ORNL/TM-2019/1385

FINAL TECHNICAL MEMORANDUM: Exploring the Use of FHWA Truck Traffic Volume and Weight Data to Support National Truck Freight Mobility Study

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Brennan Wilson

October 2019

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Energy and Transportation Science Division

FINAL TECHNICAL MEMORANDUM: EXPLORING THE USE OF FHWA TRUCK TRAFFIC VOLUME AND WEIGHT DATA TO SUPPORT NATIONAL TRUCK FREIGHT MOBILITY STUDY

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October 2019

Prepared for
Vehicle Technologies Office
Office of Energy Efficiency and Renewable Energy
U.S. Department of Energy

Prepared by
OAK RIDGE NATIONAL LABORATORY
Oak Ridge, TN 37831-6283
managed by
UT-BATTELLE, LLC
for the
US DEPARTMENT OF ENERGY
under contract DE-AC05-00OR22725

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ACKNOWLEDGEMENTS

The authors express our gratitude to the Vehicle Technologies Office (VTO), under Office of Energy Efficiency and Renewable Energy in U.S. Department of Energy, for their support of this project. The authors would also like to thank Federal Highway Administration (FHWA), especially Steven Jessberger, who provided Vehicle Travel Information System (VTRIS) and Travel Monitoring Analysis System (TMAS) data for this study.

ACRONYMS

ATRI	American Transportation Research Institute
BTS	Bureau of Transportation Statistics
CFS	Commodity Flow Survey
CFS PUM	Commodity Flow Survey Public Use Microdata
DOE	US Department of Energy
EIA	US Energy Information Administration
FAF	Freight Analysis Framework
FAF4	FAF version 4
FHWA	Federal Highway Administration
GVWR	Gross Vehicle Weight Rating
HD	Heavy Duty
IPF	Iterative Proportional Fitting
MD	Medium Duty
OOS	Out-of-Scope
ORNL	Oak Ridge National Laboratory
SCTG	Standard Classification of Transported Goods
TMAS	Travel Monitoring Analysis System
TMG	*Traffic Monitoring Guide*
VIUS	Vehicle Inventory and Use Survey
VMT	Vehicle Miles Traveled
VTRIS	Vehicle Travel Information System
WIM	Weigh-In-Motion

1. INTRODUCTION

1.1 BACKGROUND

According to the US Energy Information Administration (EIA)'s Today in Energy website,[1] petroleum (including crude oil and refined products) accounted for over 36% of the United States' total energy consumption in 2018, and more than two-thirds of finished petroleum products are consumed in the transportation sector. EIA estimated that ~28% of total US energy consumption in 2018 was for transporting people and goods (i.e., via cars, vans, buses, truck, airplane, trains). Among modes of transportation, not surprisingly, light-duty vehicles accounted for over half of the 2018 transportation energy consumption total, followed by commercial and freight trucks at 24% of total transportation energy use.

However, based on the long-term forecasts of nationwide vehicle miles traveled (VMT) produced by IHS Markit[2] and released by the Federal Highway Administration (FHWA) in May 2019, combination truck VMT is projected to increase by 1.5% annually over the 30-year forecast period of 2017–2047. During the same 30-year period, VMT of single-unit trucks is forecasted to have a higher growth rate at 1.9% annually, while light-duty vehicle VMT is expected to increase at a much slower pace of 0.7% annually. This clearly indicates a need for attention regarding energy uses by medium- and heavy-duty trucks (MD/HD) and greenhouse gas emissions being generated by these vehicles.

Unlike the extensive studies and databases[3] that have provided a better understanding of the use and energy consumption of light-duty vehicles, limited resources have been applied to exploring the overall use and energy consumption of MD/HD vehicles. The Vehicle Inventory and Use Survey (VIUS) conducted by the US Census Bureau has long been one of the few sources of comprehensive MD/HD vehicle use information available to the transportation and energy communities. This data series has served as the basis for estimating truckload factors by body type/business and VMT by fuel type, to name a few. Unfortunately, this valuable data series was discontinued due to budget cuts in 2007, making the 2002 VIUS[4] the latest data available to the data users. Given that this dataset (2002 VIUS) is now more than a decade and a half old, the user community views its use with concern but notes that it is an unfortunate necessity. Although the US Department of Transportation plans to bring back the VIUS program, significant time and effort will be required to revitalize and implement such a national-scale survey, including data collection and processing. Realistically, the earliest a new VIUS dataset is expected to be available is still a couple of years away.

Potential methods to calibrate the outdated 2002 VIUS, including the use of trend analysis on various truck characteristics (e.g., volume, weight, vehicle type), were investigated. Specifically, this exploratory effort aims at using existing traffic count and weigh-in-motion data and other supplemental HD truck mobility information obtained from the FHWA, as well as integrating and/or supplementing information gathered from other transportation entities (e.g., American Transportation Research Institute [ATRI]) to the extent possible to develop calibration factors so that statistics generated based on 2002 VIUS data can be updated.

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[1] "In the United States, most petroleum is consumed in transportation," EIA, dated August 2, 2019, accessed September 12, 2019, https://www.eia.gov/todayinenergy/detail.php?id=40752#.
[2] "FHWA Forecasts of Vehicle Miles Traveled: Spring 2019," Office of Highway Policy Information, Federal Highway Administration, dated May 2019, https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_forecast_sum.pdf.
[3] www.fueleconomy.gov, US Department of Energy, accessed September 1, 2019, https://www.fueleconomy.gov.
[4] VIUS 2002 report is available at: https://www.census.gov/prod/ec02/ec02tv-us.pdf.

1.2 MOTIVATION OF THIS STUDY

Trucks have been the dominant mode of transportation for freight shipments in the United States, accounting for over 65% in weight and 70% in value of all domestic shipments in 2017.[5] Official statistics has shown that trucks will continue to be responsible for moving the majority of freight shipments for the foreseeable future.[6] Given the large quantity of shipments, advancements in vehicle technologies (e.g., advanced combustion engines and transmissions, alternative fuel and electrification, truck platooning) have the potential to significantly reduce the total energy consumption associated with freight transportation. However, as mentioned above, the lack of the up-to-date knowledge on the use of MD/HD vehicles (e.g., vehicle types, fuel types, distance traveled, weights and volumes carried) makes it difficult to identify potential applications and effectively implement advanced vehicle technologies. Therefore, there is a need to explore the feasibility of using other data sources to statistically construct adjustment factors that could be used in combination with the 2002 VIUS data to better understand MD/HD vehicle usage.

1.3 OBJECTIVES OF THIS RESEARCH EFFORT

The main purpose of this study is to investigate ways of producing adjustment factors that could be applied to calibrate the 2002 VIUS statistics for modern uses. Specific information of interests pointed out by the Southern California Association of Governments for California's 2017 VIUS[7] includes VMT, payload by commodity, and vehicle loading. These data items are commonly used as inputs to statewide freight forecasting models and regional travel demand and emission estimation models.

The ultimate goals of this effort are to define the US Department of Energy's (DOE's) Mobility Study data needs. These may include:

- truck population and their energy use by class,
- types of truck/freight services and needs,
- issues and challenges related to fuel types used and alternative fuels,
- truck size and weight limits (limited by weight vs. volume), and VMT by vehicle/fuel type.

This research seeks to examine changes in truck populations and truck weight distributions over time and to identify trends and patterns, with the expectation of developing certain adjustments or factors (in truck type and/or weight distributions) that could be used to realign perspective VIUS data. This draft memo focuses on descriptions of the FHWA data examined thus far, including some statistics generated from a selected type of truck (e.g., five-axle combination truck).

1.4 ORGANIZATION OF THIS TECHNICAL MEMORANDUM

Section 2 addresses several different vehicle/truck classifications that are commonly used by the transportation community. An overview of major data sources used in this exploratory study can be found in Section 3, followed by a more detailed analysis at the truck counts and weights data from the FHWA under Section 4. Section 5 describes the statistical methodology developed for estimating share of empty-truck and average truck payload factors, using FHWA's truck volume and weight data. Steps taken to apply freight data to estimate truck activities is then presented in Section 6. Sections 7 and 8 summarize the findings and lessons learned from this exploratory effort and identify the challenges and future study needs.

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[5] US Department of Transportation, Bureau of Transportation Statistics and FHWA, Freight Analysis Framework, version 4.5, 2019.

[6] "Weight of Shipments by Transportation Mode," Bureau of Transportation Statistics, accessed September 3, 2019, https://www.bts.gov/weight-shipments-mode.

[7] A brief summary of California's 2017 VIUS is available at: http://www.scag.ca.gov/committees/CommitteeDocLibrary/mtf012319_CAVIUS.pdf.

2. VEHICLE CLASSIFICATION AND TYPES OF TRUCK

2.1 GROSS VEHICLE WEIGHT RATING-BASED CLASSIFICATION

Vehicles in the United States are typically classified by the FHWA based on the maximum loaded (or operating) weight measured in pounds (lb), or the gross vehicle weight rating (GVWR). The GVWR class, which defines vehicles as class 1 through 8 depending on vehicle weight, is the most commonly used vehicle classification system in the transportation industry. Figure 2-1 shows the eight GVWR classes along with examples of trucks in each class.

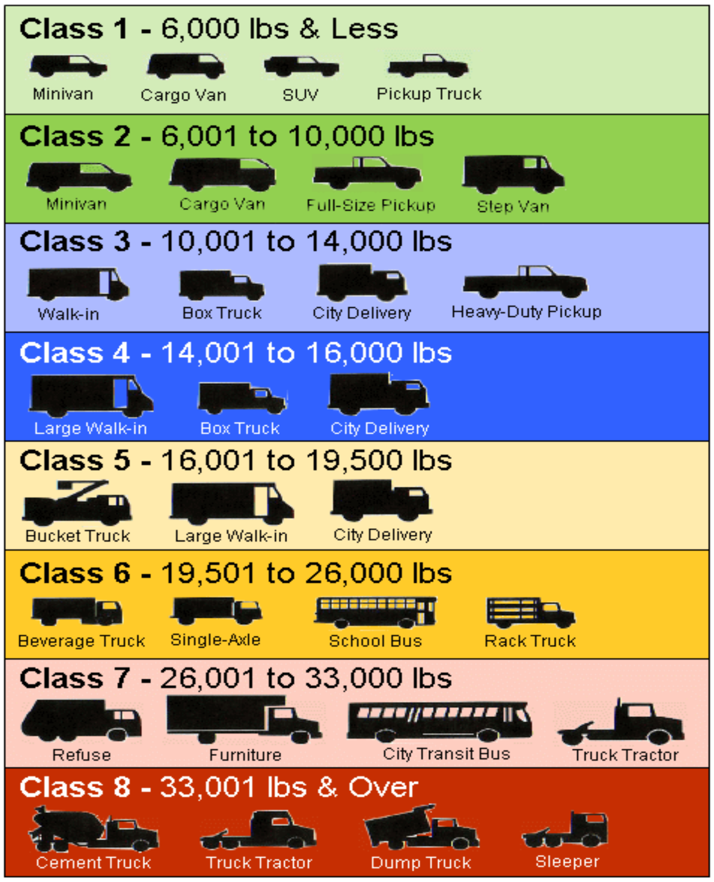

Figure 2-1. GVWR classifications and examples of trucks. (***Source***: FHWA)

In some applications and reporting, the FHWA also categorizes the eight classes of vehicles into three aggregated groups: light-duty (classes 1 & 2), medium-duty (classes 3–6), and heavy-duty (classes 7 & 8). Within the VIUS, the U.S. Census classified trucks using the same definition, further dividing the MD category into two groups: medium-duty (classes 3–5) and light heavy-duty (class 6). Similarly, the US Environmental Protection Agency defines vehicle categories by GVWR, with a slight deviation from FHWA's definition, for the purposes of emissions and fuel economy certification. The definitions used by different agencies are shown in Figure 2-2.

Gross Vehicle Weight Rating (lbs)	Federal Highway Administration		US Census Bureau
	Vehicle Class	GVWR Catagory	VIUS Classes
<6,000	Class 1: <6,000 lbs	Light Duty <10,000 lbs	Light Duty <10,000 lbs
10,000	Class 2: 6,001 – 10,000lbs		
14,000	Class 3: 10,001 – 14,000 lbs	Medium Duty 10,001 – 26,000 lbs	Medium Duty 10,001 – 19,500 lbs
16,000	Class 4: 14,001 – 16,000 lbs		
19,500	Class 5: 16,001 – 19,500 lbs		
26,000	Class 6: 19,501 – 26,000 lbs		Light Heavy Duty: 19,001 – 26,000 lbs
33,000	Class 7: 26,001 – 33,000 lbs	Heavy Duty >26,001 lbs	Heavy Duty >26,001 lbs
>33,000	Class 8: >33,001 lbs		

Gross Vehicle Weight Rating (lbs)	EPA Emissions Classification			
	Heavy Duty Vehicle and Engines			Light Duty Vehicles
	H.D. Trucks	H.D. Engines	General Trucks	Passenger Vehicles
<6,000 6,000	Light Duty Truck 1 & 2 <6,000 lbs	Light Light Duty Trucks <6,000 lbs	Light Duty Trucks < 8500 lbs	Light Duty Vehicle < 8500 lbs
8,500	Light Duty Truck 3 & 4 6,001 – 8,500 lbs	Heavy Light Duty Trucks 6,001-8,500 lbs		
10,000	Heavy Duty Vehicle 2b 8,501 – 10,000 lbs	Light Heavy Duty Engines 8,501 lbs – 19,500 lbs	Heavy Duty Vehicle Heavy Duty Engine >8,500 lbs	Medium Duty Passenger Vehicle 8,501 – 10,000 lbs
14,000	Heavy Duty Vehicle 3 10,001 – 14,000 lbs			
16,000	Heavy Duty Vehicle 4 14,001 – 16,000 lbs			
19,500	Heavy Duty Vehicle 5 16,001 – 19,500 lbs			
26,000	Heavy Duty Vehicle 6 19,501 – 26,000 lbs	Medium Heavy Duty Engines 19,501 – 33,000 lbs		
33,000	Heavy Duty Vehicle 7 26,001 – 33,000 lbs			
60,000	Heavy Duty Vehicle 8a 33,001 – 60,000 lbs	Heavy Heavy Duty Engines Urban Bus >33,001		
>60,000	Heavy Duty Vehicle 8b >60,001			

Figure 2-2. Differences in vehicle weight classes by agencies. (***Source***: Alternative Fuels Data Center, DOE)

2.2 FHWA VEHICLE AXLE-SPACING BASED CLASSIFICATION

In addition to the weight-based classifications, FHWA also defines a 13-category vehicle classification system under its traffic monitoring program. This classification system was designed to meet the needs of traffic data users. For example, electronic equipment and sensors available for traffic counting can differentiate passing vehicles into desired classifications (e.g., detecting axles and determining spacing). Currently, this 13-category classification system is used in most federal reporting requirements and state vehicle classification counting efforts.

