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California Statewide Commodity-based Truck Activity and Population Forecast and the Transition Towards Zero Emissions

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California Statewide Commodity-based Truck Activity and Population Forecast and the Transition Towards Zero Emissions

THESIS

submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Civil Engineering

by

Esmaeil (Sina) Dabbagh

Thesis Committee:
Professor Stephen G. Ritchie, Chair
Professor Michael McNally
Professor Amelia C. Regan

2022

DEDICATION

To

my mom

for her patience, and support

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ABSTRACT OF THE THESIS

California Statewide Commodity-based Truck Activity and Population Forecast

by

Esmaeil (Sina) Dabbagh

Master of Science

in Civil Engineering

Professor Stephen G. Ritchie, Chair

University of California, Irvine, 2022

Statewide travel forecasting models are developed by state agencies for different purposes such as forecasting network congestion, fuel consumption and air pollution. But in the end, they model the same travel activity from different procedures. Among those models and surveys, the California Statewide Freight Forecasting and Travel Demand Model (CSF2TDM), California Vehicle Inventory and Use Survey (CA-VIUS) from the California Department of Transportation (Caltrans), and the Emission Factor (EMFAC) model from the California Air Resources Board (CARB), are the most well-known ones in California. This thesis compared these models based on results such as Vehicle Miles Traveled (VMT) and vehicle inventory for heavy duty class 8 trucks. In addition, it connected the commodity-based activity of CSF2TDM to the CA-VIUS class 8 truck inventory and forecasted this population for future years. CSF2TDM and CA-VIUS forecasted 17, 19 and 27 percent less class 8 trucks for 2030, 2040 and 2050 target years compared to the EMFAC model. This

difference is due to the different procedures and inputs these models have. EMFAC is good at capturing all truck activity while lacking detailed characteristics such as geographical resolution, while CSF2TDM provides a detailed profile of truck activity on the network with no truck inventory associated with truck activity. Moreover, new policies in California are raising questions about the infrastructure impact of zero emission vehicles and electrification of vehicles. The second part of this thesis investigated a framework for feasibility of electric class 8 trucks in California by analyzing the optimal locations of charging stations and their impact on grid infrastructure based on forecasted travel demand from CSF2TDM. The framework would determine the fraction of truck trips that are not feasible for electrification. Feasible trips would be analyzed under two scenarios: charge at origin and charge at destination. Charge at origin means truck gets charged for the trip at the origin and charge at destination means a truck is fully charged at the origin, makes the trip and then gets charged at the destination to get the battery full. Since the OD matrix is not symmetrical, there would be a difference in charging demand on the grid network under these two scenarios.

INTRODUCTION

California has multiple statewide transportation models used by various government agencies. The most popular models and surveys are the California Statewide Freight Forecasting and Travel Demand Model (CSF2TDM) by the California Department of Transportation (Caltrans), Emission Factor model (EMFAC) by the California Air Resources Board (CARB) and California Vehicle Inventory and Use Survey (CA-VIUS) from the California Department of Transportation (Caltrans). All these models forecast travel behavior of California residents and vehicles including passengers and freight. However, this thesis is focused on the freight activity aspect of these models. These models have adopted different approaches to forecast freight activity in California based on the agency's needs; for example, CEC needs forecasts of fuel consumption whereas CARB needs emissions and hence air pollution coming from freight activity. Although every agency models its own needs, there is an underlying need for consistency across the modeling of freight activity from these models. Some metrics such as Vehicle Miles Traveled (VMT) and truck population are outputs of these models for California in future years and in some cases, they are much different from each other. On the other hand, some of the above models have better resolution in some areas of the agency's interest while having less resolution in other areas. For example, EMFAC has higher resolution in truck population characteristics and less resolution about geographic resolution of freight activity. On the other hand, CSF2TDM has higher resolution about geographic activity but does not have the ability to model the truck population. This study compared metrics obtained from these models such as VMT and truck population, tracked down probable causes of differences and made connections between the results of the models to obtain a better resolution of geographic activity and truck population. This connection serves as a platform to add truck population estimation to the CSF2TDM which was out of the scope of the model at the time CSF2TDM was built. This study connected CSF2TDM commodity-based activity to the truck population to have a better understanding about each commodity group activity and how that can affect policies by government agencies.

The transition towards zero emission trucks has been an increasing priority among policy makers to mitigate the impacts of climate change and criteria pollutants. Feasibility studies of electric trucks, power demand and the charging station location problem are essential to be analyzed. Hence, the second part of this thesis describes the development of a location optimization for candidate charging stations in California for trucks, and introduced a framework for charging demand analysis based on truck trips modeled in CSF2TDM under two scenarios of charge, at the origin or destination.

Chapter1: Background

This chapter describes detailed information about statewide models and surveys: the Emission Factors model (EMFAC), California Statewide Freight Forecasting and Travel Demand Model (CSF2TDM) and the California Vehicle Inventory and Use Survey (CA-VIUS). Models and the survey have been compared based on their input, output and the procedure of modeling.

