ton-to-truck conversion factors that are commodity, vehicle configuration, and truck body type specific *(2)*. The reliance and use of VIUS presents several limitations. First, VIUS was discontinued over a decade ago. With changes in economic conditions, truck size and weight restrictions, and operating regulations that have occurred since 2002, VIUS payloads and other essential estimates are likely no longer relevant. Second, the VIUS questionnaire asks drivers to report their 'typical' loaded and empty weights, truck/trailer configuration, and commodity transported over the course of a year. Tractor-trailers which pull different commodities on varied trailer configurations only report the most common combination. This leads to incorrect associations of commodities and trailers as well as imprecise reports of empty and loaded weights by commodity and trailer type. Third, significant limitations arise when using VIUS to derive state-level statistics. A driver's state of registration or their declared home base of operation are used to pull state-level truck statistics from the national VIUS samples. This leads to state-level samples biased toward trucks with only half of their annual mileage within state-- leaving out trucks that operate inter-state. Fourth, the resulting state-level samples tend to be very small, particularly when stratified by body configuration or commodity transported. For instance, of the trucks listed with a home base in California, there were no samples of livestock trailers for the common '3-S2' (FHWA Class 9) five axle truck configuration.

Consequently, using truck payloads and resulting ton-to-truck conversion factors gathered from outdated, inaccurate, and under representative samples, effects the accuracy of commodity-based freight forecasting models in terms of an under or over estimation of the number of truck trips. To correct for this, comprehensive calibration and validation procedures are employed. Even so, beginning with quality, precise payload and ton-to-truck conversion factors would only increase the accuracy of the forecasts.

To overcome the limitations presented by VIUS, some states have proposed their own VIUS-type surveys *(3)*. However, with increasing technological and methodological advances available to concurrently measure truck configurations, commodity, and weights, there are now alternate, non-survey means of obtaining truck payloads. New methods range from implementation of advanced sensing technologies at WIM sites *(4)* to advanced mathematical procedures based on standard WIM data *(5)*. With these technologies, truck characteristics and weights can be directly captured from sensors rather than surveys to produce more representative payload estimates. The ability to derive up-to-date, temporally continuous, and spatially representative average payloads will add value to the current tons-to-truck conversion procedures.

In this paper, a method to derive average payloads by truck body type using measured weight data is presented. This method uses truck body type and weight data collected at WIM stations to enhance the ton-to truck conversion estimates outlined in FAF by: (a) validating and/or calibrating truck configuration and body type distributions and (b) supplementing average payload estimates by body type. Consequently, (b) enhances the adjustment procedure needed to ensure mean GVWs reported in VIUS match those measured in the field.

BACKGROUND

Average payload can be calculated by subtracting the unloaded weight of the truck from the loaded weight. Payloads have been shown to be commodity specific and vary by truck axle configuration, truck body type, and travel distance *(6)*. Average payloads are major inputs to the calculation of tons-to-truck conversion factors, or truck equivalency factor (TEFs) used in FAF. The procedure to develop TEFs in FAF follows four basic steps *(7)*:

Step 1: Identify primary vehicle groups (e.g. axle configuration groups) and major truck body types
Step 2: Allocate commodities to truck body types used to transport these commodities
Step 3: Estimate average payloads by vehicle group and body type
Step 4: Calculate TEFs

VIUS is the primary input for the TEF calculations. In **Step 1,** VIUS is used to define the five vehicle groups and nine truck body types based on common average payloads and GVW within each group. In **Step 2**, VIUS is used to define commodity-vehicle group-truck body type combinations and allocations. In **Step 3**, average payloads are pulled from VIUS for each vehicle group, body class, and commodity combination. At this step, to ensure VIUS weight data matches measured weights gathered from WIM detectors, VIUS payloads are calibrated against measured weight data found in the Vehicle Travel Information System (VTRIS) *(8)*. This calibration attempts to correct for the discrepancies between VIUS and VTRIS which show weight differences of 44% and 6.6% for single unit trucks and tractors with single trailers, respectively *(6)*. In **Step 4**, the total number of trucks needed to move commodity i is calculated according to Eq. 1 *(7)*:

$$Y_{ijk} = X_i \frac{\beta_{ijk}}{\omega_{ijk}} = X_i \times TEF_{ijk} \qquad \text{Eq. 1}$$

where
Y_{ijk} is the total number of trucks to move commodity i
X_i is the total tonnage of commodity i
β_{ijk} is the fraction of commodity i moved by configuration j with body type k
ω_{ijk} is the mean payload of truck configuration j with body type k transporting commodity i
TEF_{ijk} is the conversion factor relating tons of commodity i to number of trucks of configuration j with body type k, $TEF_{ijk} = \frac{\beta_{ijk}}{\omega_{ijk}}$