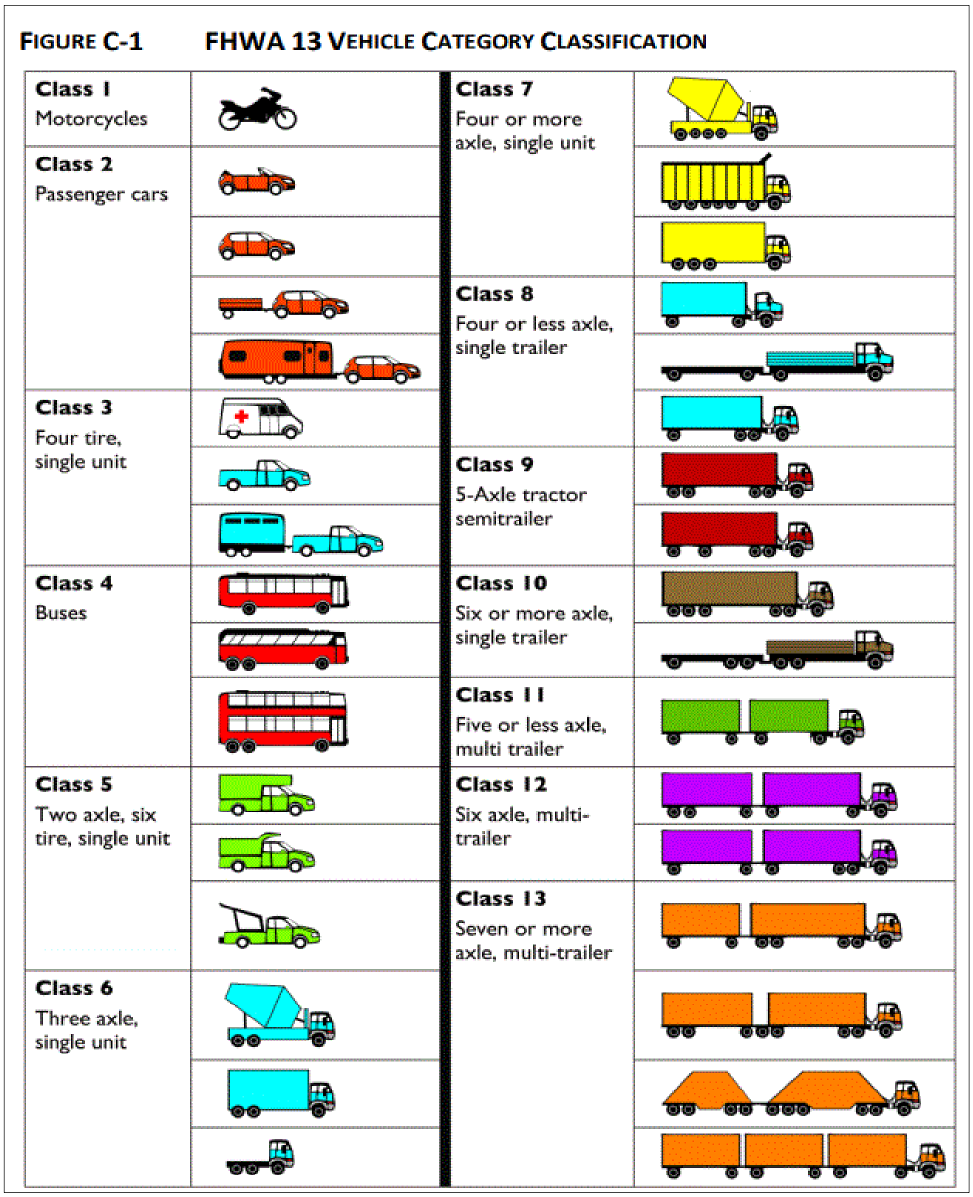

Figure 2-3. FHWA vehicle category classification. (***Source***: FHWA)

Figure 2-3 presents the 13 vehicle classes defined by the FHWA along with examples of vehicles in each class. Note that the datasets being examined under this exploratory study comprise traffic monitoring data obtained from the FHWA and thus are coded using the 13-category vehicle classification system.

2.3 VIUS TRUCK TYPES

VIUS records contain many variables related to characteristics and operations of individual trucks (i.e., VIUS samples). In addition to the GVWR, the 2002 VIUS dataset provides axle configuration information, which was utilized under this study to create a linkage to the FHWA's 13 vehicle classes. Specifically, axle configurations (*AXLE_CONFIG*) defined under 2002 VIUS are:

- Straight trucks (not pulling a trailer) and truck tractors (not pulling a trailer–not in use)
  - 01. 2 axles, 4 tires
  - 02. 2 axles, 6 tires
  - 03. 3 axles
  - 04. 4 axles
  - 05. 5 or more axles

- Straight trucks (pulling a trailer)
  - 06. 2 axles, 4 tires; 1 axle trailer
  - 07. 2 axles, 4 tires; 2 axle trailer
  - 08. 2 axles, 4 tires; 3 or more axle trailer
  - 09. 2 axles, 6 tires; 1 axle trailer
  - 10. 2 axles, 6 tires; 2 axle trailer
  - 11. 2 axles, 6 tires; 3 or more axle trailer
  - 12. 3 axles; 1 axle trailer
  - 13. 3 axles; 2 axle trailer
  - 14. 3 axles; 3 or more axle trailer
  - 15. 4 axles; 1 axle trailer
  - 16. 4 axles; 2 axle trailer
  - 17. 4 axles; 3 or more axle trailer
  - 19. 5 or more axles; 2 axle trailer
  - 20. 5 or more axles; 3 or more axle trailer

- Truck tractors
  - 24. 2 axles, 6 tires; 1 axle trailer
  - 25. 2 axles, 6 tires; 2 axle trailer
  - 26. 2 axles, 6 tires; 3 or more axle trailer
  - 27. 3 axles; 1 axle trailer
  - 28. 3 axles; 2 axle trailer
  - 29. 3 axles; 3 or more axle trailer
  - 30. 4 axles; 1 axle trailer
  - 31. 4 axles; 2 axle trailer
  - 32. 4 axles; 3 or more axle trailer
  - 37. 2 axles, 6 tires; 3 axles on two trailers
  - 38. 2 axles, 6 tires; 4 axles on two trailers
  - 39. 2 axles, 6 tires; 5 axles on two trailers
  - 41. 3 axles; 3 axles on two trailers
  - 42. 3 axles; 4 axles on two trailers
  - 43. 3 axles; 5 axles on two trailers
  - 44. 3 axles; 6 or more axles on two trailers
  - 45. 4 axles; 3 axles on two trailers
  - 46. 4 axles; 4 axles on two trailers
  - 47. 4 axles; 5 axles on two trailers
  - 48. 4 axles; 6 or more axles on two trailers

- 53. 2 axles, 6 tires; 5 axles on three trailers
- 57. 3 axles; 5 axles on three trailers
- 58. 3 axles; 6 axles on three trailers
- 60. 3 axles; 8 or more axles on three trailers

Table 2-1 lists other 2002 VIUS variables that could potentially be used to classify vehicles for various study purposes. For instance, the definition of variable *BODYTYPE* (i.e., body type) shown in Table 2-2 clearly illustrates a correlation with the commodity a given truck is carrying. Nevertheless, this subject is out of scope for this exploratory study, thus its usefulness was not further investigated.

Table 2-1. VIUS variables that can be used to classify vehicle types.

Variable Names in VIUS	Description
ADM_GVWR	GVWR code based on decoded VIN
AXLE_CONFIG	Axle configuration for vehicle or vehicle/trailer combination. There are 40–60 axle configurations.
BODYTYPE	Body type of the vehicle. There are 33–40 truck body types (e.g., pickup, basic platform, lowboy, insulated van, grain body)
OPCLASS	Operator classification with highest percent
TRAILERTYPE	Body type of trailer
VIUS_GVW	Gross vehicle weight based on reported average weight
WEIGHTAVG	Average weight of vehicle or vehicle/trailer combination
WEIGHTEMPTY	Empty weight of vehicle or vehicle/trailer combination
WEIGTHMAXIMUM	Maximum weight of vehicle or vehicle/trailer combination

Table 2-2. Body types of vehicles in 2002 VIUS.

Code	Description	Code	Description
01	Pickup	16	Service, other
02	Minivan	17	Street sweeper
03	Light van other than minivan	18	Tank, dry bulk
04	Sport utility	19	Tank, liquids, or gases
05	Armored	20	Tow/wrecker
06	Beverage	21	Trash, garbage, or recycling
07	Concrete mixer	22	Vacuum
08	Concrete pumper	23	Van, basic enclosed
09	Crane	24	Van, insulated nonrefrigerated
10	Curtainside	25	Van, insulated refrigerated
11	Dump	26	Van, open top
12	Flatbed, stake, platform	27	Van, step, walk-in, or multi-stop
13	Low boy	28	Van, other
14	Pole, logging, pulpwood, pipe	99	Other not elsewhere classified
15	Service, utility	Blank	Truck tractor

3. OVERVIEW OF MAJOR DATA SOURCES

3.1 FHWA TRAFFIC DATA

3.1.1 Traffic Data Collection System

3.1.1.1 Travel Monitoring Analysis System Data

Under an internal data program called the Travel Monitoring Analysis System (TMAS), FHWA assists states to collect and analyze data on traffic volumes, vehicle classes, and truck weights. The TMAS data are used to develop policies and regulations that are important to many highway and transportation functions in the nation. Specifically, traffic volume data are collected at approximately 5,000 continuous traffic counting locations nationwide. These data are used by FHWA to publish its monthly *Traffic Volume and Trends* reports. Truck weight data are obtained from weigh-in-motion (WIM) systems from a much smaller set of locations. Both traffic volume and weight data are collected and reported to the FHWA by the states, according to formats specified in the *Traffic Monitoring Guide* (TMG). The TMG was last released in October 2016.[8]

The TMAS data are available at station level; by direction and lane; and by hour of the day, day of the week, and day of the month throughout the year. Because of the level of detail provided, file sizes for TMAS datasets are large. An in-person request for TMAS data made to FHWA in January 2019 resulted in the receipt of nearly 60 GB of files on data collected in 2017. Because the 2017 TMAS dataset was used extensively under this exploratory research, a more in-depth analysis is provided in Section 4.

3.1.1.2 Vehicle Travel Information System Data

Prior to 2015, when the TMAS was launched, the Office of Highway Policy Information, FHWA, developed a tool called the Vehicle Travel Information System (VTRIS)[9] to provide user-friendly way to generate standard-format statistics tables (i.e., VTRIS W-tables) using data collected under FHWA's vehicle weighing and classification efforts at truck weight sites. VTRIS data are available for 1990–2015. As in the TMAS, vehicles in the VTRIS reports are characterized using the FHWA's 13-category vehicle classification system. Specific VTRIS W-tables examined under this study include W-2 (i.e., hourly vehicle counts by vehicle classification at station level); W-3 (i.e., average weights of empty, loaded, and all trucks for classes 5–13); and W-5 (i.e., number of trucks in various gross weight ranges at selected stations for vehicle classes 3–13).

3.1.2 Geographic Coverage of FHWA Traffic Data

3.1.2.1 Traffic Monitoring Stations across the United States

TMAS/VTRIS data provide detailed location information on FHWA's traffic monitoring stations throughout the United States. Traffic volume, vehicle classification, and truck weight monitoring information are all recorded for each station by year. Figure 3-1 illustrates the geospatial distribution of traffic monitoring stations in 2017 based on the TMAS. The density of stations clearly varies among states. Not surprisingly, the stations are concentrated around major cities.

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[8] FHWA. *2016 Traffic Monitoring Guide*, available at: https://www.fhwa.dot.gov/policyinformation/tmguide/tmg_fhwa_pl_17_003.pdf.

[9] The VTRIS tool is available at: https://fhwaapps.fhwa.dot.gov/vtris-wp/. The User's Guide is available at https://www.fhwa.dot.gov/ohim/ohimvtis.cfm.

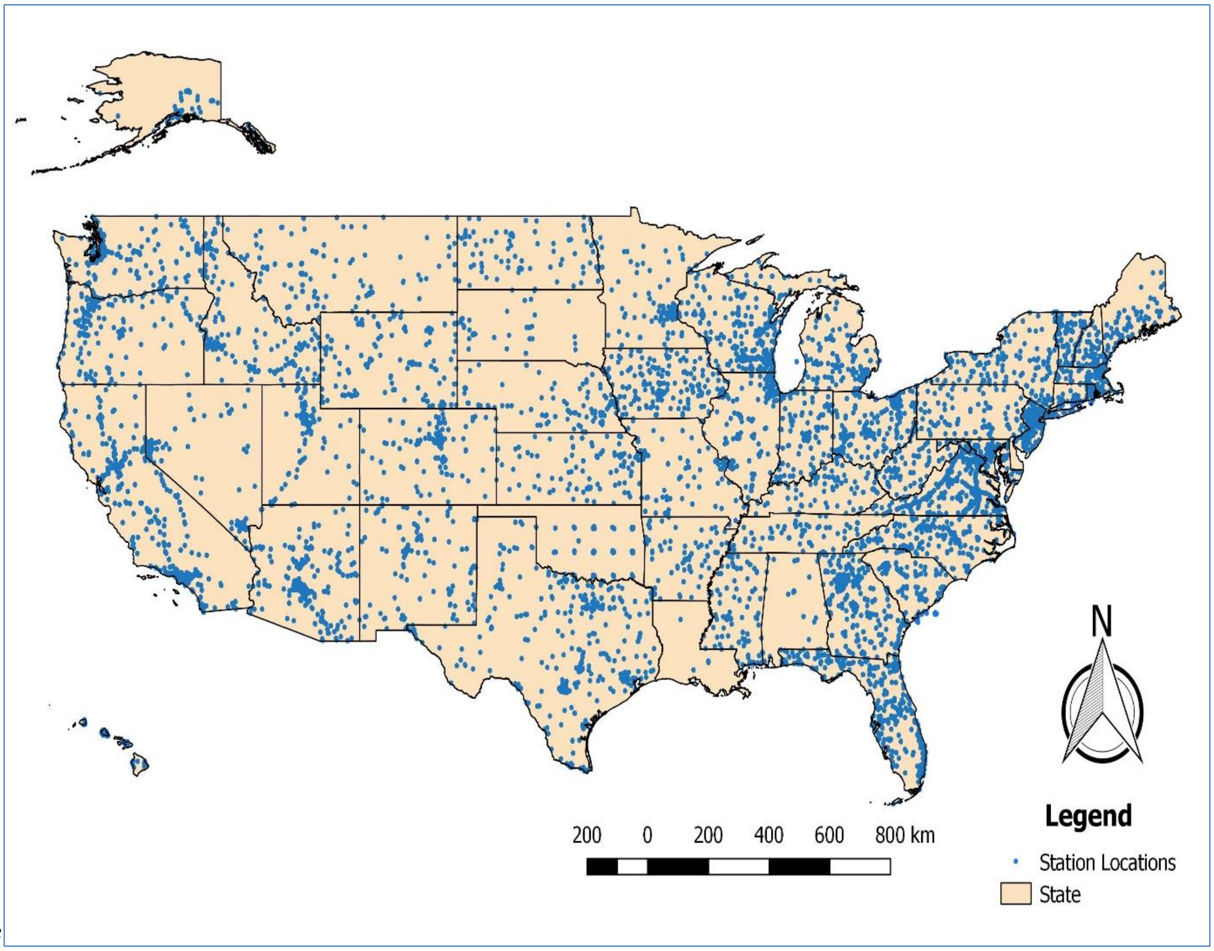

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Figure 3-1. FHWA TMS traffic monitoring stations, 2017.