1.1 EMFAC

EMFAC is an emission model developed by the California Air Resources Board (CARB) for air quality and transportation planning purposes. The latest released version is EMFAC2021 and continues to use the heavy-duty new vehicle sales forecasting method adopted in EMFAC2014 and EMFAC2017 as shown in Figure 1 and Figure 2. [1]

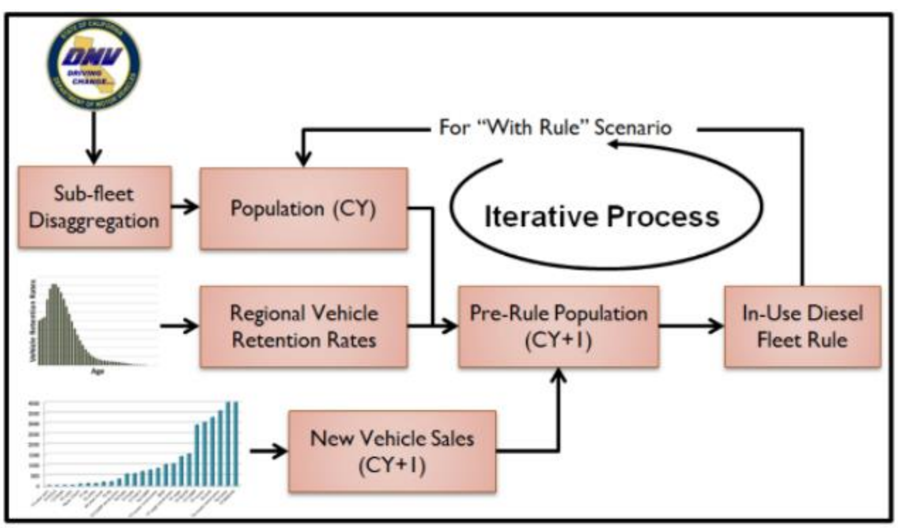

Figure 1 - Methodology to forecast HD (Heavy Duty) vehicle population [2]

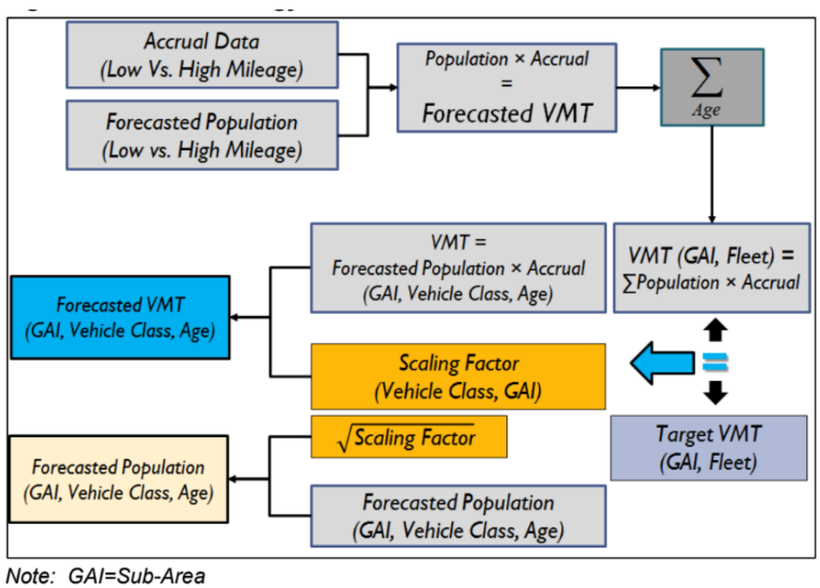

Figure 2- EMFAC Methodology to forecast HD vehicle VMT [2]

EMFAC uses national new vehicle sales and Vehicle Miles Traveled (VMT) growth based on Annual Energy Outlook (AEO) with California's VMT growth rates to calculate the number of vehicles. The AEO growth rates year-to-year forecast is as shown in Figure 3. [3]

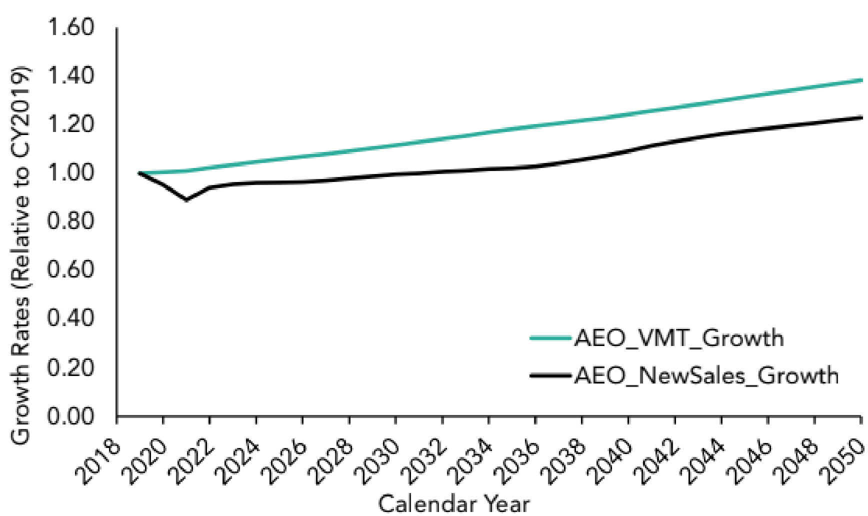

Figure 3- National heavy duty VMT and new sales growth trend reported by AEO [2]

Based on this model the California new sales growth rate and absolute new sales are calculated as shown below: [1]

California New Sales growth rate =

AEO New Sales Growth Rate × (California VMT Growth Rate / AEO National VMT Growth rate)

New Sales (Year, Vehicle type) =

New Sales (2019, Vehicle type) × California New Sales growth rate (Year)