As evident in the TEF procedure, researchers rely solely on VIUS for commodity specific average payloads *(7)*. This is because VIUS is one of the only combined sources of truck weight, configuration, VMT, and commodity data *(8)*. As previously mentioned, VIUS has several limitations that restrict its use at the state-level and lead to inaccuracies in estimated payloads. While the TEF calibration procedure attempts to account for discrepancies between VIUS and VTRIS GVWs, the different classification schemes found in VIUS and VTRIS limit the scope of the comparisons (existing measured weight data is limited to axle–based classification). Also, the assumption that calibrating mean GVW by vehicle group implicitly calibrates GVW or average payloads by body type does not necessarily hold. As shown in this paper, the discrepancy between measured and VIUS GVWs varies by body type. So applying adjustments based only on the mean GVW would not be sufficient as the adjustments vary by body class as well.

To calculate payloads from measured weight data, the unloaded weight can be subtracted from loaded weight. While the loaded weight, e.g. GVW, can be obtained from WIM devices, it is more difficult to determine the unloaded weight. Theoretically, if one knew the make, model, and year of the truck then the unloaded weight would be known with some accuracy and the payload could be calculated after measuring the GVW. However, this is not practically feasible. Instead, static breakpoints for each axle group are used in VTRIS to determine

whether a truck is empty or loaded *(8)*. But, static breakpoints do not account for geographic variation in truck configurations and/or commodities transported. Alternatively, methods have been developed to depict GVW distributions as mixtures of two or three of normal distributions where each distribution represents a specific loading class: the lower distribution represents empty trucks, the middle represents partially loaded trucks, and the upper represents loaded trucks *(9)*.

Since weights and payloads can be derived from non-survey data sources, body type and commodity carried are the remaining data elements needed to replace VIUS with measured data. Hyun et al. *(5)* developed a method using axle spacing, vehicle length, and other WIM measured features to determine volume and weight distribution by body type. Volumes of five trailer body classes were estimated with 95% accuracy. This method does not require additional field hardware or sensing technologies. Hernandez et al. *(4)* developed a high resolution body classification model by fusing advanced inductive loop detector outputs with traditional WIM outputs. The model predicted 23 single unit and 31 tractor-trailer body types with classification accuracies higher than 80%. This approach requires minor adaptations of the roadside detection hardware which California is currently undertaking (*10*). Either approach would produce the type of truck body class data needed for the average payload calculations described in this paper.

METHODOLOGY

This paper proposes two enhancements to the TEF estimation, both based on inclusion of measured weight data into the estimation procedure. First, measured body type distributions within vehicle groups were used instead of those from VIUS. Truck body class volumes estimated from Hyun et al. *(5)* or Hernandez et al. *(4)* can be used as substitutes for the body class distributions found in VIUS. Second, a procedure to extract payloads from measured GVW distributions by body type was developed in this paper for five axle tractors trailers specified as '3-S2' trucks in FHWA Class 9. These trucks are the most common freight truck configuration. For '3-S2' trucks body class refers to the body type of the single trailer.

A Gaussian Mixture Model (GMM) procedure is used to define the empty and loaded weights for each body class group from the measured GVW data. A GMM is a linear composition of normal distributions combined via a mixing parameter *(11)*:

$$f(x) = \sum_{m=1}^{M} p_m \cdot \mathcal{N}(x|\mu_m, \Sigma_m) \qquad \text{Eq. 2}$$

where
x = continuous-valued data vector
m = number of mixture components, m = 1…M where M = {2,3}
$\mathcal{N}(x|\,\mu_m, \Sigma_m)$ = Gaussian distribution of component m with mean μ and covariance matrix Σ
p_m = mixing proportion of the m^{th} component such that $\sum_{m=1}^{M} p_m = 1$

To estimate a GMM, the number of components must be predetermined. Previous studies show GVW distributions can be modeled with two or three components (*9*). The Akaike Information Criterion (AIC) is a goodness-of-fit measure to select the appropriate number of components in a GMM *(11)*. Once a best-fit GMM was established, the average payloads were calculated as:

$$\omega_{jk} = \mu_{jkM} - \mu_{jk1} \qquad \text{Eq. 3}$$

where
ω_{jk} = average payload for vehicle configuration j with body type k
μ_{ikM} = mean of the mixture component corresponding to the highest GVW weight range such that M is the index of the mixture component {2,3} for vehicle configuration j with body type k

μ_{jk1} is the mean of the mixture component corresponding to the lowest GVW weight range for vehicle configuration j with body type k