Traffic data collected at each station are generally available by travel direction (e.g., eastbound, northbound) and at lane level, as well as by roadway functional class (e.g., rural vs. urban, interstate vs. others). Further detailed station-level discussions, with examples, are included in Section 4.

Under this study, information from three VTRIS data years (i.e., 2002, 2007, and 2012) was used along with the 2017 TMAS dataset. This limited selection of datasets was made mainly due to the exploratory nature of this research effort and associated resource constraints. Moreover, for the purpose of establishing a potential linkage between results from this research and the existing freight data (i.e., Commodity Flow Survey (CFS) and Freight Analysis Framework (FAF), discussed in Sections 3.2 and 3.3), only years following the Economic Census cycles were selected for this investigation.

3.2 COMMODITY FLOW SURVEY DATA

The CFS is a shipper-based survey conducted as a joint effort of the Bureau of Transportation Statistics (BTS) and the US Census Bureau. It collects commodity movement information from selected industries in the United States, including mining, manufacturing, wholesale, auxiliaries, and retail and services trade industries. Specifically, the CFS provides data on shipment origins and destinations, values, weights, modes of transport, distance shipped, and ton-miles for commodities transported domestically as well as for exports. Shipments originating from Puerto Rico and other US territories were excluded. The CFS data, which were released in 1993, 1997, 2002, 2007, and 2012, are used by federal, state, and regional transportation agencies in freight demand analysis, freight planning, and policy making. Data from the 2017 CFS are expected to be released in July 2020.

With the 2012 CFS, the US Census released a new data product, CFS Public Use Microdata (CFS PUM), to provide data at the individual shipment level. The CFS PUM data provides information on 4,547,661 shipment records from ~60,000 responding establishments. Data elements included in CFS PUM shipment record are:

- Shipment origin
  - State
  - Metropolitan area
- Shipment destination (in the United States)
  - State
  - Metropolitan area
- Shipper's industry classification based on North American Industry Classification System
- Quarter in 2012 in which the shipment was made
- Type of commodity
- Mode of transportation
- Value of the shipment (dollars)
- Weight of the shipment (pounds)
- Great circle distance between the shipment origin and US destination (miles)
- Routed distance between the shipment origin and US destination (miles)
- Whether or not the shipment required temperature control during transportation
- Whether or not the shipment was an export
- If an export, the final export destination country
- Hazardous material code
- Shipment tabulation weighting factor (expansion factor used to represent shipment weight (tonnage) and value of the total in-scope population)

The CFS PUM enables data users to construct different levels of freight demand models. A few key national-level goods movement statistics derived from the 2012 CFS are highlighted below.

3.2.1 Mode Shares Estimated Based on 2012 CFS Data

Based on 2012 CFS data (Figure 3-2), most US freight shipments were transported by truck, accounting for 71% and 73% of the total goods moved in 2012 as measured in shipment weights and values, respectively. Mode shares for trucks were likely much higher than those shown, when taking into account multimodal movement (e.g., truck-rail, truck-water) of freight. This results from the fact that trucks are frequently used as the mode for the first leg and/or the last leg of a shipment.

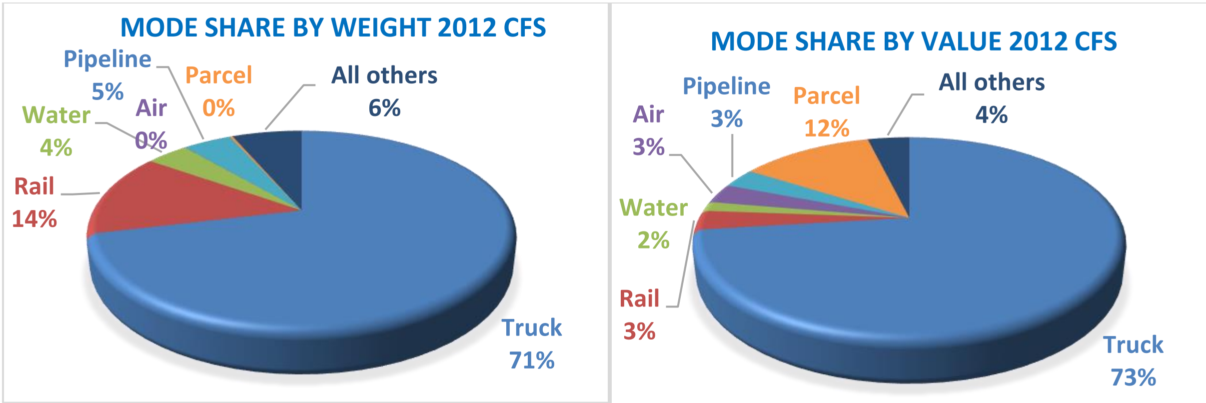


Figure 3-2. Mode shares by shipment weight and value in 2012. (***Source***: CFS)

Even though these CFS-based mode shares are based on shipment weight/value and not truck counts, they clearly support the notion that freight trucks could play a significant role in the effort to reduce transportation energy use and the associated greenhouse gas emissions.

3.2.2 Distance Range for Truck Travel Using 2012 CFS PUM

The 2012 CFS PUM provides information at the shipment level. Table 3-1 shows the overall distribution of distance-ranges of movement for shipments transported by truck in 2012, as measured by shipment value (dollars) and weight (tons). As expected, heavy shipments tend to be moved within shorter distances. Specifically, when measured by weight, nearly 60% of shipments transported by truck in 2012 were local shipments (i.e., moved within 50 miles), while only 16% of truck shipments traveled 250 miles or more during the same year. Travel range, on the other hand, is more evenly distributed when measured by shipment values.

Table 3-1. Share of truck shipments by travel-distance range in 2012.

Distance range	% value	% ton
Local (<50 miles)	35.5%	59.8%
Regional (50–250 miles)	26.8%	24.6%
Long distance (250+ miles)	37.8%	15.6%

Figure 3-3 shows shares of truck shipments by value and weight (tonnage) with a more detailed breakdown of distance ranges. In 2012, over 70% of truck shipments by weight was moved within 100 miles, while less than 10% by weight traveled 500 miles or more.

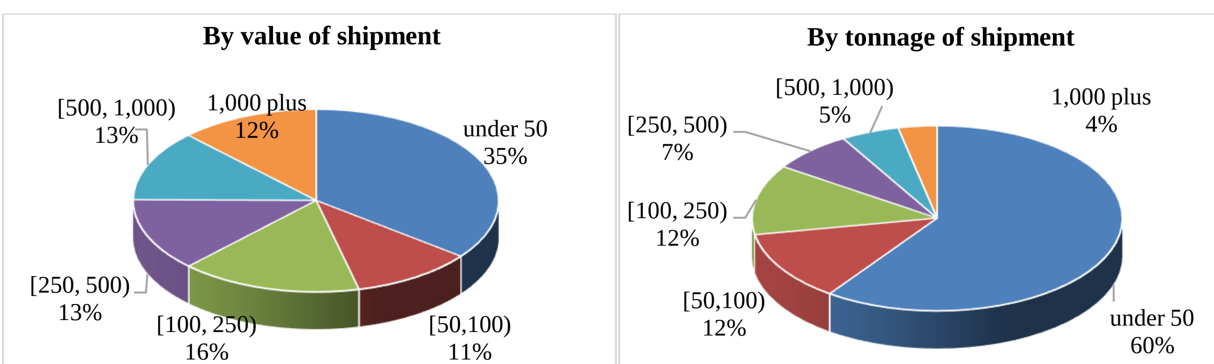


Figure 3-3. Shares of value and weight of shipments by travel distance in 2012.

Figure 3-4 presents the distribution of truck shipments by travel distance (i.e., distance from shipment origin to destination) in 2012. It is important to point out that the number of shipments does not indicate the number of trucks being utilized for those shipments. For example, multiple packages (i.e., small shipments) would likely be loaded onto a single truck. Figure 3-4 clearly indicates that the volume (i.e., count) of shipments is significantly higher for truck shipments that moved within 500 miles, as compared to shipments moved 500 or more miles in distance. Considering shipment values and weights, Figure 3-5 shows nearly 5 billion tons of truck shipments (vertical axis in red), worth over $3.5 trillion in value (vertical axis in blue), were local shipments being transported within a 50-mile radius.

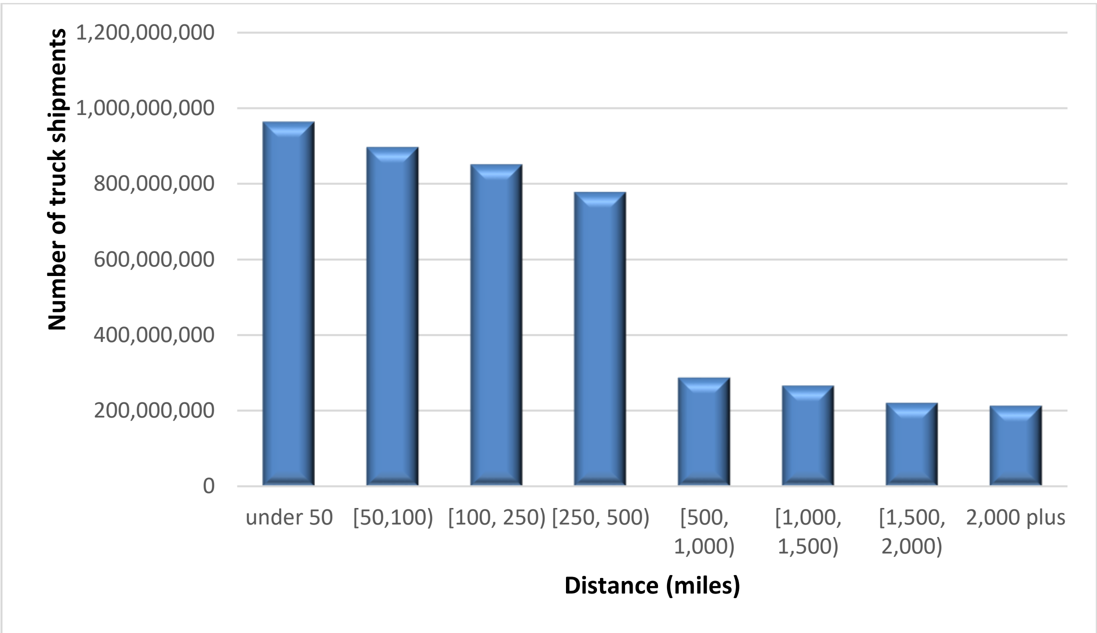


Figure 3-4. Distribution of truck shipments by travel distance.

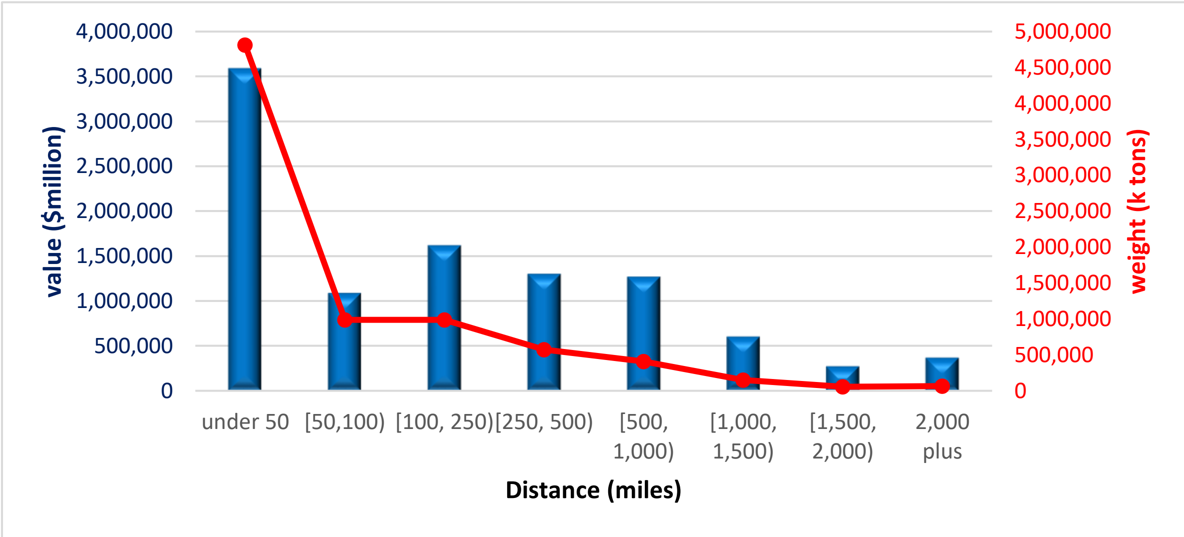


Figure 3-5. Truck shipment value and weight by distance range in 2012.

3.2.3 Truck Ownerships

CFS also provided information regarding truck carrier types (i.e., private and for-hire). A private truck is one that transports its own company's cargos; the establishment usually produces, uses, sells, or buys the cargo being hauled (e.g., Walmart, Kroger). A for-hire truck, on the other hand, provides transportation of cargo belonging to others and is paid for doing so (e.g., J.B. Hunt, US Xpress). With this definition, UPS and FedEx are considered for-hire carriers.

As shown in Figure 3-6, operations for the two types of trucking business are different. Based on data from the 2012 CFS, although private trucks moved about 50% more volume of shipments than for-hire trucks, the total value of shipments moved by for-hire trucks was nearly 80% higher than those of private trucks. Considering the weight of shipments, for-hire trucks also moved more tonnage (>14% more) than private trucks in 2012.

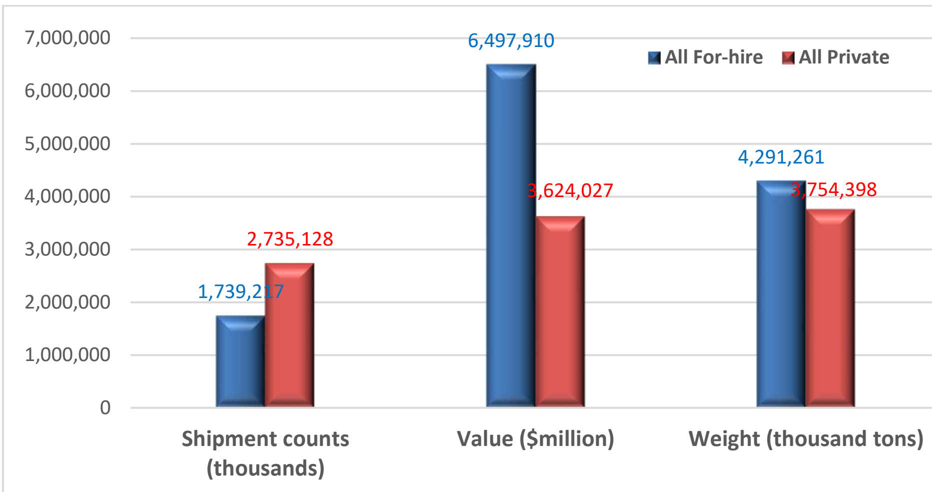


Figure 3-6. Comparison of shipment statistics by truck industry type.