EMFAC retention rates are obtained from historical DMV data (survival and migration). Total statewide VMT can be obtained by multiplying the vehicle population to the accrual rates. [2]

EMFAC2017 uses historical data on taxable diesel fuel sales to normalize the statewide HD VMT rates, so that fuel usage results would match actual fuel sales results. [2] For EMFAC2021, historical taxable diesel fuel sales continue to be used to normalize the statewide VMT rates, so fuel usage matches the actual historical fuel sales for 2000-2019. However, fuel sales data used to be obtained from the California Board of Equalization for EMFAC2017 but for EMFAC2021, this data resides with the California Department of Tax and Fee Administration. The annual diesel consumption is forecasted as shown below [1]:

Forecasted statewide annual diesel consumption (billions of gallons) = 1.353 + 1.140×State disposable personal income (trillions of 2015 dollars) - 0.0543× Statewide unemployment rate (percentage)

EMFAC2021 has improved the HD VMT forecasting method by using the California Statewide Travel Demand Model (CSTDM) VMT forecasting. County level VMT growth rates are extracted from the CSTDM and used to obtain these rates. Figure 4 shows these rates for heavy duty and medium duty trucks.

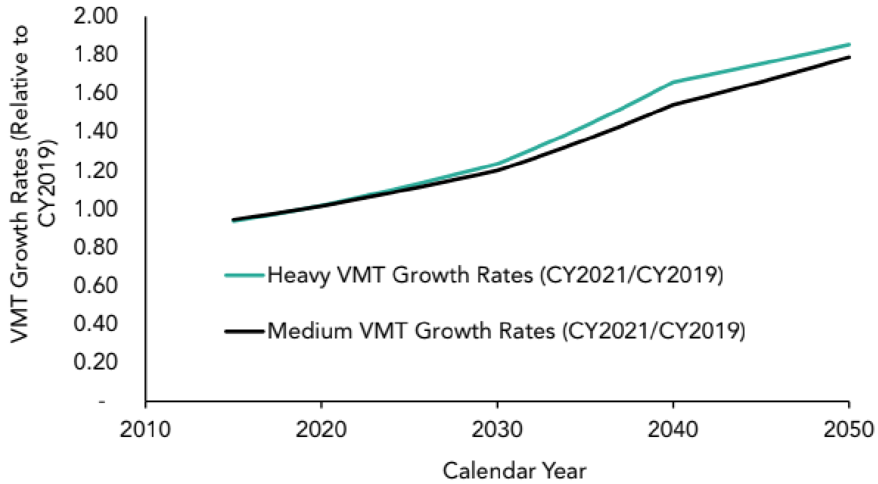

Figure 4- CSTDM HD VMT growth rates- Statewide [1]

Based on the above charts and equations, EMFAC calculates truck inventory and VMT based on new vehicle sales forecasts and California Department of Motor Vehicles (DMV) accrual rates, and then normalizes it to CSTDM VMT rates. There is no open-source model of EMFAC to explain more about this model at the time this study has been conducted.

1.2 CSF2TDM

The California Statewide Freight Forecasting and Travel Demand Model (CSF2TDM) represents the integration of the California Statewide Freight Forecasting Model (CSFFM) originally developed by the UCI Institute of Transportation Studies (ITS) for Caltrans in 2015 and the California Statewide Travel Demand Model (CSTDM). Personal trips from

CSTDM and commercial vehicle trips from CSFFM are combined in CSF2TDM and are assigned to the same network to capture congestion effects on the network. [4]

CSTDM is a multimodal, tour-based passenger travel demand model that can forecast all types of travel, including intrazonal, interzonal and external trips to other states. The model was developed to forecast all personal trips made by every California resident for modes including single occupancy vehicle (SOV), high occupancy vehicle 2 passengers (HOV2), high occupancy vehicle 3 or more passengers (HOV3+), transit, bike, walk and rail and air for only long-distance trips (more than 50 miles). It incorporates statewide networks for roads, rail, bus, and air travel. There are 5,474 Traffic Analysis Zones (TAZs) in California represented by this model. [4]

CSFFM is a freight forecasting model which produces production, attraction and distribution of freight commodities based on demographic and economic data of zones inside California and other states based on national Freight Analysis Framework (FAF3) data. This model has 97 Freight Analysis Zones (FAZs) in California that are defined at the county and sub-county level. [5] There are 38 import/export gateways (19 land ports, 8 airports, and 11 seaports), and 31 Transport logistics nodes - TLNs (13 airports and 18 rail terminals including five virtual rail terminals) inside of California. The model includes fifteen commodity groups (CGs) based on the aggregation of the two-digit Standard Classification of Transported Goods (SCTG) commodity classes used by FAF. [4]

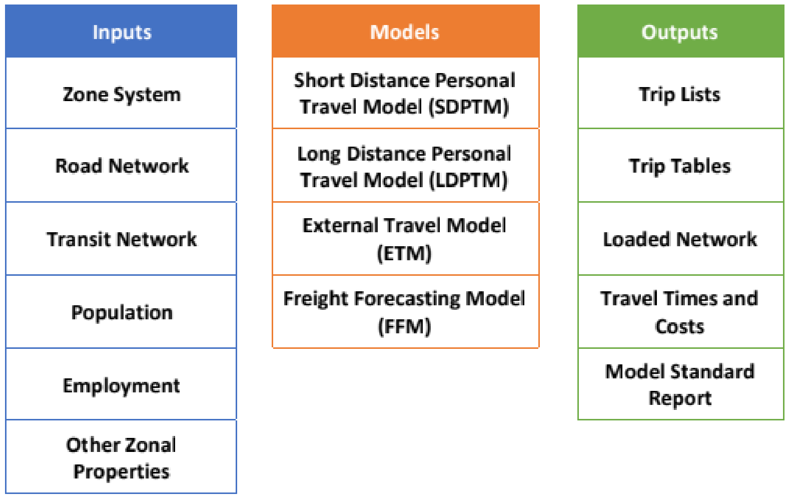

Figure 5- CSF2TDM Overview [4]