The TEFs (Eq. 1) were then calculated using body type distributions and average payloads derived from measured weight data. First, the tonnage of commodity i was distributed across vehicle groups and distance ranges based on VIUS data. Second, tonnages of commodity i in each vehicle group were distributed across body types using VIUS commodity-to-body type distributions. At this stage, VIUS body type distributions are calibrated to match truck body type distribution gathered from measured weight data. Third, the total number of trucks needed to move X_i tons of commodity i was calculated as:

$$Y_{ijk} = X_i \frac{\beta_{ijk}}{\omega_{jk}} \qquad \text{Eq. 4}$$

where
Y_{ijk} = number of trucks needed to transport X_{ijk} tons of commodity i by truck configuration j with body type k
X_i = total tonnage of commodity i
β_{ijk} = fraction of commodity i moved by configuration j with body type k
ω_{jk} = mean payload of truck configuration j with body type k

Note the estimated average payload is not commodity specific since it is derived from measured data which does not contain commodity information. However, the body type distribution is related to the commodity by using VIUS data. This ensures commodity tonnages are only assigned to body types which transport said commodity. The proposed method replaces survey-derived average payloads that vary by commodity type, vehicle configuration, and body type (ω_{ijk}) with measured average payloads that vary by vehicle configuration and body type (ω_{jk}) under the assumption that measured payloads are more accurate than those derived from VIUS even though they are not commodity specific.

CASE STUDY

Measured Truck Weight and Body Type Data

Data were collected at the four WIM sites in California listed in **Table 1**. Data was collected over several two to three day periods spanning the fall, winter, and spring seasons between 2012 and 2013 and covering a range of time periods. Truck body types vary by location due to the presence commodity specific industries and land uses so the selected sites span metropolitan and agricultural regions to capture the full diversity of the California truck population. In northern California forestry is a dominant industry so a heavy population of logging trucks was captured at the Redding and Willows sites. In central California agriculture is widespread so many agricultural and farm trailers were captured at the Fresno site. Southern California is characterized by urban land uses and international import/export movements so many van, reefers, and intermodal containers were found at the Irvine site. Each of these sites capture inter- and intra-state travel since they are located on state routes and major interstates.

TABLE 1 INSERT HERE

For each passing vehicle a digital camera captured a series of still images which were manually matched to the WIM records by comparing the timestamps and vehicle configurations of the photos and WIM records. Around 35,000 vehicle records were processed, 10,241 of which were five axle tractor trailers. The resulting dataset contained the following information for each truck:

1. Manually identified vehicle body type

2. GVW
3. Axle configuration (e.g. spacing between each axle and axle count)
4. Vehicle class based on the FHWA 13 class scheme

WIM data may be prone to measurement errors in the weight data due to vehicle dynamics over the sensor, rounding errors produced by the system electronics, and poor pavement quality. Therefore, the data was quality checked using the Southgate (*13*) procedure. This procedure compares axle weight and spacing ratios of measured FHWA Class 9 trucks to a standard log-log regression function representing calibrated axle weight and spacing ratios and adjusts measured weights as necessary. The data collected from the four sites did not exhibit significant errors in the weight data.

VIUS Samples

To obtain the VIUS estimates used in the comparative analysis, samples were drawn from the 2002 VIUS for trucks with axle configurations listed as 'truck tractors' with '3 axle tractors and 2 axle trailers' to correspond with the five axle tractor trailer ('3-S2') configured trucks in the measured data. To obtain the California samples from the national VIUS database, trucks reporting a home base in California were selected. In total there were 16,585 records in the national sample and 330 in the California sample for the '3 axle tractors and 2 axle trailer' vehcile configuration.

Comparisons

This section compares the body type distributions, loaded and empty weights, and payloads of '3-S2' trucks. An unequal variances two sample t-test, also known as Welch's t-test, was applied to the measured truck weight data, national VIUS, and California VIUS samples. The unequal variances t-test is an adaptation of the student t-test that provides more reliable statistical evidence for two-samples that have unequal variances and sample sizes. The null hypothesis, test statistic, and degrees of freedom are as follows (Eqs. 5 and 6, *14*):

$$H_o: \mu_A - \mu_B = 0$$
$$H_1: \mu_A - \mu_B \neq 0$$

$$t = \frac{\bar{x}_A - \bar{x}_B}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}}} \qquad \text{Eq. 5}$$

$$v = \frac{\left(\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}\right)^2}{\frac{s_A^4}{n_A^2(n_A - 1)} + \frac{s_B^4}{n_B^2(n_B - 1)}} \qquad \text{Eq. 6}$$

where
t = test statistics distributed according the student's t-distribution
μ_A, μ_B = population means for data sets A and B, respectively
$\bar{x}_A, \bar{x}_B$ = sample means for data sets A and B, respectively
s_A^2, s_B^2 = sample variance for data sets A and B, respectively
n_A, n_B = sample sizes for data sets A and B, respectively
v = degrees of freedom

Pairwise comparisons were made between the national, California, and measured data for all eight body types and resulting p-values are provided. At the 95% confidence level, the null hypothesis is rejected when the p-value is less than 0.025 for the two-tailed hypothesis test, concluding the two populations do not have the same mean.