Furthermore, in terms of distances, private trucks basically operated in local and regional markets while for-hire trucks covered all range of distances, regardless of measuring by shipment values or shipment weights (see Figure 3-7 and Figure 3-8).

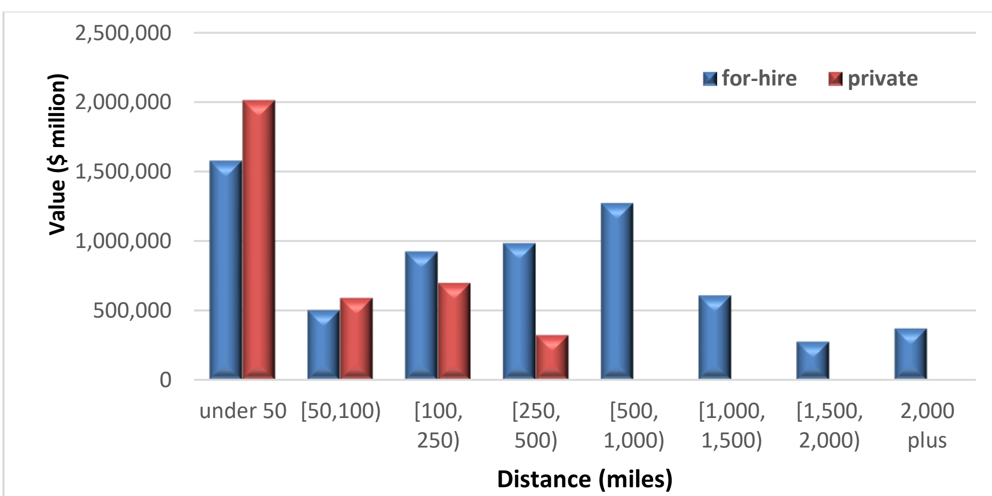


Figure 3-7. Shipment values moved by private truck and for-hire truck by distance range.

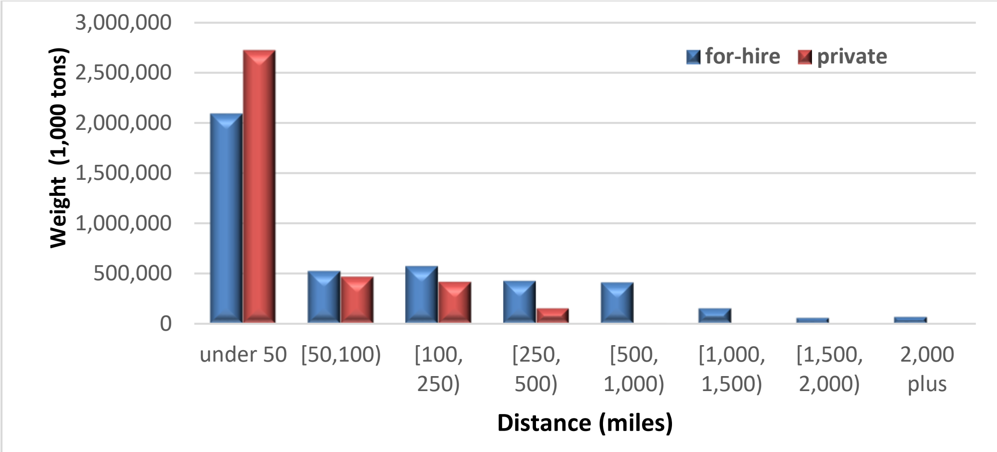


Figure 3-8. Shipment weights moved by private truck and for-hire truck by distance range.

3.2.4 Shipments of Parcel Delivery/Couriers/US Parcel Post

With the increasing popularity of e-commerce over the last decade, there is growing interest in examining how e-commerce influences transportation of goods, specifically by truck, and the travel behaviors of people. Clearly, the increase of online shopping has resulted in a reduction of shopping trips, thus reducing the total VMT made by personal vehicles, as well as decreasing the average number of daily trips per person for shopping purposes.[10] However, it is commonly known that e-commerce–induced trucking activities (e.g., package deliveries) are growing.

Note that under the CFS, “parcel delivery/courier/U.S. parcel post” is a mode of transportation considered to be part of “multiple mode shipments.”[11] Specifically, shipments of packages and parcels that weigh 150 pounds or less, and were transported by a for-hire carrier, are classified in the CFS as “Parcel Delivery/Courier/U.S. Parcel Post,” rather than ground (i.e., truck, rail) or air shipments. Heavier packages and parcels (i.e., >150 pounds) are still transported under other transportation modes, typically by truck or air, and are classified as such under the CFS.

[10] FHWA, *Travel Profile: United States*, *2017 National Household Travel Study*, available at: https://nhts.ornl.gov/assets/2017_USTravelProfile.pdf.
[11] See “Multiple Mode Shipments,” entry on “Key CFS Terms,” Bureau of Transportation Statistics, at: https://www.bts.gov/archive/publications/commodity_flow_survey/def_terms.

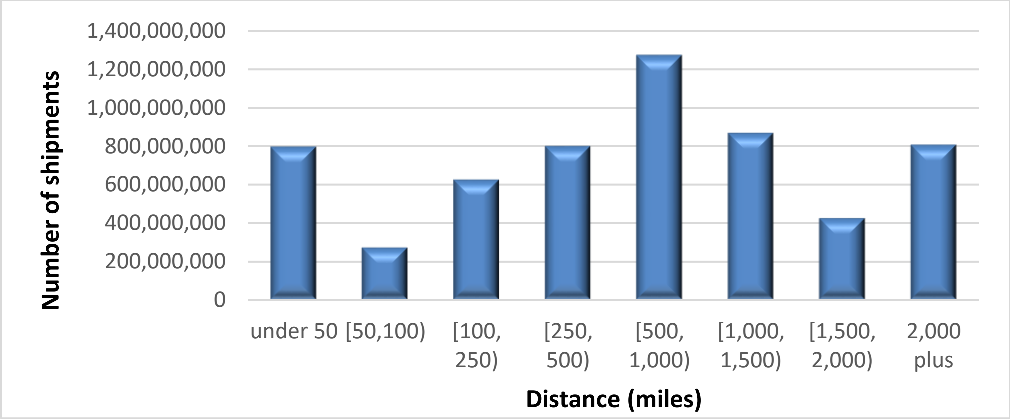


Figure 3-9. Distribution of parcel shipments by distance.

Based on a review of the 2012 CFS PUM data on shipments with the mode of "parcel," Figure 3-9 shows that "parcel" shipments cover all distance ranges. Except for shipments of very short distance (i.e., <50 miles), the distribution of shipments by other distance ranges followed a relatively normal distribution pattern, with the average distance in the range of 500–1,000 miles. Distributions of weight (tonnage) and value by distance range are very similar (Figure 3-10) for parcel shipments.

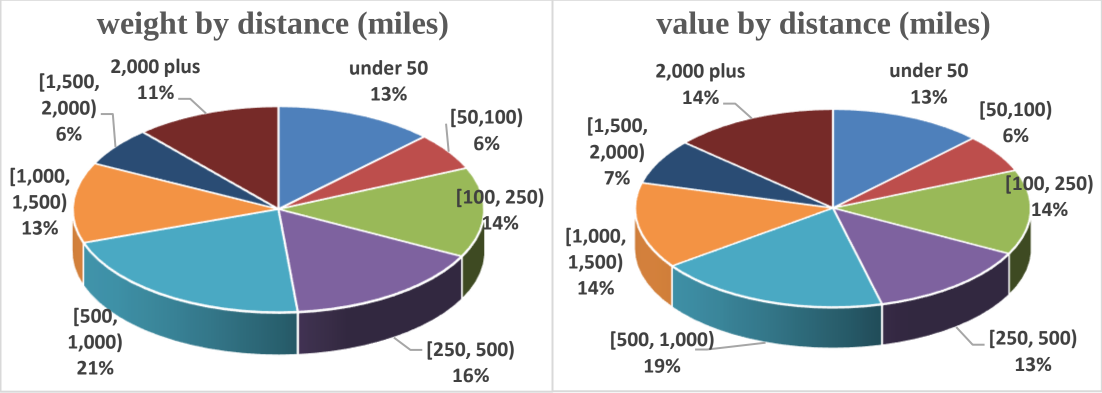


Figure 3-10. Weight and value shares by distance range for parcel shipments.

3.3 FREIGHT ANALYSIS FRAMEWORK DATA

The FAF, which is produced through a partnership between BTS and FHWA, estimates the total volume of freight flows and related freight transportation activities among states, sub-state regions, and international gateways. Built on the CFS data, the FAF estimates include tonnage, value, and ton-miles by origin/destination zones, commodity types, transportation modes, trade types, and foreign zones for imports/exports. Specifically, FAF integrates data from a variety of sources with the CFS to create a comprehensive picture of freight movement among states and major metropolitan areas by including shipments from the following out-of-scope (OOS) industries not covered in the CFS:

- Farm-based agricultural
- Fishery
- Logging
- Crude oil
- Natural gas
- Municipal solid waste

- Construction and demolition debris
- Household and business moves
- Imports and exports (foreign trade)
- Retail
- Services

Because truck weight has a more direct impact on a truck's energy uses, as compared to the value of shipments it carries, the statistics presented in Figure 3-11 and Figure 3-12 were derived using weight data (tonnage) from FAF version 4 (FAF4). Note that modes of transportation included under FAF4 are truck, rail, water, air, pipeline, multiple modes, and others/unknown. Based on FAF4 estimates, trucks carried about 63% by weight of all shipments being moved in 2012. This FAF4 mode share is lower than the 71% estimated from 2012 CFS data (see Figure 3.2), mainly due to the inclusion of OOS shipments. Particularly, the addition of crude oil and natural gas, which increased pipeline share significantly (18%) in FAF4 as compared to the 2012 CFS (5%), impacted the distribution of mode share for other modes.

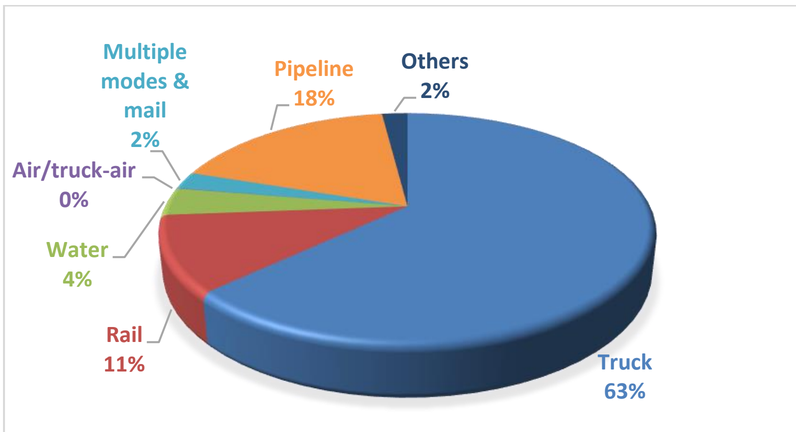


Figure 3-11. Mode share by total weight. (***Source***: FAF4)

As shown in the left chart in Figure 3-12, local shipments (i.e., within 50 miles) accounted for 42% of FAF4 weight (tonnage) when all modes were combined. The share of local shipments is significantly higher (at 56%) when shipments transported by truck are exclusively considered (right chart).

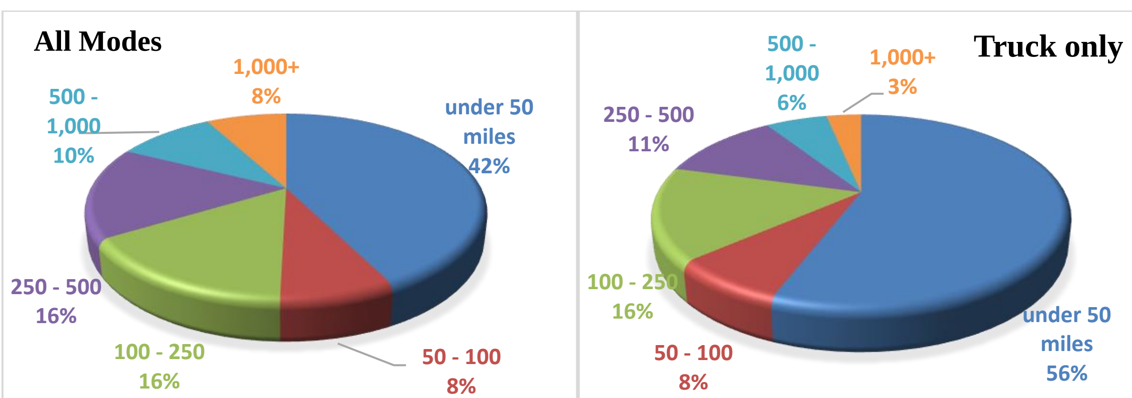


Figure 3-12. Share of FAF4 weight (tonnage) by distance range.

4. OVERVIEW & ANALYSIS OF TMAS DATA

4.1 TRUCK CLASS DISTRIBUTIONS

Based on the 2017 TMAS, Figure 4-1 shows that vehicle class 2 (i.e., passenger vehicles) accounted for about 60% of the total national traffic volumes in 2017, followed by 19% for vehicle class 3 (i.e., larger minivans, vans, pickup trucks). However, only vehicles classes 5–13 of the FHWA 13-category classification system, which include most of the MD and HD vehicles), are of the interest for this exploratory study.

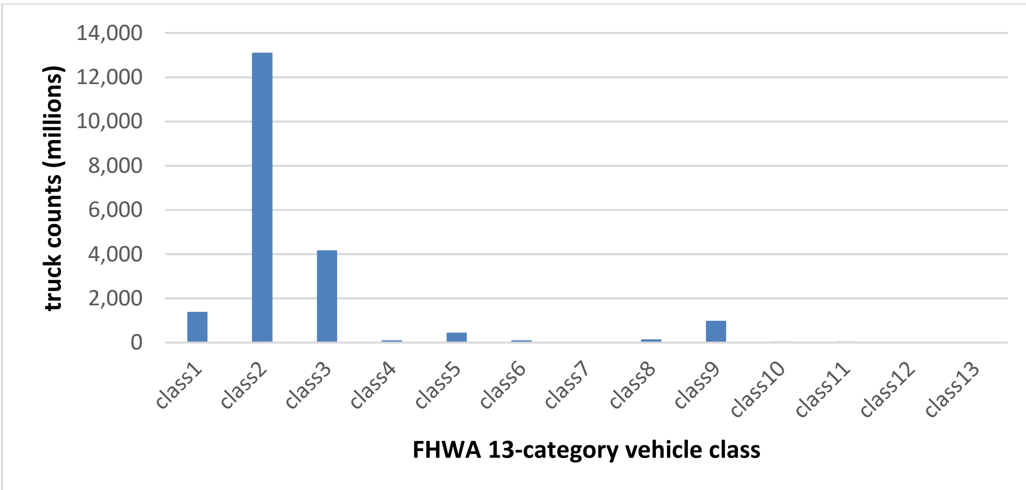


Figure 4-1. Traffic volume by FHWA vehicle class.