As shown on Figure 5 and Figure 6 CSFFM is a module in CSF2TDM and is based on FAF data which has commodity flows for road, rail, air, water and pipeline. CSFFM forecasts commodity flows based on tonnage and splits that to truck only, rail only, water, pipeline and multimodal. Air mode is a combination of air and road which has tonnage and trips in the model but there is no air network to assign them to. [6]

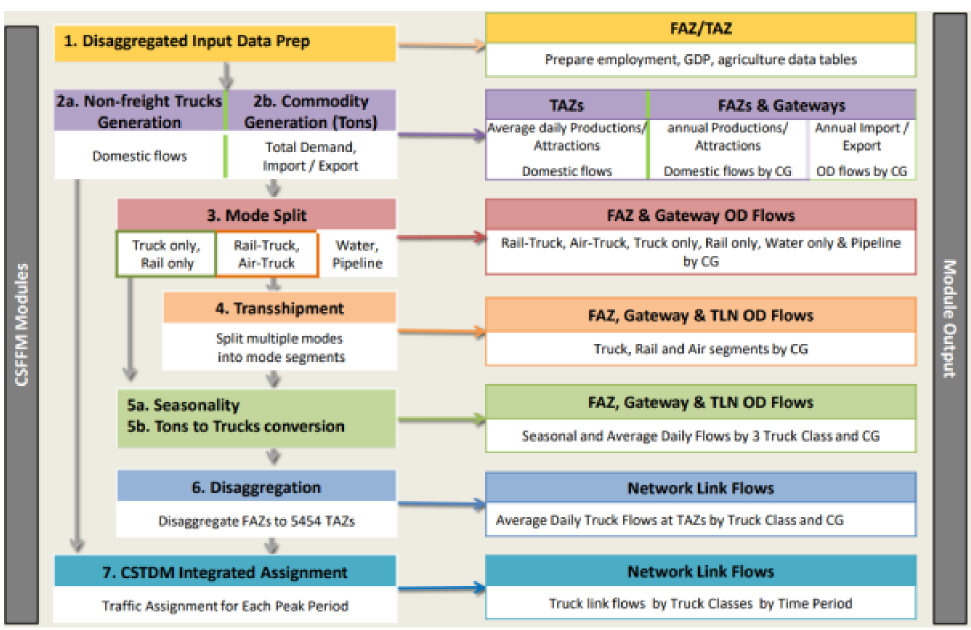

Figure 6- CSFFM Overview [6]

CSFFM generates production, attraction and distribution of commodities based on demographic and economic data of zones inside California as well as all other states in the US, together with network impedance information (i.e., travel time and cost) between these zones. These data include employment, establishment numbers, population, agriculture related variables such as farm acreages and tonnage of sold livestock, diesel fuel prices, energy-related data such as capacities of refineries, annual consumption and production of power plants and manufactured gross domestic product (MGDP). [6]

CSFFM 3.0 by Fehr & Peers is based on the version of CSFFM by UC Irvine with some updates as shown in Figure 7.

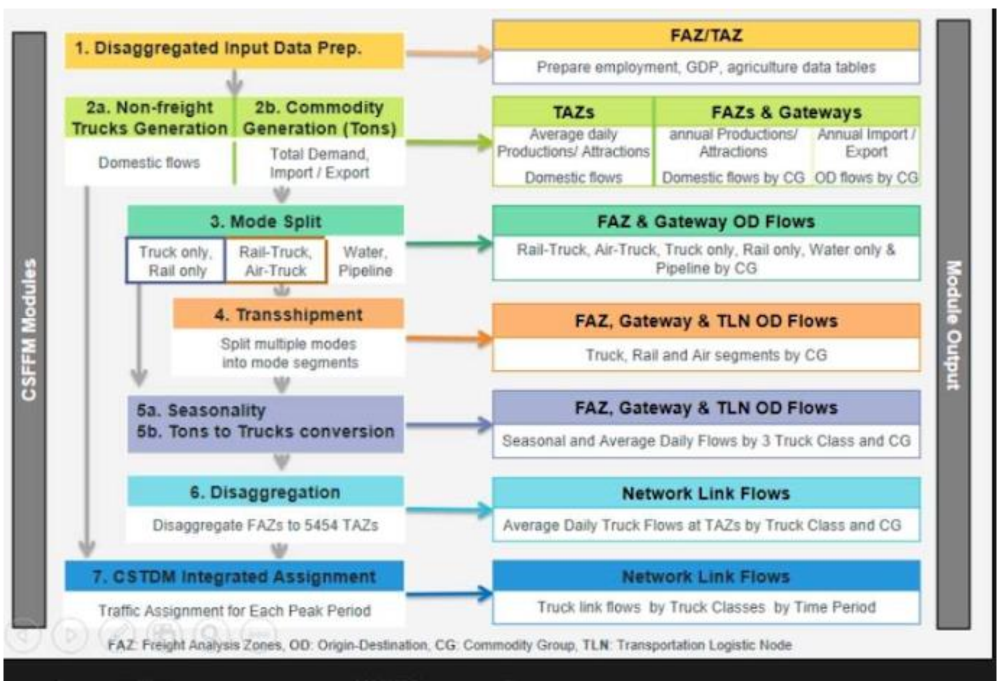

Figure 7- CSFFM 3.0 Overview [4]