Body Class Distributions

Table 2 summarizes the body type distributions found in the national VIUS, the California VIUS, and measured data. Vans are the dominate body type, representing around 40% of the sample in all three datasets. Discrepancies exist in the proportions of platforms, bulk, reefer, and tanks between the three datasets. These more specialized trailers tend to be more commodity specific than vans. For example, California is a heavy agriculture state and thus there may be more reefer trailers to transport fresh produce *(15)*. Note the California VIUS sample does not contain livestock trailers, although these were found in the measured data, suggesting state-level VIUS samples do not represent all truck types found in the population. Under the assumption that conditions under which the measured weight data were collected produced a representative sample of truck body types, the measured proportions of body types most closely capture the body class distributions in California.

TABLE 2 INSERT HERE

Gaussian Mixture Models (GMM)

The GMMs of the GVW distribution estimated for each body type are shown in **Figure 1**. For all but the logging body type, a three component GMM was the best fit model based on AIC. The inclusion of the third mixture component helped to reduce the variance of component distributions and better match the location of the empty and loaded mean weights seen in the raw data. Since the middle distribution is not used in the calculation of average payload, the location (e.g. mean and variance) are not as critical to the analysis. The weight distribution for auto carriers does not appear to fit as cleanly into a GMM. Coincidently, the component distribution representing empty auto carriers produces a mean empty weight which approximates VIUS.

FIGURE 1 INSERT HERE

Loaded Weights

Figure 2(a) compares the loaded weight by body type with error bars depicting the one standard deviation about the mean. The 'measured' loaded weights refer to the mean of the upper range of the GVW distributions, i.e. the upper component of the GMM. For all body types the measured weight distribitions have much smaller variance than the VIUS samples. For five of the eight body types, the measured weight distribitions have systematically lower means than the VIUS samples. This is due to two issues with how data is reported in VIUS.

First, reported loaded weights in VIUS are partially a result of censored responses where the censored value corresponds to the 80,000 lb legal GVW limit set in most states (*16*). The majority of the national and California VIUS samples, 34% and 20% of the responses, respectively, reported an average loaded weight of 80,000 lbs. The measured weight data does not show this same trend. Instead, the measured data follow a normal distribution centered near 70,400 lbs with a small peak at 80,000 lbs. Second, the systematic upward bias in the loaded weights reported in national and California VIUS are influenced by GVW limits greater than 100,000 lbs set in nine states (*15*).

Table 3 provides the resulting p-values for the pairwise comparisons by body type. Overall, at the 95% level of significance, the measured data have statistically different loaded weight distributions than the national VIUS sample. Compared to the California VIUS sample, four of the seven body classes have statistically different loaded weight distributions.

TABLE 3 INSERT HERE

Empty Weights

The 'measured' empty weights shown in **Figure 2(b)** and compared in **Table 4** correspond to the mean of the normal distribution at the lower end of the GVW distribution. With the exception of logging trucks, the measured empty weights are systematically higher than those reported in the national and California VIUS

samples. It is difficult to obtain the weight of empty logging trucks because they commonly transport their empty two axle trailers in a piggyback configuration and are thus measured as three axle bobtails. The method proposed in this paper to define the empty weight of logging trucks used the weight of bobtail tractors as a supplement. This results in a much lower estimate than VIUS. However, the definition of empty weight for the particular case of logging trucks is not clearly stated in VIUS. A driver would not be able to report in the questionairre whether his or her five axle truck travels as a three axle bobtail when empty.

For all three datasets, the average empty weights fall below the VTRIS defined breakpoint of 37,500 lbs for empty five axle trucks with the exception of auto carriers. Compared to other body types, auto carriers do not have distinct GVW distributions representing empty, partially loaded, and fully loaded trucks, however similar to the national and California VIUS, the GMM approach produces an average empty weight above the VTRIS defined breakpoint. This could indicate high variability in the body configuration and/or loading arrangement for this class. The purpose of the VTRIS breakpoint comparison is to demonstrate that comparisons between VTRIS data and VIUS at the vehicle group level (e.g. five axle tractor trailers) rather than at the body type level would not capture these subtle differences. Thus, calibration practices such as the FAF TEF estimation which compare only vehicle groups may result in skewed payload estimates.