Figure 4-2 clearly shows that, when class 1–4 vehicles are eliminated, over half (54%) of the volumes reported in the 2017 TMAS was for class 9 (i.e., five-axle semis) vehicles, and another 25% involved class 5 vehicles (two-axle single unit). Most of the research efforts for this study focused on vehicle class 9.

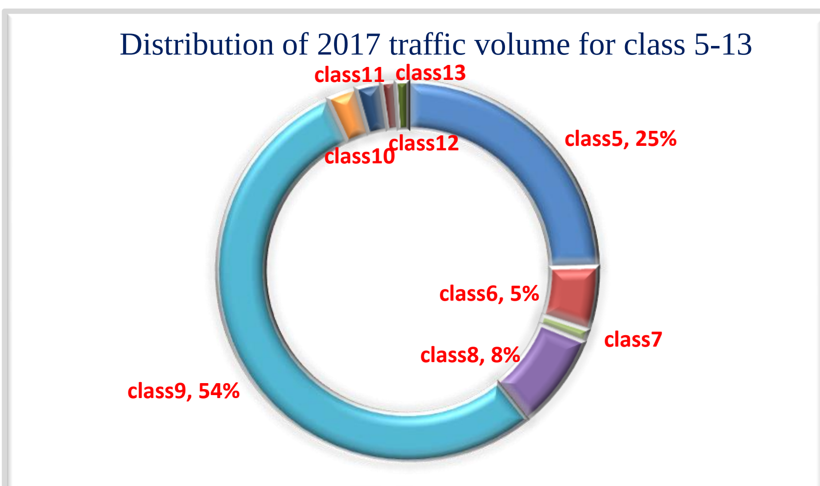


Figure 4-2. Distribution of traffic volumes for class 5–13 vehicles in 2017.

4.2 INVESTIGATING STATION-SPECIFIC 2017 TMAS DATA

4.2.1 Directional Variations

It is commonly known that traffic pattern of trucks, as well as their weight distributions, vary spatially and temporally. With TMAS WIM monthly data for January 2017, information from two travel directions (i.e., northbound, southbound) of a selected traffic monitoring station in Georgia was extracted and examined. As illustrated in Figure 4-3 and Figure 4-4, a vehicle class 9 truck's weight distribution patterns are clearly different for the two travel directions.

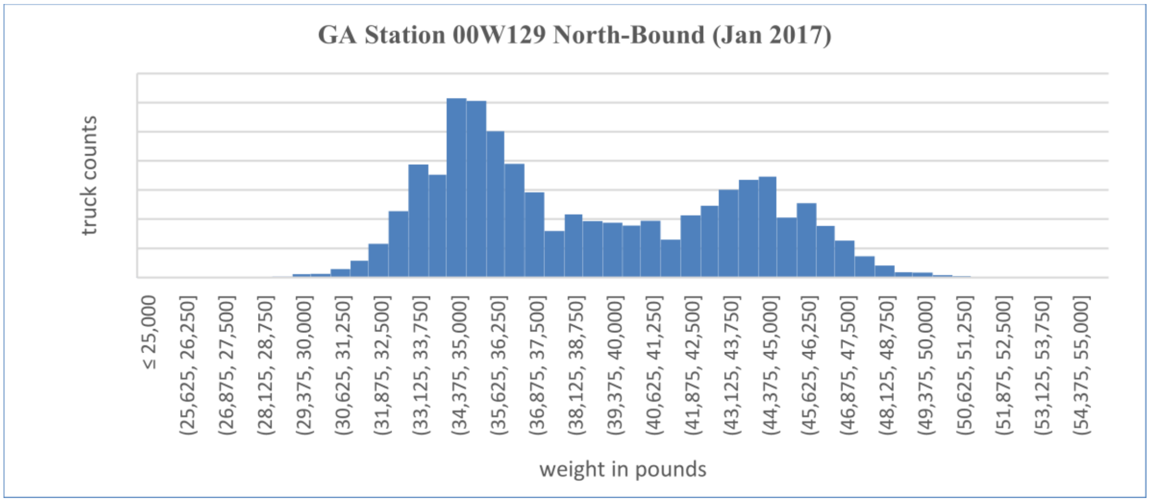


Figure 4-3. Weight distribution of vehicle class 9 for northbound at a Georgia station in 2017.

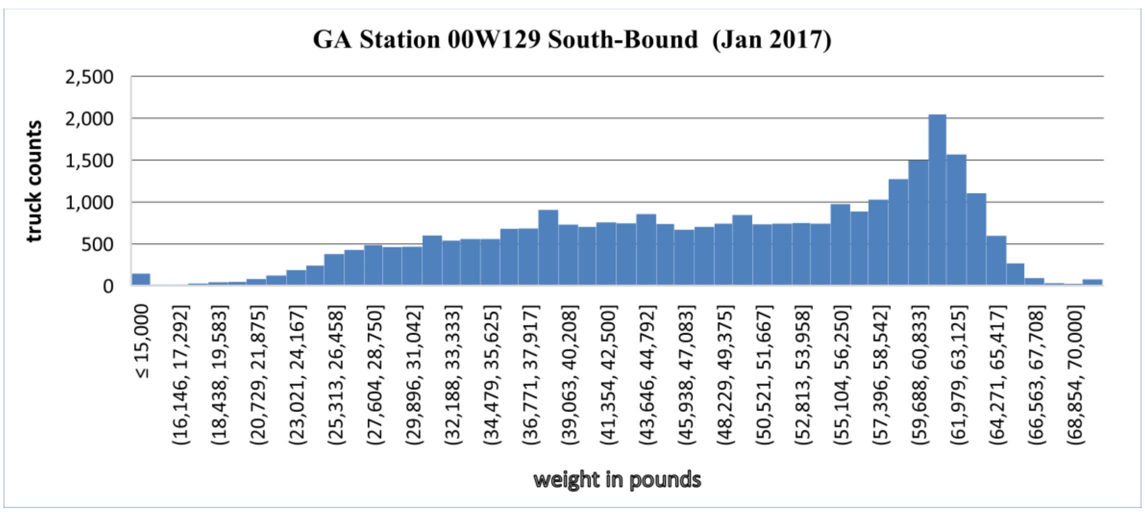


Figure 4-4. Weight distribution of vehicle class 9 for southbound at a Georgia station in 2017.

In fact, the scale of these two charts also reveal a directional difference in traffic volumes and weights of class 9 trucks passing through this station. Trucks heading north have weights of 30,000–50,000 lb, while southbound trucks have a wider spread of weights from <20,000 to >65,000 lb for the study period. Further investigations into associated regional business patterns would be helpful to explain the differences in truck traffic behaviors found for the Georgia station.

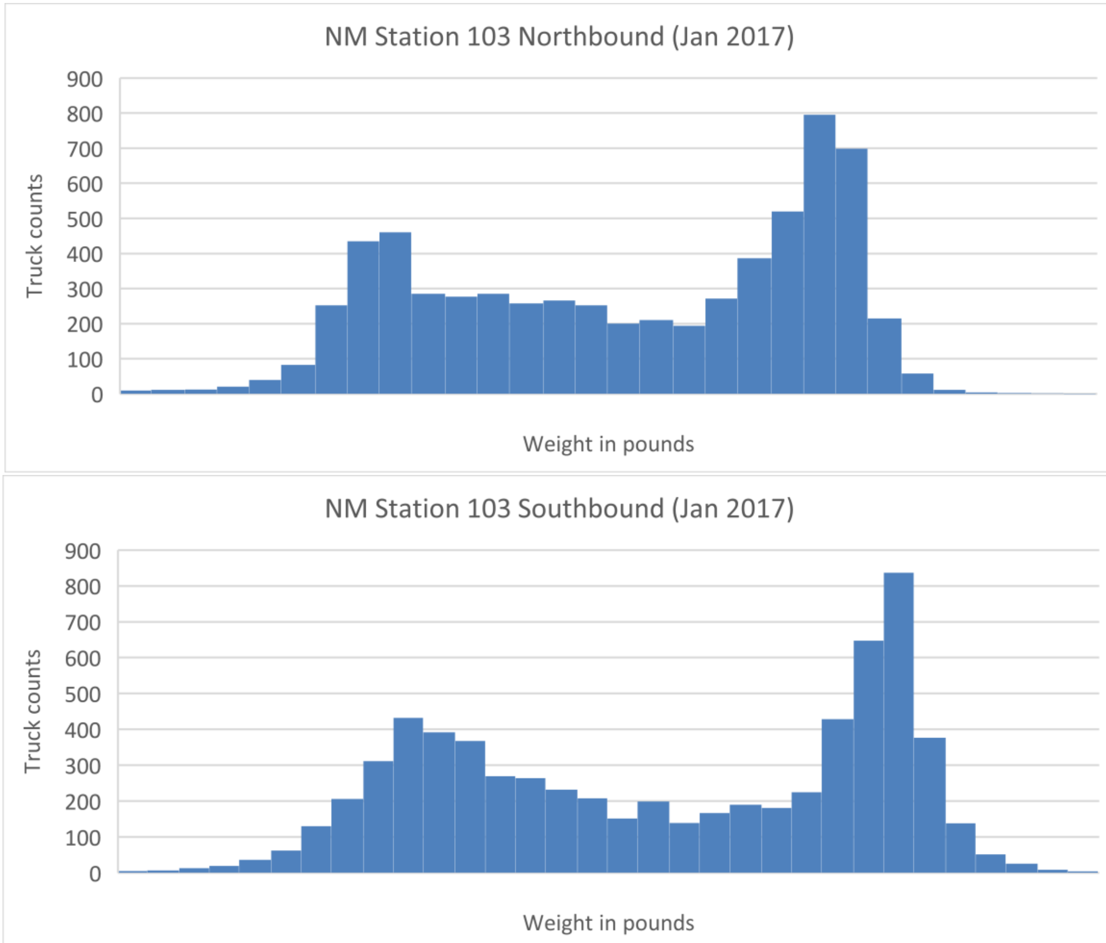


Figure 4-5. Weight distributions at a selected station in New Mexico in 2017.

As another example, Figure 4-5 shows weight distributions for truck traffic in January 2017 for two different travel directions at a traffic monitoring station located in New Mexico. Variations in truck weight distributions between the two different states (i.e., Georgia and New Mexico), as well as directional differences, are clearly demonstrated. Again, this level of detail requires significantly more extensive efforts in data processing and analysis beyond the exploratory nature of the current study. Therefore, data analysis and modeling in this research effort, and reported in the remaining sections of this document, were mainly conducted at the national and state levels.

4.3 INVESTIGATING 2002 VTRIS DATA

To establish relationships between VIUS variables and the FHWA's traffic volume and weight information, data from the 2002 VTRIS were examined. Figure 4-6 provides an example of class 9 truck weight distributions in two directions at a station in Alabama based on VTRIS–generated outputs.

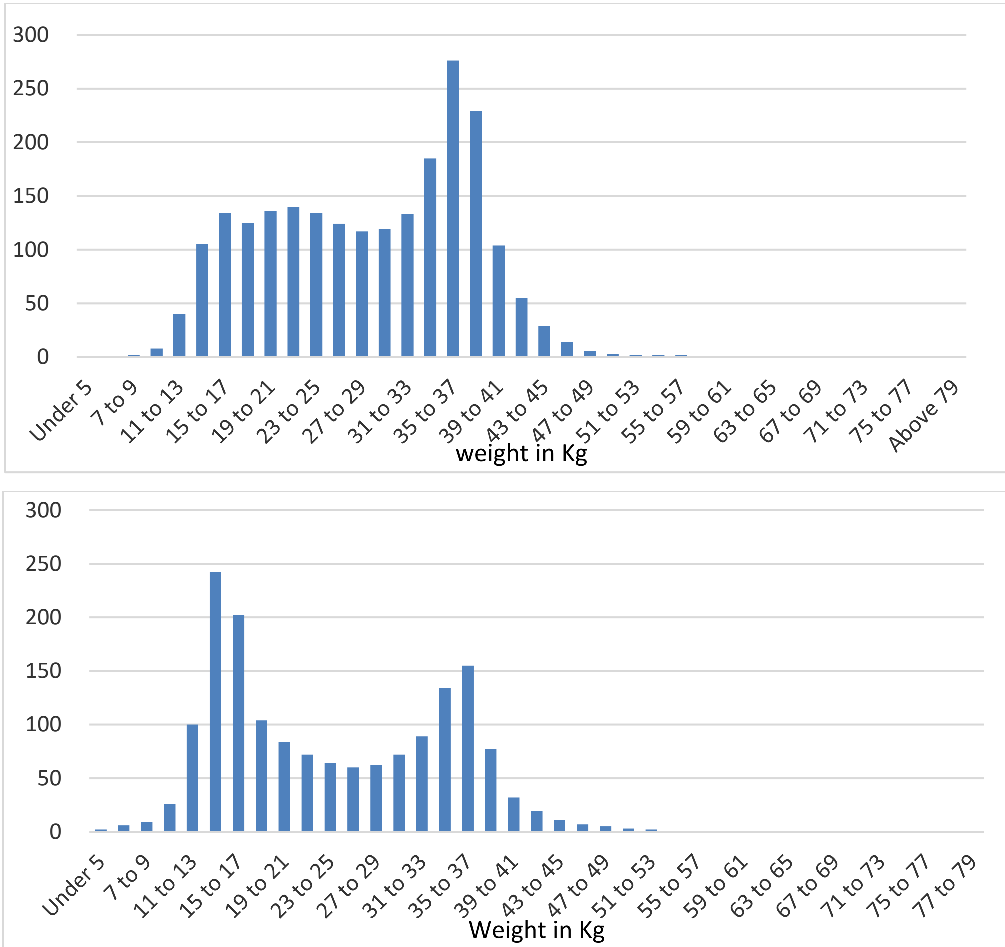


Figure 4-6. Weight distribution of class 9 trucks at a selected station in Alabama in 2002.

As mentioned earlier in this report, TMAS-type data prior to 2015 were available only from VTRIS. Data generated at the same level of detail as the TMAS, unfortunately, are not available from the VTRIS W-reports. Typically, VTRIS W-reports provide annual statistics that are aggregated to FHWA-preset weight categories (e.g., under 5, 5–7, 7–9 in kilograms). W-reports must be generated separately by state and by selected functional class (or stations); thus a large number of runs were conducted to obtain information from all available states. Although this is a rather inconvenient setup, it does not prevent performance of trend analyses over time. Because of resource limitations and the need for processing multiple years of VTRIS and TMAS datasets (i.e., 2002, 2007, 2012, and 2017), this exploratory research was limited to developing national-level estimates. State-level results were produced when feasible.