The model comprises five core modules [4]:

1- The Commodity Module consists of total generation of commodities transported, domestic flow distribution, and import/export gateway distribution. As a result of these three steps, the module produces production, attraction and distribution of commodities transported based on demographic and economic data and network impedance information (i.e., travel time and cost) for freight and non-freight truck movements for 8500lb gross vehicle weight rating (GVWR) and above truck classes.
2- The Mode Split Module determines the mode-share for each mode (truck, rail and intermodal) in each origin-destination pair. Incremental logit models are used in this module to evaluate the impact of changes in mode attributes.
3- The Transshipment Module splits intermodal trips into segments by mode and assigns commodity flows to transport logistics nodes (TLNs).
4- The Seasonality and Payload Factor Module uses truck tonnage, multimodal information, and truck shares from transshipment to produce seasonal and annual flows by truck class and commodity group.
5- The Network Module consists of route choice and traffic assignment. This module uses multi- class assignment to assign trucks to the network and all-or-nothing rail assignment.

The non-freight module consists of any truck activity that is not captured by FAF database. These categories are as below:

- Empty trips: unavoidable, non-profit-generating long- and short-haul trips that reconcile imbalanced production and consumption patterns.
- Local delivery trips: short-haul trips made by small- or medium-sized trucks for the following trip purposes:

- Truck trips from distribution centers to local retail stores
- Truck trips between retail stores or business
- Mail delivery services to businesses and households: FedEx, UPS, USPS, Amazon

- Service trips: usually short-haul trips that might not deliver any shipments but may carry cargo or tools to provide services. These include various truck sizes and types, such as:
  - Municipal/waste collection trucks
  - Utility/street sweeping trucks
  - Construction/concrete trucks
  - Services: gardening, landscaping

CSFFM is based on a direct demand generation model. These models are meant to predict the "flow" of transported commodities directly based on demographic and economic parameters. Basic formulation of these models is as below:

$$T_{ij} = f(O_i).f(D_j).f(c_{ij})$$

where Tij is any transaction between region i and region j such as dollar value or tons of goods or number of people migrated; f(Oi) is a function based on parameters in the origin such as population or wage, f(Dj) is a function based on measures of attractiveness in destination such as number of jobs, and f(cij) shows relative accessibility or cost of flow or transaction between origin and destination. In the transportation literature, this model is known as a direct demand distribution model. The equation is rewritten in a log-linear form for ease of computation. These models work well for interregional settings with sparse OD pairs. [7]

CSFFM uses a multi-commodity direct demand model written in a structural equation modeling (SEM) framework. SEM is a flexible linear-in-parameters multivariate statistical modeling technique which can handle many endogenous, exogenous, and latent variables with inter-dependencies between each other. SEM can be used to capture inter-dependencies between flows of different commodity groups. [7]

Goods movements in CSFFM are based on Freight Analysis Framework (FAF3) data [5]. FAF3 is a public data source and provides tonnage of commodity flows between 123 FAF regions in the United States including Alaska and Hawaii. The zones are designed to separate metropolitan areas from the remainder of each state. In FAF3 there are 43 commodity groups based on 2-digit Standard Classification of Transported Goods (SCTG). In the model these were grouped into 15 groups based on the characteristics of industries, major mode for each group and trip length distribution.

The Structural Equations for the Multi-Commodity OD Distribution (SEMCOD) model based on simultaneous direct demand equations with structural relationships between dependent and independent variables of each mode. SEMCOD is a flexible model that integrates the generation and distribution steps in conventional four-step demand models. The general formulation of the model is [7]:

$$
\begin{aligned}
Ln\left(f_{ij}^{m}\right) = {} & \underbrace{\sum_{l} \beta_{l}^{m} Ln(X_{il})}_{\{\text{origin variables}\}} + \underbrace{\sum_{k} \gamma_{k}^{m} Ln\left(X_{jk}\right)}_{+\{\text{destination variables}\}} + \underbrace{\sum_{l}\sum_{k} \delta_{lk}^{m} Ln(X_{il}) \cdot Ln\left(X_{jk}\right)}_{+\{\text{interaction variables}\}} + \underbrace{\sum_{n \neq m} \gamma^{n} Ln\left(f_{ij}^{n}\right)}_{+\{\text{relationship with other commodities}\}} \\
& \underbrace{+ \lambda^{m} Ln(dist_{ij})}_{+\{\text{distance funciton}\}} \underbrace{+ \mu^{m} U_{ij}^{m}}_{+\{\text{utility function}\}} \underbrace{+ \varepsilon_{ij}^{m}}_{+\{\text{error term}\}}
\end{aligned}
$$

where f is the flow of commodity group m from zone i to zone j, X is the set of demo-economic attributes of the origin and destination zones i and j, "dist" is the distance between origin and destination, and U is a logsum of the generalized cost of transportation between the origin and destination for all available modes of transportation for every commodity group. For intra-zonal flows, dest is a measure of the size of the zone and U is a measure of the generalized cost of transportation in zone i. "dist" from a zone to itself is defined as the diameter of a circle with the same area of the respective zone for disaggregated FAZs.