From the statistical comparison, it can be concluded that for all body types except vans, the national and California VIUS samples are not statistically different; the difference between the national VIUS and measured data is statistically significant for all body types; and the difference between the California VIUS and measured data is statistically significant for all but auto carriers and tanks.

TABLE 4 INSERT HERE

Average Payload

Figure 2(c) compares the average payloads by body type. 'Measured' payloads are calculated by subtracting the estimated loaded weight from the empty weight for each body type. The error bars for the measured payload estimates are calculated by summing the variances of the normal distributions representing the empty and loaded trucks. Estimated average payloads from measured weight data were systematically lower than both the national and California VIUS samples with the exception of logging trucks. Since the loaded weights derived from measured data were generally lower than VIUS and the empty weights derived from measured data were generally higher than VIUS, the resulting payload estimates are lower than VIUS.

At the 95% level of significance, the statistical comparison summarized in **Table 5** reveals the national and California VIUS derived payloads are not statistically different; the national VIUS and measured payloads are statistically different for all body types; and the California VIUS and measured payloads are statistically different for all but logging and auto carriers.

TABLE 5 INSERT HERE

FIGURE 2 INSERT HERE

CONCLUSIONS

The purpose of this paper is to demonstrate how measured weight, truck configuration, and body type data can be used to enhance the current method used in FAF and several state freight forecasting models to convert tons of commodity to number of trucks. The current approaches to estimate ton-to-truck conversion factors rely solely on survey data from VIUS. This is an issue not only because VIUS has been discontinuted since 2002, but also because several reports show weight data recorded in VIUS do not accurately reflect actual loading characteristics seen on the road. For example, in VIUS, the majority of drivers reported loaded weights

of 80,000 lbs while measured weight data from WIM show much more variation at the upper weight range. Futher, state trends in payloads may differ from national trends and the format of VIUS does not permit representative sampling at the state level. State specific statistics from VIUS are typically extracted based on a driver's delcared home base or state of registration, neither of which necessarily capture all trucks operating within the state. Measured weights from WIM stations, on the other hand, capture both in-state and out-of-state registered trucks operating in a specific region, on a specific route, and thus provide state-specific data.

The methodology described in this paper fits a GMM to measured GVW distributions to extract empty and loaded weights of trucks. Average payloads by body type are calculated by subtracting estimated loaded and empty weights. The approach is applicable to WIM locations where truck body class can be estimated from advanced sensor technologies, mathematical modeling approaches, or through direct observation. As direct observation would be time consuming, states wishing to adopt the proposed payload estimation methodology are advised to implement advanced sensors technologies as described in Hernandez et al. (*4*) to collect truck body class data from the field. The California Department of Transportation (Caltrans) is in the process of implementing advanced inducitve loop detector technology at 76 WIM and traffic count locations along their state highway network to estimate more than 50 truck body classes (*10*).

Comparisons of empty, loaded, and payload estimates resulting from the proposed approach to national and California VIUS samples show significant differences between the three datasets for the majority of body types. Measured loaded weights have systematically lower mean weights and smaller variation than the VIUS samples. This is due to reported weights in VIUS representing censored responses corresponding to 80 kip legal weight limits and upwardly biased responses corresponding to legal limits greater than 100 kips. Measured empty weights are systematically higher than those reported in VIUS. If VIUS overestimates loaded weights and underestimates empty weights, then resulting VIUS derived payloads are overestimated. The consequence of overestimated payloads is an underestimate of the number of trucks which cascades to underestimated emissions, congestion, pavement loadings, etc.. Further, the comparison to the VTRIS showed that measured empty weights were well below the VTRIS defined breakpoint. This points to possible inaccuracies arising from using VTRIS breakpoints in the FAF TEF procedure.

The difficulty in this analysis centers on establishing a 'correct' set of weights and average payloads. Neither the VIUS or measured data provide true payloads. The VIUS data have no complimentary comparison other than the WIM data with which only aggregate comparisons at the truck axle configuration level are possible. Even highly aggregate analyses of GVW comparions by truck axle configuration group show significant differences between the VIUS and measured weight data. To correct for the discrepancy between measured and surveyed weights, VIUS estimates are typically calibrated to match measured weight data. This is problematic since differences between measured and VIUS weights vary by body type. Therefore, calibration without considering body types can lead to inaccuracies. Another issue that arises is determining adequate sample size and geographic distribution of sites to sample. For this study, four disparate sites in California were sampled. Based on prior knowledge, the research team strategically selected study sites to provide ample coverage truck body types and loadings. As a result, the number of samples per body class ranged from 50 to 4,200 and the distribution of body classes at each site differed. Without a true population estimate of the body class distributions or loading spectra, it is difficult to select locations to provide representative coverage. As an extention of this work, truck body and weight data collected from the 76 sites in California (*10*) will be leveraged to examine the applicability of sample size estimation methods and to develop guidelines on adequate samples size and geographic distribution of sample collection sites.