4.4 CHARACTERISTICS OF FHWA CLASS 9 VEHICLES

Using the 2017 TMAS data for vehicle class 9, Figure 4-7 presents monthly truck volumes in four states: California, Florida, New York, and Pennsylvania. Although traffic monitoring stations are not set up to collect statistically representative samples, states are guided by the FHWA on how to select proper locations to set up sensors or traffic counting devices. Therefore, these data should allow general traffic patterns and characteristics to be examined or compared among states. As seen in Figure 4-7, monthly volumes of class 9 trucks were relatively stable for Florida and New York in 2017, while vehicle counts were higher in Pennsylvania in the second half of 2017 and California had a much higher volume of class 9 trucks during the spring months.

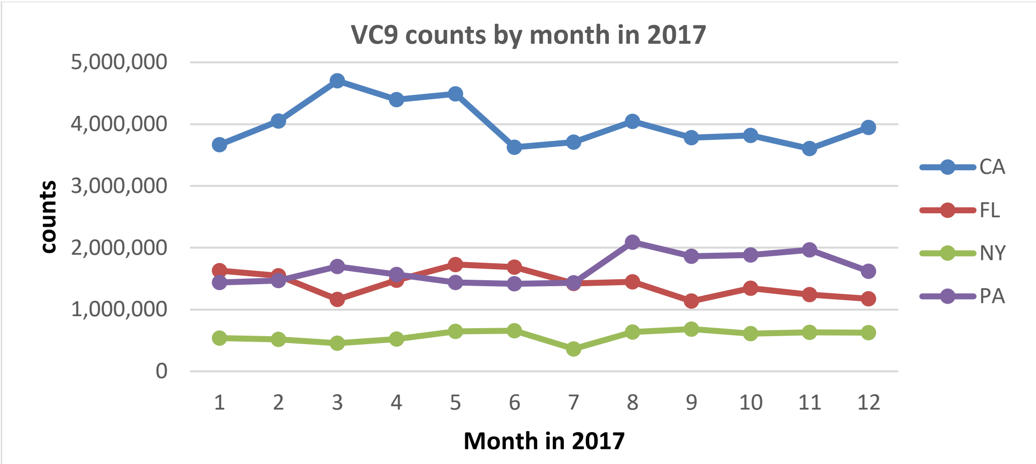


Figure 4-7. Monthly variations in class 9 truck volume for selected states in 2017.

Investigation of the aggregated 2017 state-level FHWA TMAS data, specifically on distributions of weights on class 9 trucks, also yielded similar patterns as shown on the station-level charts displayed in section 4.2. The aggregated state-level distributions have a smoother pattern, simply because variations among stations, and their directional differences, are balanced out when combined into a higher-level state view. Figure 4-8 through Figure 4-11 shows the weight distributions for Florida, New York, Pennsylvania, and California, respectively.

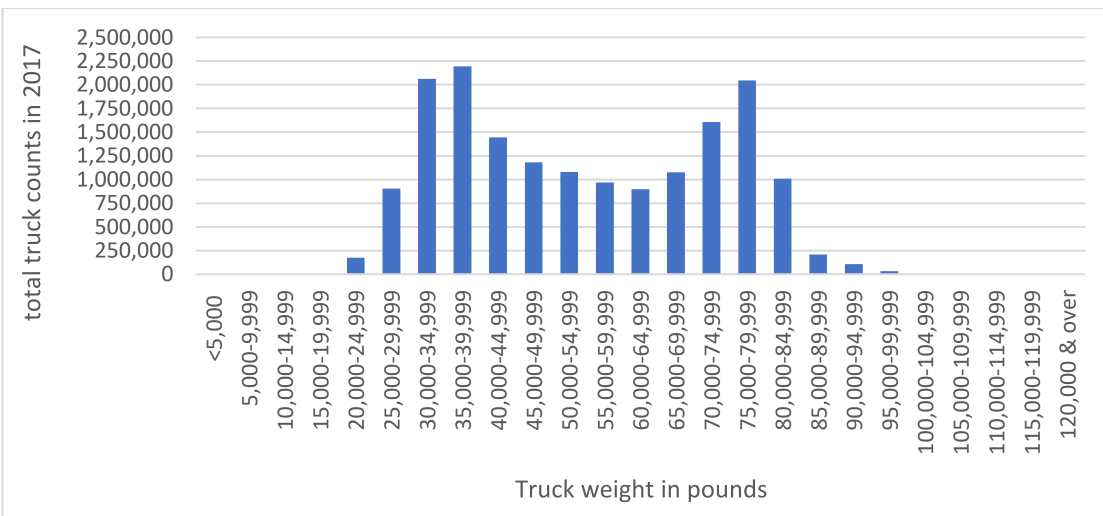


Figure 4-8. Vehicle class 9 truck weight distribution in Florida (2017 data).

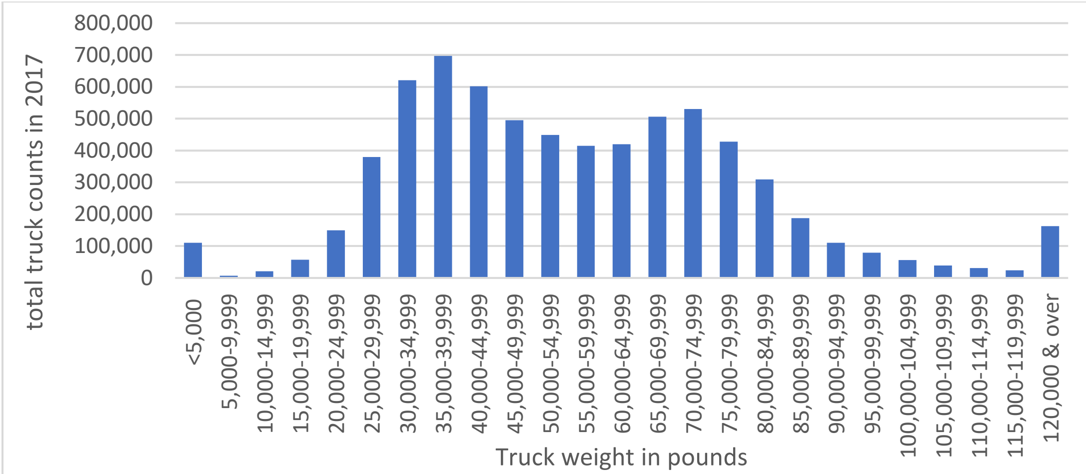


Figure 4-9. Vehicle class 9 truck weight distribution in New York (2017 data).

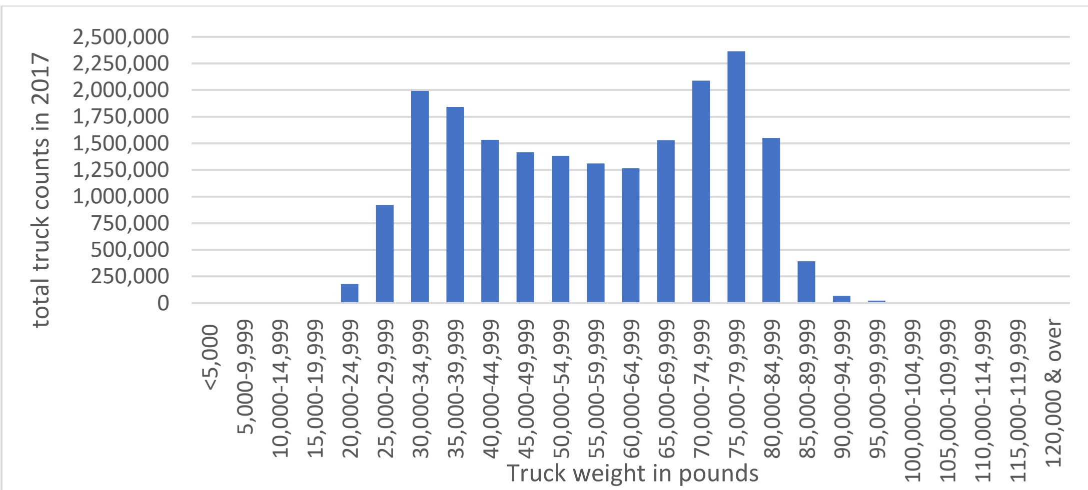


Figure 4-10. Vehicle class 9 truck weight distribution in Pennsylvania (2017 data).

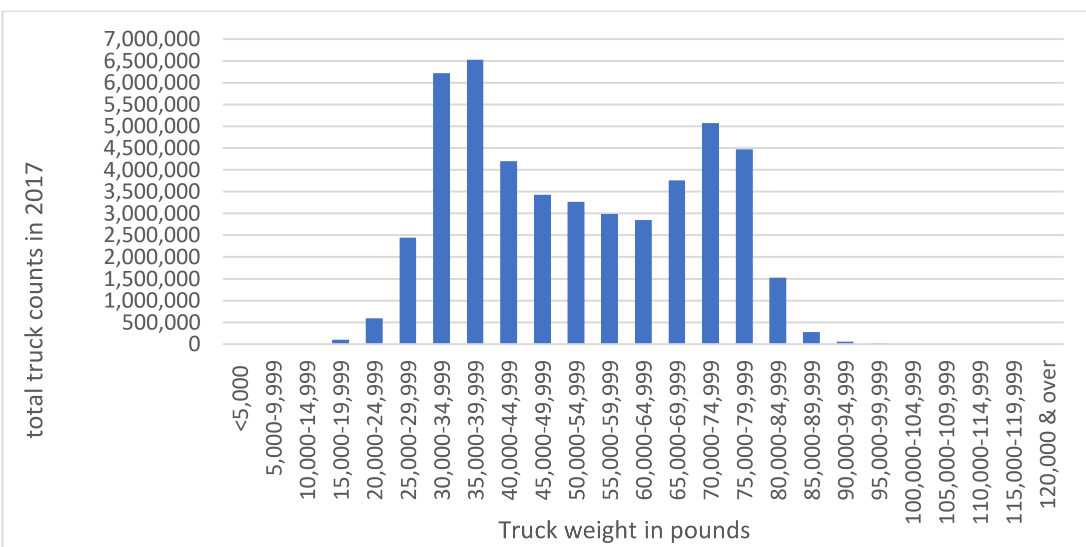


Figure 4-11. Vehicle class 9 truck weight distribution in California (2017 data).

5. ESTIMATION FOR SHARE OF EMPTY/LOADED AND PAYLOAD

5.1 OVERVIEW

Truck payload factors are not only important to pavement and bridge designs; they also impact accuracy of energy usage estimates (e.g., the heavier the truck, the higher the fuel consumption). Without data that allow for direct measurements or estimates of truckload factors, such as those provided by the 2002 VIUS, alternative modeling efforts become necessary. A methodology for using truck weight data to estimate truckload factors, developed by Oak Ridge National Laboratory (ORNL) researchers[12] under an earlier study, was adapted for this current research. The method postulated that truck gross operating weight distribution is composed of three normal weight distributions:

- empty trucks,
- partial truckloads or "loaded to size limit" trucks (e.g., a truck fully loaded with Styrofoam packaging material, full but nowhere near the weight limit), and
- "loaded to weight limit" trucks.

5.2 MAPPING VEHICLE CLASSIFICATION BETWEEN VTRIS/TMAS AND VIUS

As described in sections 2.2 and 2.3, VIUS and VTRIS/TMAS data define vehicle classes in different ways. To compare and evaluate calibrated statistics and trend factors generated from the 2002 VIUS data, vehicle classifications need to be matched across all data sources. Because the FHWA's 13 vehicle classes are based on axle configurations, the variable *AXLE_CONFIG* in the 2002 VIUS data was utilized to convert the FHWA classification system as used in the VTRIS/TMAS data.

Table 5-1 maps VIUS axle configurations to FHWA vehicle classes. (This lookup table was developed for converting truck weight (tonnage) to truck volume under the FAF program effort.)

Note that some VIUS axle configuration codes were not included in Table 5-1 due to lack of applicability or no available sampled data within the 2002 VIUS. For example, axle configuration code 36, which is defined as a "single-unit, two-axle, six-tire truck with 8 or more axles on three trailers" does not exist in the 2002 VIUS dataset. In addition, the axle configuration codes in the 2002 VIUS are not continuous (e.g., there are no 21–23 codes).

Table 5-1. Mapping VIUS axle configurations to FHWA's 13 vehicle classes.

FHWA vehicle class	2002 VIUS Axle configuration codes
5: 2-axle, 6-tire single units	2
6: 3-axle single units	3
7: 4+-axle single units	4, 5
8: 3/4-axle single trailer	6, 7, 9, 27
9: 5-axle single trailer	13, 15, 28, 30
10: 6+-axle single trailer	8, 11, 14, 16–20, 29, 31, 32
11: 4/5-axle multi trailer	37
12: 6-axle multi trailer	38, 41
13: 7+-axle multi trailer	39, 42–64

[12] S. M. Chin and H. L. Hwang, "Converting Freight Flow Information to Truck Volumes," Transportation Research Board 85th Annual Meeting, January 2006, available at: https://trid.trb.org/view/777552.

5.3 ADJUSTMENT OF VEHICLE CLASS DISTRIBUTION

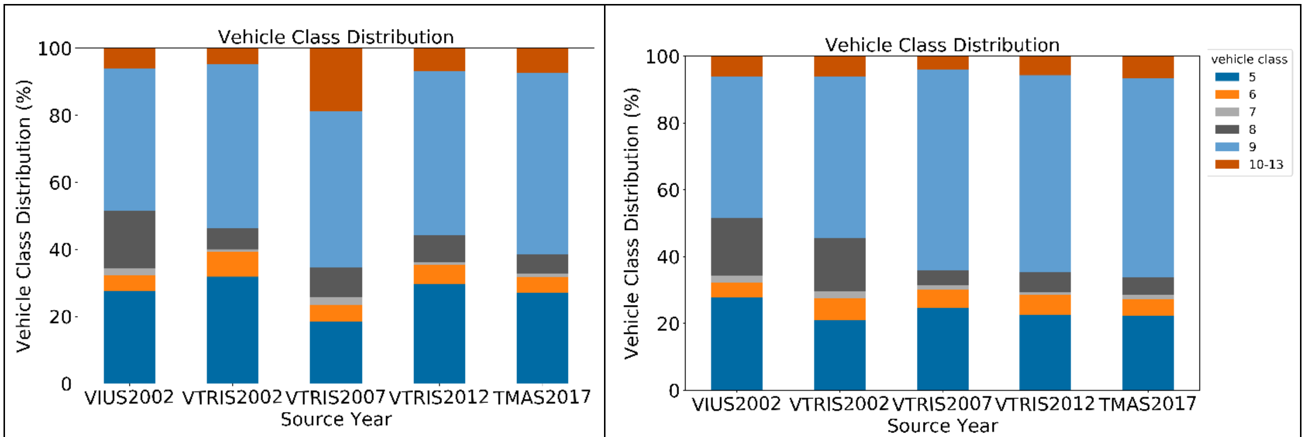
Traffic monitoring stations are not set up to collect samples statistically representing the entire truck population, although states are guided by the FHWA on how to select proper locations to set up sensors or traffic counting devices. To minimize the impact of this gap and examine general traffic patterns and characteristics among states, the truck volume in this study was adjusted using truck VMT obtained from the annual *Highway Statistics Data Series*[13].

$$Adjusted\ VMT_{sfv} = \ Highway\ Statistics\ VMT_{sf} \times \frac{Volume_{sfv}}{\sum Volume_{sfv}}$$

where,

$Volume_{sfv}$ is traffic counts observed in state s, functional class f (rural/urban), and vehicle class v.
VMT_{sf} is vehicle miles traveled for state s and rural/urban f from the *Highway Statistics Data Series*.
$Adjusted\ VMT_{sfv}$ is adjusted vehicle miles traveled for state s, functional class f (rural/urban), and vehicle class v.