The model does not assume independence between explanatory variables (indicators) and error terms. The estimation method depends on the input data and CSFFM uses Maximum Likelihood (ML) method which is the most widely used method. The R-squared of production and attraction models for all 15 commodity groups are between 0.639 and 0.952 and average R-squared is 0.825.

Import and export flows are not modeled explicitly, because it would require economics and international trade data that were not available to the modelers. The difference between total generation and marginals of the domestic distribution model for each commodity group is assumed to be equal to the total import/export flows of each zone [7].

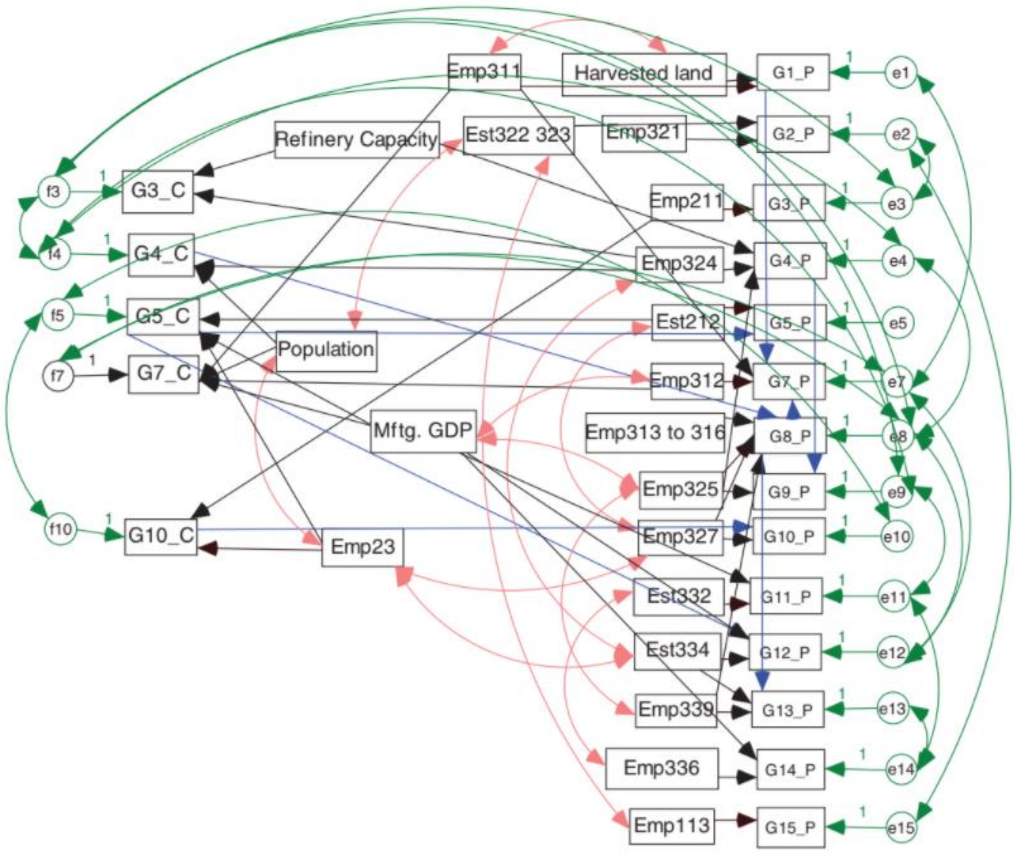

Figure 8- Simplified graph of CSFFM structural equation model [6]

In Figure 8 f and e are error terms, “emp” is employment, “est” is establishment, “mftg” is manufacturing, “GDP” is gross domestic product, “_P” and “_C” are production and consumption signs for different commodity groups. (Some consumption boxes are eliminated from the Figure 8 for ease of showing all dependencies). Root mean square error of approximation (RMSEA) is a common measure of how well the proposed model fits sample data; the lower it is, the better the fitness of the model. Models with RMSEA less than 0.08 show a good fit. The overall RMSEA in this model is 0.078. [7]

The structural commodity generation model is estimated using national Freight Analysis Framework (FAF3) data. The parameters of the model are estimated based on the base year observed OD flows from FAF3 for 2007 and forecasted for target years based on forecasted demographic and economic data for those years. Demographic and economic data are derived from multiple sources such as:

- Population projections produced by the Weldon Cooper Center (WCC) for Public Service (2012) at the University of Virginia
- County-level population projections produced by the Demographic Research Unit of the California Department of Finance (2013)
- County-level employment projections produced by the California Employment Development Department (2012)
- Diesel price forecasts produced by U.S Energy Information Administration (EIA)
- Monthly Gross Domestic Product (MGDP) forecasted by national GDP projections published by the Congressional Budget Office (2013)
- Harvested acreage and livestock sales variables forecasted by US Census of Agriculture and variables from USDA's Agricultural Baseline Projection Tables (2012)

Assignment of heavy-duty vehicle trips to the network is done along with passenger vehicle trips from CSTDM for taking the congestion effects (travel time and travel routes) into account. CSFFM was calibrated and validated using available truck count data at Weigh-In-Motion sites in California for the years 2007 and 2010, respectively. [7]

CSFFM 15 commodity groups and 4 truck classes are shown in Table 1 and Table 2. Assigned Standard Classification of Transported Goods (SCTG) to each commodity group is shown below as well.