Several improvements to the proposed approach are possible in future studies. First, the measured GVW data is prone to error as the WIM sensors themselves can introduce measurement errors. However, with proper calibration and maintenance, differences between measured and actual weights are as low as 6% (*17*). Some state agencies have implemented quality control/assurance (QA/QC) checks to insure valid WIM

measurements (*18*). Caltrans, for instance, provides a data quality table indicating whether the daily weight and volume data is 'good', has 'acceptable minor errors', or is in need of calibration. Robust QA/QC procedures can be assessed and applied prior to estimating payloads. Second, while the fit of the GMM were optimized, the mean empty and loaded weights derived from the GMM contain some error resulting from the fit of the estimated model. Third, the assumption that the lower and upper components of the GMM represent empty and loaded trucks is partially sensitive to the commodity being transported. Certain light-weight commodities may meet the volume limits before reaching weight restrictions, e.g. a truck transporting a low density commodity may be fully loaded even though its measured weight is lower than the empty breakpoint.

With the increasing availability of methods and tools to concurrently gather truck configuration, commodity, and weight data through non-survey approaches, methods like that presented in this paper are needed to adapt these new data sources to meet freight planning needs. While this paper presents a viable approach for obtaining payloads from measured weight and body type data, several challenges still need to be addressed. Ideally, payloads from measured weight data need to be commodity specific. It may be possible to meet this need through further development of advanced sensors that capture commodity type such as volumetric load scanners (*19*) or inductive signature based technologies. Further, to establish the accuracy of the proposed approach, estimated payloads based on measured weight data could be used to calibrate a state freight forecasting model. The resulting errors in truck volumes could be compared to those resulting from VIUS estimated payloads. Lastly, the insights presented here can be used to better the design of new state and national VIUS-like surveys for freight planning applications. For instance, a trip-diary format requiring weigh station measurements may provide more accurate payload data and allow drivers to report empty and loaded weights for each truck configuration. Ultimately, a blend of survey and measurement-based data sources would be an apt platform to collect commodity, weight, and truck configuration data needed to support freight forecasting models.

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TABLE 1 Summary of Data Collection Sites

Site	Description	Date	Time Period	Avg. Speed (mph)
Irvine	I-5 Southbound, Southern California, Urban, Approx. 45mi from San Pedro Bay Ports, 5% truck traffic[1]	Sept. 21, 2012	10:45AM – 6:00PM	56.4
		Oct. 2nd, 2012 Oct. 3rd, 2012	1:00PM – 6:45PM 6:30AM – 9:15AM	57.7 48.2
		March 20th, 2013 March 25th, 2013	6:30AM – 7:45PM 7:30AM – 4:15PM	61.9 59.1
Fresno	SR-99 Southbound, Central California, Semi-Urban, Agricultural, 22% truck traffic	Nov. 7th, 2012 Nov. 8th, 2012	10:15AM -5:15PM 6:15 AM – 4:45PM	57.6 56.8
Willows	I-5 Northbound, Northern California, Rural, 25% truck traffic	Dec. 10th 2012 Dec. 11th,2012 Dec. 12th,2012	10:30AM – 4:45PM 7:15AM - 4:45PM 7:00 AM – 3:00 PM	62.1 59.0 61.9
Redding	I-5 Southbound, Northern California, Rural, Approx. 120mi from OR-CA border, 25% truck traffic	Dec. 10th 2012 Dec. 11th,2012 Dec. 12th,2012	1:30 PM – 5:00 PM 7:00 AM – 4:45PM 7:00 AM – 1:00PM	57.8 57.7 58.8
Total		*13 days*	*97.25 hours*	*58.5mph*

1 Percent of total trucks, Source: Caltrans Traffic Counts for AADTT *(12)*

TABLE 2 Distribution of Body Types Across National, California, and Measured Samples

Body Type	National VIUS		California VIUS		Measured	
Van	5,983	36%	136	41%	4,286	42%
Platform	3,462	21%	72	22%	1,519	15%
Bulk	3,071	19%	41	12%	637	6%
Reefer	1,701	10%	35	11%	2,834	28%
Logging	378	2%	3	1%	54	1%
Livestock	269	2%	0	0%	94	1%
Auto Carrier	142	1%	5	2%	176	2%
Tanks	1,579	10%	38	12%	641	6%
Total	*16,585*		*330*		*10,241*	