Figure 5-1 shows the vehicle class distribution at the national level before and after the *Highway Statistics*–VMT adjustment. As seen in Figure 5-1, more consistent trends in the vehicle class distribution over the selected years are more visible after the adjustment. Based on the adjusted vehicle class distribution, the distribution of vehicle class 9 increased overall while the distribution of vehicle class 8 decreased.



(a) Before adjustment **(b) After adjustment**

Figure 5-1. Vehicle class distribution before and after adjustment by VMT.

[13] Highway Statistics Data Series, available at: https://www.fhwa.dot.gov/policyinformation/statistics.cfm

5.4 THE ESTIMATION PROCEDURE WITH GAUSSIAN MIXTURE MODEL

A methodology for using truck weight data to estimate truckload factors, developed by ORNL researchers[14] under an earlier study, was adapted for this current research. This method postulated that the truck gross operating weight distribution is composed of three normal weight distributions: (1) empty trucks; (2) partial truckloads or "loaded to size limit" trucks (e.g., a truck fully loaded with Styrofoam packaging material, full but nowhere near the weight limit); and (3) "loaded to weight limit" trucks.

The decomposition of truck weights by load types provided a statistically sound estimate of the percentage of empty trucks, which is a great concern for the freight transport industry and logistics/fleet management systems. Because trucks are the largest source of freight emissions and energy consumption, a better measure to quantify empty trucks is certainly critical for understanding associated energy losses.

By applying statistical modeling techniques, the changes and trends of truck weight distributions over time (i.e., between 2002 and more recent years), such as changes in percentage of empty trucks and average truck payload by vehicle class, can be identified. As mentioned, the goal of this exploratory research effort is aiming to develop trend factors or adjustments that could be applied to update 2002 VIUS variables that are correlated to truck volume and weights.

Figure 5-2 shows an example of applying the Gaussian mixture model to estimate empty truck percentage and average payload of class 9 vehicles at a given California station on I-15, based on 2017 TMAS data. The three decomposed Gaussian distributions clearly separate the unloaded trucks (i.e., those with the lowest mean of vehicle weight) from loaded trucks. This method can be used to estimate the percentage of empty trucks (30% in this case), as well as the average weight of empty trucks (~34,199 lb). The average payload of loaded trucks can be derived by simply subtracting the empty trucks' estimated average gross vehicle weights from the loaded trucks' average gross vehicle weights (i.e., the rest of two groups that have higher vehicle gross weights within the same vehicle class). In this example, the estimated average payload for the two loaded groups, excluding the empty trucks, is 28,207 lb.

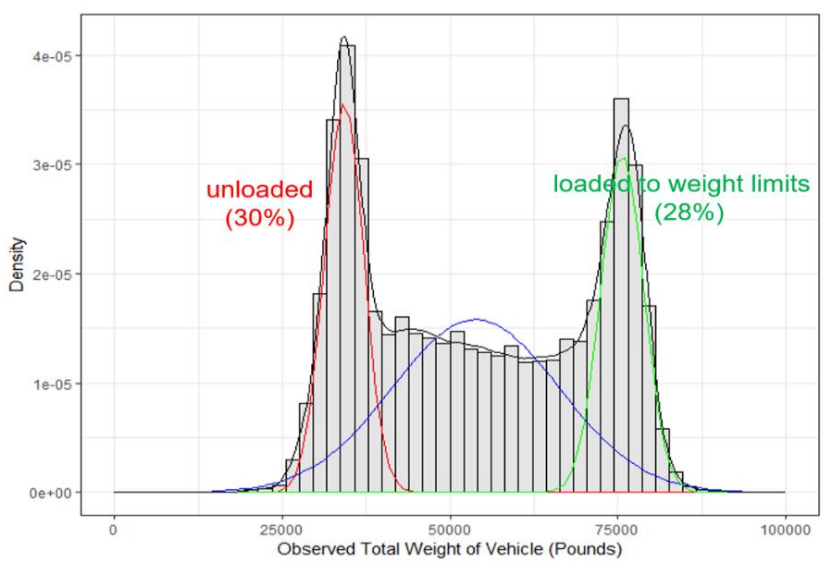


Figure 5-2. Example of mixed gross operating weight distributions for class 9 (WIM station in California).

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[14] S. M. Chin and H. L. Hwang, "Converting Freight Flow Information to Truck Volumes," Transportation Research Board 85th Annual Meeting, January 2006, available at: https://trid.trb.org/view/777552.

5.5 FINAL ADJUSTMENT AND COMPARISON OVER TIME

Again, this study aims to estimate trends or factors to calibrate statistics in the outdated VIUS data. Because no data are readily available for validation, the weight (tonnage) estimate (i.e., payload × volume by vehicle class) was compared to the FAF data at the state level, as shown in Figure 5-3. Note that this is a relative comparison to examine which data source has a higher correlation with weight information from the FAF; therefore, no measurement unit was displayed on the horizontal and vertical axes. By comparing the correlation of weight (tonnage) estimates from the two data sources (i.e., VIUS and VTRIS) with the FAF weight, it is concluded that the average payload and vehicle volume obtained from VIUS seemed to be better correlated with the FAF weight (i.e., closer to the diagonal line). Therefore, it is determined that the estimates based on the VTRIS and TMAS data need to be adjusted.

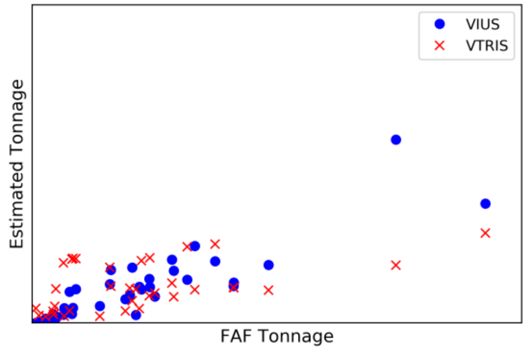

Figure 5-3. Comparison of estimated weight (tonnage) from VIUS and VTRIS to FAF in 2002.

Specifically, to overcome this gap and to realign the estimates produced using the TMAS/VTRIS data, further adjustment factors were derived by comparing estimated payloads from the 2002 VTRIS data and those of the 2002 VIUS statistics, by state and vehicle class. Then, these adjustment factors were applied to the VTRIS and TMAS estimates from subsequent years when VIUS data were not available.

Figure 5-4 shows the final (i.e., adjusted) estimates of average payloads by vehicle class at the national level over the study years. Note that the vertical bars (shown in gray) represent the average payload by vehicle class based on the 2002 VIUS data. The dotted lines illustrate the adjusted estimates of average payloads by vehicle class using VTRIS and TMAS data, for 2002, 2007, 2012, and 2017. Based on Figure 5-4, the average payloads for vehicle classes 6, 7, 12, and 13 have been decreasing over the last 15 years, while average payloads for vehicle classes 5, 8, 9, and 10 have been increasing. Unfortunately, no external data were readily available for validation of these estimated results.

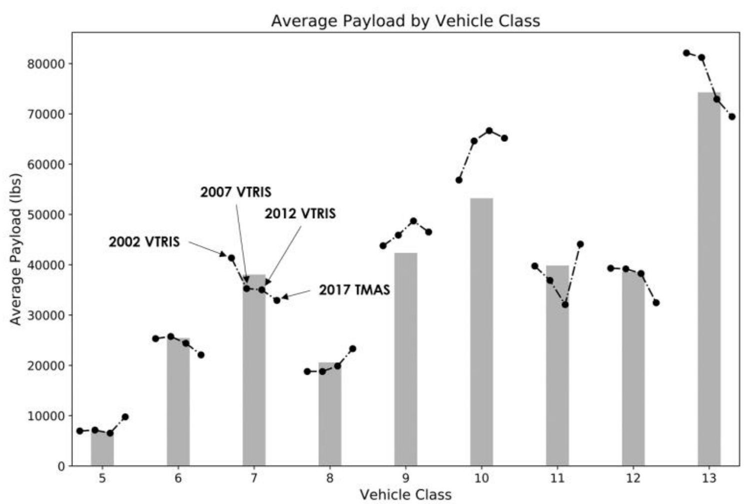

Figure 5-4. Adjusted average payload by vehicle class over selected years (2002–2017).

6. UTILIZATION OF FREIGHT DATA TO EXAMINE TRUCK ACTIVITIES

6.1 OVERVIEW OF FREIGHT FLOW DATA

This section describes how other publicly available freight data sources, specifically CFS and FAF, can potentially be applied to examine truck operation characteristics. Methodology and process for incorporating multiple freight data sources to update trends and distributions of other VIUS-based truck statistics. This excludes empty truck and average truck payload as described in Section 5. This process could be a critical step toward better understanding of truck activities because the obtainable information from a singular data source (e.g., TMAS, VTRIS) might be limited.

6.2 ITERATIVE PROPORTIONAL FITTING PROCEDURE

Iterative proportional fitting (IPF) is a procedure commonly used to iteratively estimate cell values of a contingency table (or matrix) with fixed or known marginal totals. The initial matrix with unadjusted cells at prior to iterations is referred to as the seed matrix. During each iteration, cell values are updated by the cell values from the previous step and their associated marginal totals, while the marginal totals remain fixed and the estimated table decomposes into an outer product.

This study applied the IPF procedure to update the pattern of statistics from the 2002 VIUS data, where the marginal totals are obtained from different datasets separately. For instance, the truck distance distribution and vehicle class distribution can be obtained from the CFS and the VTRIS and TMAS, respectively. As illustrated in Figure 6-1, the 2D distribution of vehicle class and distance group from the 2002 VIUS data were used as an initial seed matrix in this IPF procedure. During iterations, the seed matrix will be updated and eventually converged to the final estimates of distance distribution by vehicle class.

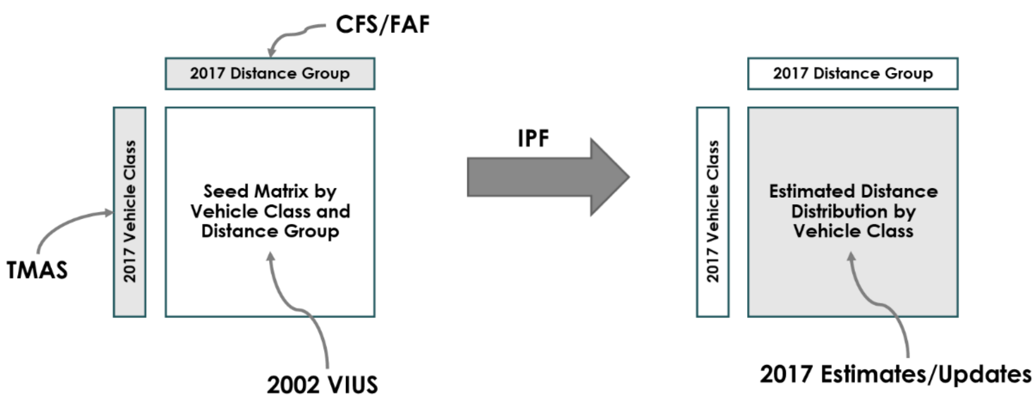

Figure 6-1. Example of iterative proportional fitting for calibrating distributions in VIUS.

6.3 EXAMPLES OF APPLICATIONS

6.3.1 Distance Distribution by Vehicle Class

The distance distribution by vehicle class, or commodity type, is one of the most important statistics for understanding vehicle operation characteristics. For truck operations, long-haul and short-haul trucks have different impacts and present different challenges to the overall performance of freight transportation networks, as well as energy and smart mobility. Currently, no single dataset provides information to estimate distance distribution by vehicle class. Therefore, it is necessary to combine information from multiple data sources and identify patterns that could be applied to update the distance distribution statistics produced from the 2002 VIUS data.

As stated earlier, distance distributions can be obtained from CFS data and distributions on vehicle classes can be derived using the VTRIS and TMAS data. With these distributions, the IPF procedure described in Section 6.2 can be applied to update the distance distribution by vehicle class generated from the 2002 VIUS data (see Figure 6-1) while confirming that the marginal totals are met. This example analysis was provided just for illustrating one of the applications of updating distributions with the IPF procedure. Therefore, some processes were simplified at the national level in this exploratory study.

Table 6-1 summarizes the national-level distance distribution by vehicle class based on 2002 VIUS (rows labeled "VIUS") and the 2002/2012 estimates based on VTRIS and CFS (rows labeled "Estimate"). The distance distribution of VIUS is based on the primary range of operation reported by respondents of VIUS, where the distance ranges are defined as: less than 50 miles, 51 to 100 miles, 101 to 200 miles, 201 to 500 miles, 501 miles or more. Note that trucks operated primarily "off-the-road" were excluded from the analysis. For the vehicle class in VIUS, the axle configurations were used to assign VIUS records to the FHWA 13 vehicle classes, as discussed in Section 5.2.

Table 6-1. Distance distribution by vehicle class in 2002 and 2012.

Vehicle Class	Source	Year	< 50 miles	51-100 miles	101-200 miles	201 - 500 miles	> 500 miles
5	VIUS	2002	80%	14%	3%	2%	1%
	Estimate	2002	88%	8%	3%	1%	1%
		2012	88%	8%	2%	1%	1%
6	VIUS	2002	82%	14%	3%	1%	1%
	Estimate	2002	89%	7%	3%	0%	0%
		2012	89%	8%	2%	1%	0%
7	VIUS	2002	83%	14%	1%	1%	1%
	Estimate	2002	91%	7%	1%	0%	0%
		2012	90%	8%	1%	0%	0%
8	VIUS	2002	61%	17%	8%	7%	8%
	Estimate	2002	74%	10%	9%	3%	4%
		2012	75%	11%	6%	4%	4%
9	VIUS	2002	29%	17%	12%	17%	24%
	Estimate	2002	45%	13%	17%	11%	14%
		2012	46%	14%	12%	14%	13%
10	VIUS	2002	50%	25%	12%	6%	6%
	Estimate	2002	64%	16%	14%	3%	3%
		2012	66%	17%	11%	4%	3%
11	VIUS	2002	28%	13%	28%	24%	7%
	Estimate	2002	39%	9%	35%	14%	3%
		2012	41%	10%	27%	19%	3%
12	VIUS	2002	16%	12%	24%	32%	16%
	Estimate	2002	26%	9%	35%	22%	9%
		2012	27%	10%	26%	28%	9%
13	VIUS	2002	28%	25%	20%	17%	11%
	Estimate	2002	40%	18%	26%	10%	6%
		2012	42%	20%	20%	13%	6%

Overall, the MD and HD trucks with higher vehicle classes (i.e., 9–13) seem to show more long-distance operations than other vehicle classes. Specifically, the proportion of "over 500 miles" for vehicle class 9 (i.e., five-axle tractor, semitrailer) is the highest among all vehicle classes considered. For vehicle classes 5–7, the proportion of <50 miles traveled was over 80% based on the VIUS and estimates from VTRIS and CFS. It also appears that the shares of local shipments (within 50 miles) tend to be higher for the estimates generated from the VTRIS and CFS, as compared to those from VIUS data, in all vehicle classes. The estimated distance distributions by vehicle class generated from the VTRIS and CFS data are relatively similar in 2002 and 2012, compared to those from the VIUS data.