Table 1- CSFFM commodity groups [6]

Commodity group	SCTG Codes
CG-1 Agriculture products	1-4
CG-2 Wood, printed products	26-29
CG-3 Crude petroleum	16
CG-4 Fuel and oil products	17,18,19
CG-5 Gravel/ sand and non-metallic minerals	10-13
CG-6 Coal / metallic minerals	14-15
CG-7 Food, beverage, tobacco products	5-9
CG-8 Manufactured products	24,30,39,40,42,43
CG-9 Chemical/ pharmaceutical products	20-23
CG-10 Nonmetal mineral products	31
CG-11 Metal manufactured products	32-34
CG-12 Waste material	41
CG-13 Electronics	35,38
CG-14 Transportation equipment	36-37
CG-15 Logs	25

Table 2- CSFFM Truck classes [6]

CSFFM truck class	US Truck class	Gross Vehicle Weight Rating
Class A	Class 2b,3	8,501–14,000 pounds
Class B	Class 4,5,6	14,001–26,000 pounds
Class C	Class 7	26,001–33,000 pounds
Class D	Class 8	33,001 pounds and above

1.3 CA-VIUS

CA-VIUS is an inventory survey for freight and service trucks conducted by Caltrans. It captures trucks class 3 (above 10,000 lb gross vehicle weight) and above in California.

This survey was conducted in 2017 for a total of around 14,000 in-state and out-of-state trucks and was expanded by weight classes and other specifications to match the total number of in-state trucks based on DMV registered trucks and out-of-state trucks based on the International Registration Plan (IRP) reporting [8] [9].

CA-VIUS is segmented by registration, geography, vehicle type, and vehicle age. The CA-VIUS is the largest statewide commercial vehicle survey in the United States, and replaces the 2002 National VIUS for transportation planning and emissions studies in California. [10]

CA-VIUS uses DMV data for in-state trucks and IRP data for out-of-state trucks expansion. Strata for in-state trucks are based on 4 geographical areas, two fleet sizes, and two gross weight categories, totaling 16 strata with minimum 51 trucks in a stratum. For out-of-state trucks, 2 geographical areas, two fleet sizes, two vehicle age categories and two vehicle type groups totaling 16 strata with minimum 2 trucks in a stratum are used.

This study aims to forecast truck population based on commodity groups for future years based on CSF2TDM. In order to do this forecast, the CA-VIUS survey in 2017 can be used as a snapshot of this connection since CA-VIUS has the same resolution of commodity-based activity along with truck population and other truck characteristics. This approach can be developed into a framework for future years.

Chapter2: Literature Review

The Emission Factors (EMFAC) model is the standalone model for heavy duty truck inventory in California and most of the studies and statewide reports are based on EMFAC results. Some studies that used EMFAC or other databases to do analysis on the heavy duty truck population in California are discussed below.

Lane [11] used EMFAC heavy duty truck inventory and categorized it into four groups as linehaul, waste management (refuse), drayage and construction in his study to model fuel pathway and powertrain optimization in California (linehaul trucks transport goods long distances; drayage trucks transport goods from ports to distribution centers; refuse trucks collect waste from various locations and transport it to processing centers or landfills; and construction trucks move construction material or assist in construction of buildings and other built structures.

Lane used the above four categories for the study by assigning EMFAC categories to those. That is a good effort to categorize truck activity patterns, but it is not enough detail to capture all heterogeneity of activity among different truck classes and commodity groups. Each commodity group has its own characteristics that needs to be modeled individually. For example, the activity of a truck hauling manufactured goods is completely different in type of origin and destination and fleet characteristics like age, than a truck hauling logs. This is covered in Chapter 3 in detail.

Miller et al. modeled California truck fleet transitioning with regards to California mandates for zero emission trucks. The study developed a choice model based on zero emission costs and types. This study used the EMFAC truck inventory and categorized them into 8 groups: long haul, short haul, heavy-duty vocational, medium-duty vocational, medium-duty urban, urban bus, other bus and heavy-duty pickups & vans. [12]

Miller et al. defined more detailed truck categories for urban truck activity compared to Lane's study but fewer categories for suburban truck activity and long-haul trucks. His study aimed to categorize trucks into commodity groups to capture most of the heterogeneity among those groups.

Hevi-pro is a model for medium and heavy-duty electric vehicle infrastructure projections in California, by the Lawrence Berkeley National Laboratory. Hevi-pro is supposed to project infrastructure needs for decarbonizing the above vehicles. Hevi-pro development is still ongoing and categorizes trucks into different groups based on the EMFAC truck inventory as shown in Table 3. [13]

Table 3- Hevi-pro truck groups and charging behavior

Vehicle use pattern	Region	Vehicle application and type	Charging		
			Behavior	Accessibility	Technical design
Fixed route, fixed time, return-to-base	Urban	(1) Transit bus (2) School bus (3) Refuse truck	Overnight slow charging	Private (i.e. dedicated)	Slow-charging, lower charging power
Fixed route	Urban	(4) Port drayage trucks	Between trips	Public/Private (Shared/dedicated)	Fast-charging, high charging power Opportunities to co-support several types of LDV/MHDVs
Non-fixed route	Urban	(5) Last mile delivery (e.g. package delivery trucks) (6) Local-haul trucks (merchandise) (7) Regional-haul trucks (8) Vocational vehicles (e.g. emergency vans/trucks, construction trucks)			
	Rural area	(9) "Rural trucks" (e.g. farm trucks)	Before, during, or after trips.	Public/Private (Shared/dedicated)	Heavy-duty accessible, very high charging power (e.g. 1 MW)
	Inter-county	(10) Heavy-duty local-haul trucks		Public (shared)	
	Highways	(11) Heavy-duty long-haul trucks			

As seen in the above table, 11 groups of trucks in EMFAC are categorized into three vehicle pattern use groups, six activity region groups and other charging behavior groups.