TABLE 3 Statistical Comparison (p-values) of Loaded Weight by Body Type

Body Type	Nat. vs. CA	Nat. vs. Measured	CA vs. Measured
Van	0.000*	0.968	0.000*
Platform	0.336	0.022*	0.518
Bulk	0.061	0.000*	0.000*
Reefer	0.127	0.000*	0.387
Logging	0.435	0.000*	0.000*
Livestock	+	0.003*	+
Auto Carrier	0.334	0.003*	0.683
Tanks	0.018*	0.000*	0.004*

+ No samples contained in the CA VIUS dataset for Livestock

* Reject the null hypothesis at the 95% level of significance (p-value < 0.025)

TABLE 4 Statistical Comparison (p-values) of Empty Weight by Body Type

Body Type	Nat. vs. CA	Nat. vs. Measured	CA vs. Measured
Van	0.000*	0.000*	0.000*
Platform	0.393	0.000*	0.000*
Bulk	0.769	0.000*	0.000*
Reefer	0.243	0.000*	0.000*
Logging	0.190	0.000*	0.006*
Livestock	+	0.000*	+
Auto Carrier	0.733	0.000*	0.207
Tanks	0.790	0.024*	0.931

+ No samples contained in the CA VIUS dataset for Livestock

* Reject the null hypothesis at the 95% level of significance (p-value < 0.025)

TABLE 5 Statistical Comparison (p-values) of Average Payloads by Body Type

Body Type	Nat. vs. CA	Nat. vs. Measured	CA vs. Measured
Van	0.034	0.000*	0.000*
Platform	0.304	0.000*	0.002*
Bulk	0.287	0.000*	0.000*
Reefer	0.172	0.000*	0.001*
Logging	0.844	0.000*	0.001*
Livestock	+	0.000*	+
Auto Carrier	0.816	0.000*	0.065
Tanks	0.046	0.000*	0.000*

+ No samples contained in the CA VIUS dataset for Livestock

* Reject the null hypothesis at the 95% level of significance (p-value < 0.025)