6.3.2 Distance Distribution by Commodity and Truck Operation Type

In the 2002 VIUS data, truck travel distance information is also provided by the principle product type that the vehicle carried (i.e., *PRODUCT_PRINCPL* variable). Because these product types do not exactly match the standard classification of transported goods (SCTG) used in the CFS data, a lookup table (Table 6-2) was created to link the VIUS product types into nine SCTG groups. Note that certain product types in VIUS (46–mail and courier parcels; 47–empty shipping containers; 48–passengers; 50–multiple categories; 99–products, equipment, and materials not elsewhere classified) are not directly associated with the SCTG groups (1G–9G); for simplicity, they were excluded from this analysis.

Unlike other VIUS-based statistics that require multiple steps to estimate the numbers, distance distribution by commodity type can be directly obtained from published CFS tables and the CFS PUM for 2012.

Table 6-2. Mapping VIUS product types to SCTG groups.

SCTG group	Product type (*PRODUCT_PRINCPL*) in 2002 VIUS
1G–Agricultural products and fish	1–Live animals and fish, 2–Animal feed or products of animal origin, 3–Cereal grains, 4–All other agricultural products, 11–Meat, seafood, and their preparations
2G–Grains, alcohol, and tobacco products	9–Alcoholic beverages, 10–Bakery and milled grain products, 12–Tobacco products, 13–All other prepared foodstuffs
3G–Stones, nonmetallic minerals, and metallic ores	34–Gravel or crushed stone, 35–Metallic ores and concentrates, 36–Monumental or building stone, 37–Natural sands, 38–All other nonmetallic minerals
4G–Coal and petroleum products	32–Coal, 33–Crude petroleum, 39–Fuel oils, 40–Gasoline and aviation turbine fuel, 42–All other coal and refined petroleum products
5G–Basic chemicals, chemical, and pharmaceutical products	5–Basic chemicals, 6–Fertilizers and fertilizer materials, 7–Pharmaceutical products, 8–All other chemical products and preparations, 41–Plastics and rubber
6G–Logs, wood products, and textile and leather	14–Logs and other wood in the rough, 15–Paper or paperboard articles, 16–Printed products, 17–Pulp, newsprint, paper, or paperboard, 18–Wood products, 29–Textile, leather, and related articles
7G–Base metal and machinery	19–Articles of base metal, 20–Base metal in primary or semi-finished forms, 21–Nonmetallic mineral products, 22–Non-powered tools, 23–Powered tools, 26–Machinery
8G–Electronic, motorized vehicles, and precision instruments	24–Electronic and other electrical equipment, 28–Precision instruments and apparatus, 30–Vehicles, including parts, 31–All other transportation equipment
9G–Furniture, mixed freight and misc. manufacture products	25–Furniture, mattresses, lamps, etc., 27–Miscellaneous manufactured products, 43–Hazardous waste, 44–All other waste and scrap, 45–Recyclable products, 49–Mixed freight (for-hire carriers only)

In the example given in Figure 6-2 and Table 6-3, the distance distribution is further broken down by commodity and truck operation type (i.e., for-hire or private). Figure 6-2 shows the distance distribution by operation type for SCTG21 (i.e., pharmaceutical products) based on 2012 CFS data. While 60% of pharmaceutical products by weight (tonnage) are shipped by for-hire trucks, private trucks account for ~40%. Among the for-hire trucks shipping pharmaceutical products, ~64% of the total weight (tonnage) (based on 38% of the total 60%) was transported >200 miles, whereas the majority (21% of the total 40% = 53%) of pharmaceutical products, by tonnage, transported by private trucks are short-distance shipments (i.e., within 50-mile radius). This is consistent with the national-level distance distributions presented in Figure 3-7 and Figure 3-8, which show that private trucks mostly operated in local and regional markets while majority of long hauls are completed by for-hire trucks.

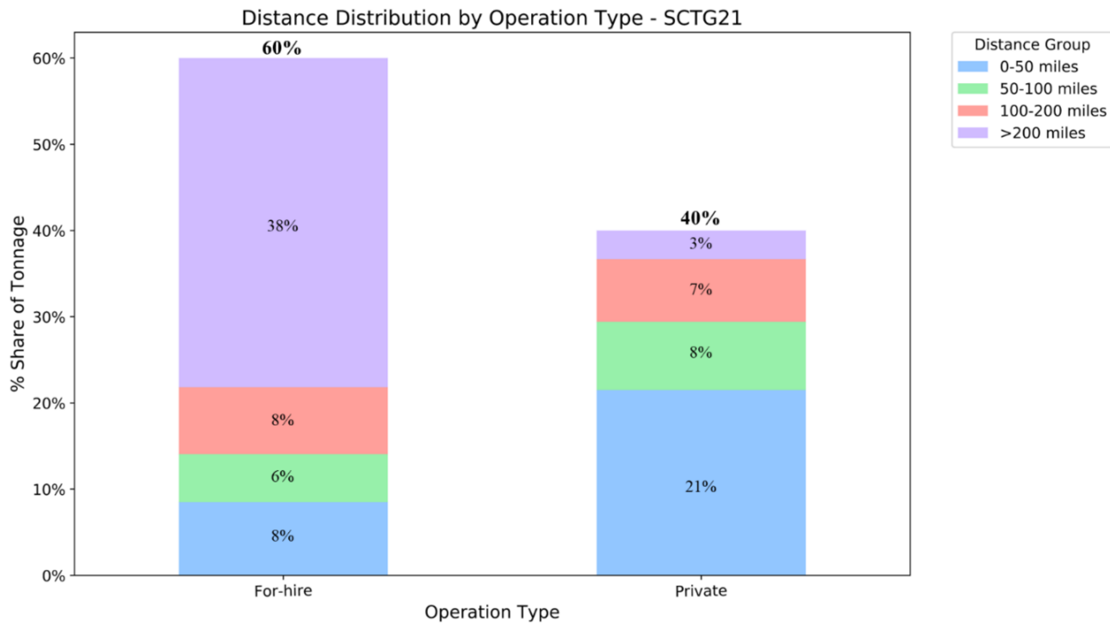

Figure 6-2. Distance distribution by commodity and truck operation type for SCTG21.

A complete set of distance distribution by commodity, for all commodity types, and by truck operation type at the national level is provided in Table 6-3. Note that SCTG16 (i.e., crude petroleum) is not included in the CFS sampling frame; therefore, SCTG16 is excluded from Table 6-3. In addition, no commodity was defined under SCTG42.

Table 6-3. Distance distribution by commodity and operation type in 2012 CFS.

SCTG	% Share of for-hire	For-hire				Private			
		<50 miles	51–100 miles	101–200 miles	>200 miles	<50 miles	51–100 miles	101–200 miles	>200 miles
1	83%	9%	8%	6%	77%	13%	12%	66%	9%
2	64%	53%	20%	15%	11%	81%	13%	5%	1%
3	55%	29%	21%	11%	39%	60%	19%	14%	7%
4	51%	40%	15%	13%	32%	64%	16%	11%	8%
5	66%	10%	6%	9%	76%	51%	15%	18%	16%
6	62%	22%	9%	11%	59%	56%	14%	14%	16%
7	51%	17%	10%	16%	57%	64%	14%	13%	10%
8	41%	15%	9%	15%	60%	85%	9%	4%	1%
9	75%	69%	0%	1%	30%	52%	16%	16%	16%
10	54%	51%	7%	11%	31%	73%	10%	9%	8%
11	49%	65%	23%	7%	6%	85%	9%	3%	3%
12	45%	84%	11%	4%	1%	90%	6%	3%	1%
13	53%	50%	12%	10%	27%	80%	7%	8%	5%
14	84%	8%	9%	24%	58%	36%	4%	57%	3%
15	55%	65%	20%	7%	8%	83%	14%	2%	0%
17	70%	84%	10%	4%	2%	77%	13%	7%	3%
18	45%	77%	11%	8%	4%	79%	11%	5%	5%
19	57%	54%	9%	11%	27%	67%	12%	13%	8%
20	47%	25%	9%	12%	54%	49%	22%	17%	11%
21	60%	14%	9%	13%	64%	54%	20%	18%	8%
22	38%	28%	15%	15%	42%	64%	19%	10%	8%
23	66%	21%	5%	11%	63%	49%	18%	16%	18%
24	74%	17%	6%	9%	68%	49%	19%	16%	16%
25	53%	47%	32%	12%	9%	54%	21%	11%	14%
26	60%	24%	22%	18%	36%	51%	20%	19%	9%
27	78%	15%	7%	9%	69%	60%	14%	13%	13%
28	73%	25%	11%	15%	49%	58%	17%	16%	9%
29	69%	25%	5%	12%	58%	81%	7%	6%	6%
30	70%	11%	6%	8%	75%	58%	12%	10%	20%
31	34%	40%	14%	15%	31%	85%	7%	5%	2%
32	73%	21%	10%	15%	54%	47%	19%	19%	15%
33	69%	19%	7%	12%	62%	53%	17%	16%	14%
34	73%	25%	5%	7%	63%	65%	13%	9%	12%
35	71%	20%	3%	6%	71%	63%	12%	14%	12%
36	76%	20%	10%	9%	61%	55%	14%	11%	19%
37	91%	23%	4%	6%	66%	39%	18%	18%	25%
38	82%	10%	3%	8%	79%	68%	10%	14%	8%
39	66%	10%	4%	7%	78%	40%	17%	18%	25%
40	54%	11%	6%	12%	71%	74%	10%	9%	7%
41	63%	44%	10%	12%	34%	55%	19%	16%	10%
43	35%	17%	16%	21%	47%	40%	21%	24%	15%

7. CONCLUSIONS

7.1 SUMMARYS AND LESSONS-LEARNED FROM THIS EXPLORATORY STUDY

The goal of this exploratory study was to investigate alternative data sources and develop methodologies to estimate trends and adjustment factors that could be applied to calibrate statistics generated from the outdated 2002 VIUS. The main focus of this study was on utilizing the FHWA's traffic data (i.e., VTRIS and TMAS), along with other supplemental freight data (i.e., FAF and CFS), to examine changes in truck volumes and truck weight distributions over time. Ultimately, this effort seeks to develop certain adjustments/factors that could be used to realign perspective VIUS data.

Unfortunately, as pointed out previously in this technical memorandum, there are no readily available data sources that could be used to explicitly validate the estimated results from this study. This study compared the estimated distributions from the 2002 VTRIS to the 2002 VIUS data to establish linkages between the two datasets. With distributions and patterns generated based on VTRIS and TMAS data series for additional years, trend factors were then estimated and applied to "update" VIUS-based information.

This study resulted in three key highlights:

- Updated estimates on truck volume and truck VMT can be utilized to better estimate on energy uses by truck.
- Vehicle class distribution, percent/share of empty trucks, and average truck payload could be updated by utilizing more current annual data series such as VTRIS and TMAS.
- Additional information could be estimated (e.g., distance distribution by operational type) by integrating other data sources, such as CFS and FAF, instead of relying on the 2002 VIUS data.

7.2 CHALLENGES AND FUTURE STUDIES

Several challenges and limitations remain after this exploratory study, along with some areas of potential future research and improvements. A few key questions directly related to this study are:

1. Are there any external data sources that could be used to validate the estimated results?
2. What is the best way to classify vehicle types?
3. How should the data coverage issue resulting from limited WIM data collection stations be addressed?

For example, on the vehicle type, instead of the FHWA 13 vehicle classes used in this study, the body types variable (*BODYTYPE*) in the VIUS data might potentially be examined to establish associations between the truck's body type and the primary commodity it carried. Furthermore, the TMAS and VTRIS data alone, if not integrated with other data, do not directly provide estimates for energy consumption or emission information needed to address the main concerns of DOE's mobility studies. Nevertheless, analysts from other federal and regional agencies might be able to use the findings (e.g., trend factors) from this study in their own freight/truck emission models.

The methodologies examined in this study are mainly based on statistical modeling such as Gaussian mixture model and IPF. It might be useful to consider other methodologies and analytical techniques in future studies of this kind to improve performance. These could include regression-based trend analysis, truck body classification using WIM and inductive signature technologies, compressive sampling (or compressed sensing) for reconstructing distribution of vehicle types or commodity shipments, classification algorithms, and machine learning (e.g., decision tree, boosted tree, random forest, neural network).

Many other studies have examined truck operation characteristics, although the scope and the level of detail vary by study. The following major studies could be incorporated for supplemental information):

- Studies conducted by ATRI
  - "An Analysis of the Operational Costs of Trucking: 2018 Update," http://atri-online.org/wp-content/uploads/2018/10/ATRI-Operational-Costs-of-Trucking-2018.pdf.
  - "An Analysis of the Operational Costs of Trucking: 2017 Update," http://atri-online.org/wp-content/uploads/2017/10/ATRI-Operational-Costs-of-Trucking-2017-10-2017.pdf.
  - "A Survey of Fuel Economy and Fuel Usage by Heavy-Duty Truck Fleets" (with University of Michigan in 2016), http://atri-online.org/wp-content/uploads/2016/10/2016.ATRI-UMTRI.FuelEconomyReport.Final_.pdf.

- Reports and information published in the *Highway Statistics Data Series*[15]
  - Specifically, changes, and trends over time regarding truck registration statistics and distributions of vehicle types relevant to this study (particularly since 2002) (e.g., share and growth of MD/HD vehicles).

- Further investigation on the uses of CFS and FAF information to supplement this current study, such as freight flow trends; other transportation modes for freight movements; trade type (i.e., domestic, imports, exports); correlation to FHWA truck data; utilization of CFS and FAF commodity-specific information

- Other data sources
  - National Performance Management Research Data Set.
  - Electronic Logging Device data.
  - California VIUS study for benchmarking and validation.
  - Other mobility data from private vendors, such as Streetlight, IHS/Polk, INRIX, HERE.

[15] *Highway Statistics Data Series*, available at: https://www.fhwa.dot.gov/policyinformation/statistics.cfm.