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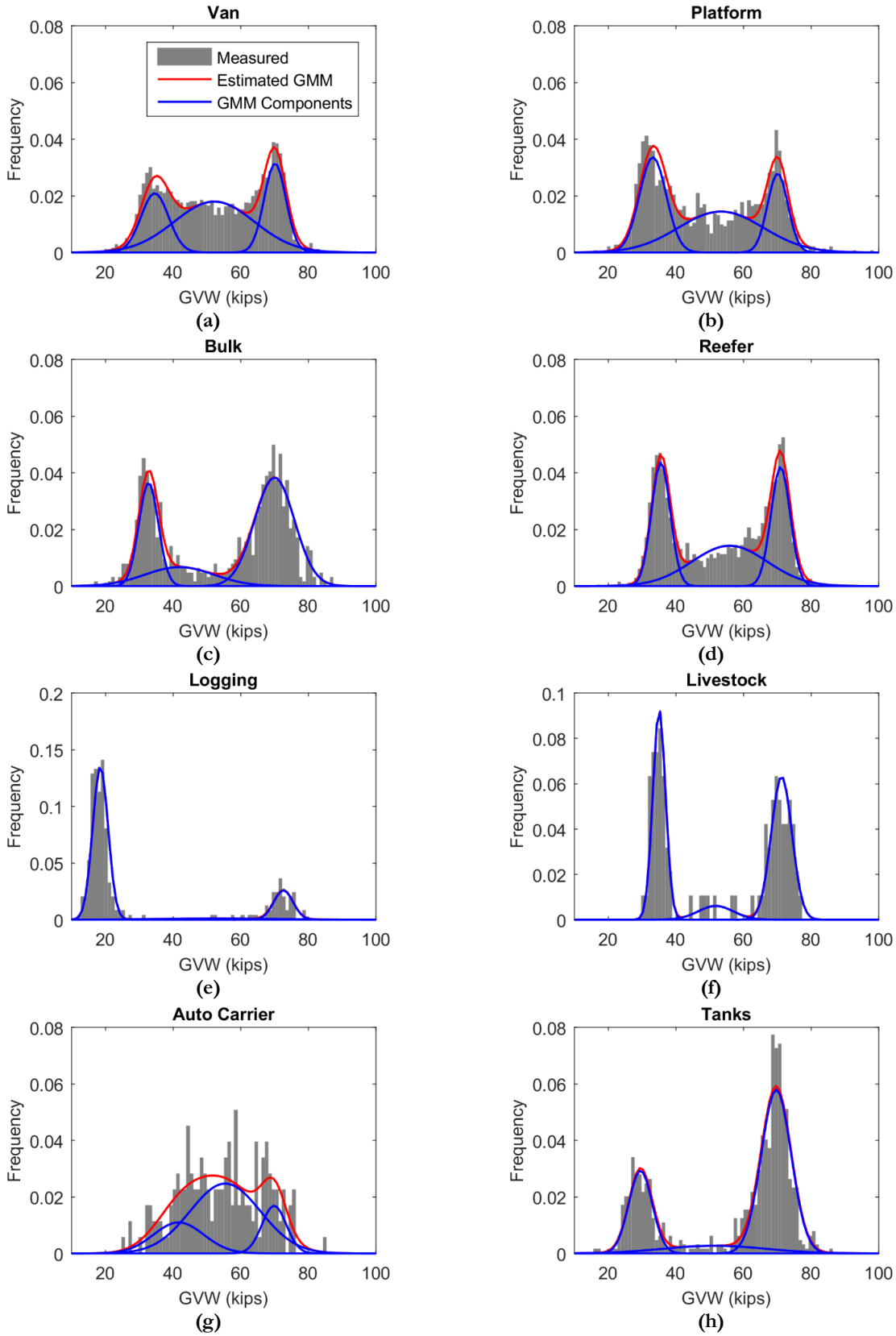
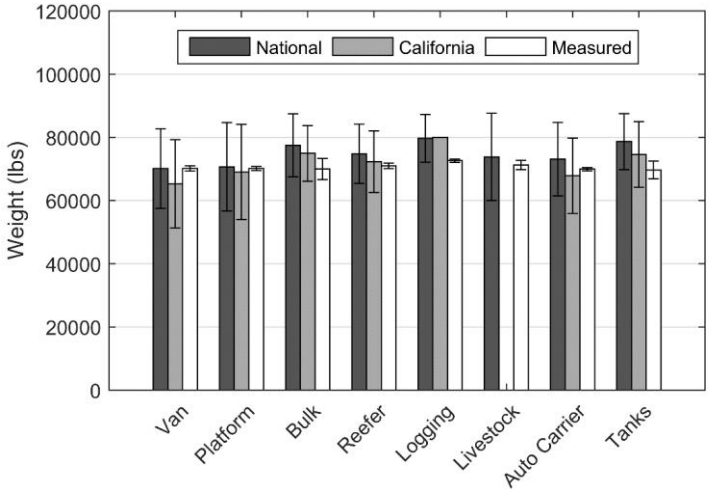
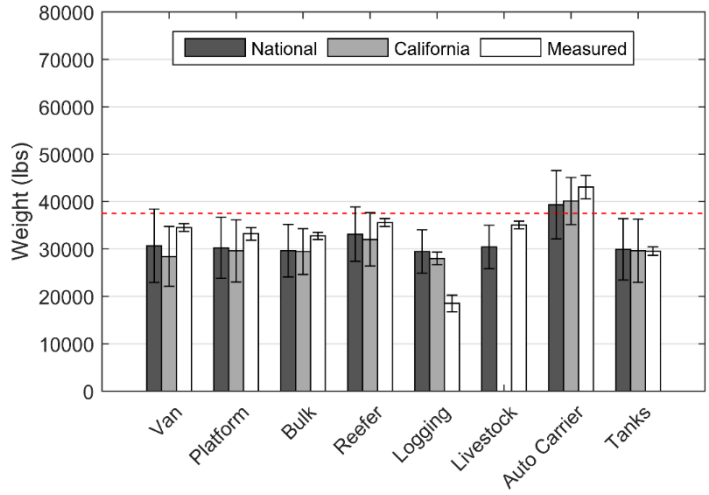


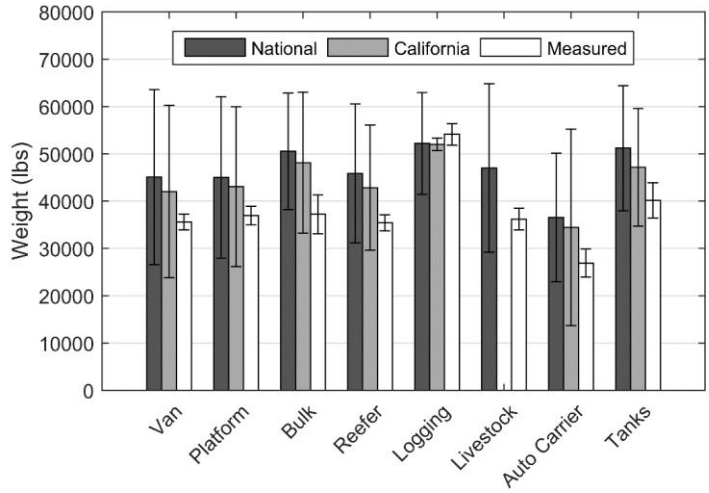
FIGURE 1 GMM by body class.



(a) Loaded weight



(b) Empty weights



(c) Average payloads

FIGURE 2 Comparison of Loaded Weights, Empty Weights, and Average Payloads by body type.