This categorization of trucks is more detailed than the other sources mentioned above but still there are some other characteristics of trucks like payload rate that affects electrification and is missing in Hevi-pro due to lack of this data in EMFAC.

Based on the literature, there is no effort of truck population forecasting based on commodity groups to capture commodity specific characteristics such as age, annual mileage, range of activity and region of activity.

All the above studies are based on the EMFAC model fleet inventory which is a hybrid model of supply and demand with focus on the supply side and less resolution on geographical analysis compared to CSF2TDM. On the other hand, CSF2TDM is purely based on a demand side approach and forecasts the truck activity demand based on socio-economic parameters. That means CSF2TDM forecasts travel demand regardless of vehicles that serve those trips. It also has better geographical resolution and with connection to California Vehicle and Use Survey (CA-VIUS) can forecast detailed truck inventory based on commodity groups that has valuable information like payload factors for other analyses like electrification in future.

Chapter3: Truck population analysis

This study aims to connect commodity-based heavy duty truck travel forecasts from the California Statewide Freight Forecasting Travel Demand Model (CSF2TDM) to truck population based on the California Vehicle Inventory and Use Survey (CA-VIUS) snapshot in 2017. This integration was intended to add truck population estimation to the CSF2TDM which was not inherently developed as a population-based model. This effort facilitates a better understanding about each commodity group activity and its associated population and can provide guidance to developing a portfolio of effective policies that strive towards zero emission by targeting segments in the truck population that will achieve the highest emissions improvements.

Two main approaches were considered for connecting truck activity with truck population: a tour-based and a VMT-based (Vehicle Miles Traveled) approach. In the tour-based approach, individual trips are grouped into tours and tours are subsequently assigned to truck population or vice versa. In this approach the tour making process and considerations for empty truck trips are essential parts of the analysis. After tours are made, there will be a list of tours and an inventory of trucks. Each of those tours can be assigned to the specific truck based on location, truck specification and time depending on how tours are made in terms of tour cycle, whether it is a day-long tour or week-long etc. In the VMT-based approach, the base year truck population seed would get adjusted based on the VMT rates for future years. The truck population seed is the base year population of trucks. In this approach truck inventory for the base year and VMT numbers for the base year as well as future years must be available. VMT numbers are the total VMT forecasted for all trips on the network. Annual or daily VMT per vehicle should be defined as fixed or variable for future years in this approach. This study applied the VMT-based approach based on the CA-VIUS truck population seed and VMT numbers obtained from the California Statewide Freight Forecasting Model (CSFFM), which is the freight module of CSF2TDM.

3.1 Model Comparison

The CSFFM within CSF2TDM is a standalone modeling framework designed to forecast California state freight and non-freight truck detailed activity at a disaggregated geographic resolution. However, it does not model the truck population inventory associated with these activities. On the other hand, EMFAC estimates truck population and activity at a more aggregate geographic resolution but does not model detailed activity patterns such as commodity type or trip origin destination details. The Department of Motor Vehicles (DMV) and CA-VIUS provide snapshots of fleet inventory across different years with no forecast. Table 4 provides a summary of fundamental differences between these models and inventory databases.

Table 4- California State freight forecasting models and data sources comparison

	Truck Inventory	*VMT forecast*	*Trip forecast*	*Vocation vehicles*	*Supply / Demand*
DMV	✓	Current (based on accrual rates)	N/A	✓	Supply
EMFAC	✓	✓	✓ (Number of trips)	✓	Supply/Demand

CA-VIUS	✓ Current only Fleet-based Industry-based	Current only (Split between loaded and empty)	N/A	Service vehicles	Supply
CSFFM/ CSF2TDM	N/A	✓ Commodity-based	✓	Non-freight	Demand

As seen in the above table, CSF2TDM is the only demand-based model for truck activity in California but has no connection to truck inventory (supply). The missing connection between truck activity in CSFFM and truck population could be made by CA-VIUS survey. Hence, this study attempted to connect the finer activity resolution (geographic and activity details) of CSF2TDM to truck population in order to better understand heterogeneity of truck activity by commodity groups and how they can affect policy questions.

For connecting CSF2TDM to CA-VIUS, each dataset and their scope of work is analyzed first. CSF2TDM has two modules for forecasting truck activity: freight module and non-freight module. The freight module forecasts all trips based on FAF data [5]. And the non-freight module forecasts all other truck activity which is not captured in the freight module. On the other hand, CA-VIUS and EMFAC have another way of categorizing truck activity into freight trucks and service trucks. As seen in Figure 9, the non-freight module comprises three trip types: freight empty trips, non-FAF freight trips (freight trips that are not in FAF database) and non-freight trips including service trips. This presents a challenge to match all activity from CSF2TDM to CA-VIUS or EMFAC as the non-freight module possesses some freight activity in it. This study assumes the freight activity in non-freight module is negligible compared to FAF freight activity and ignores that.

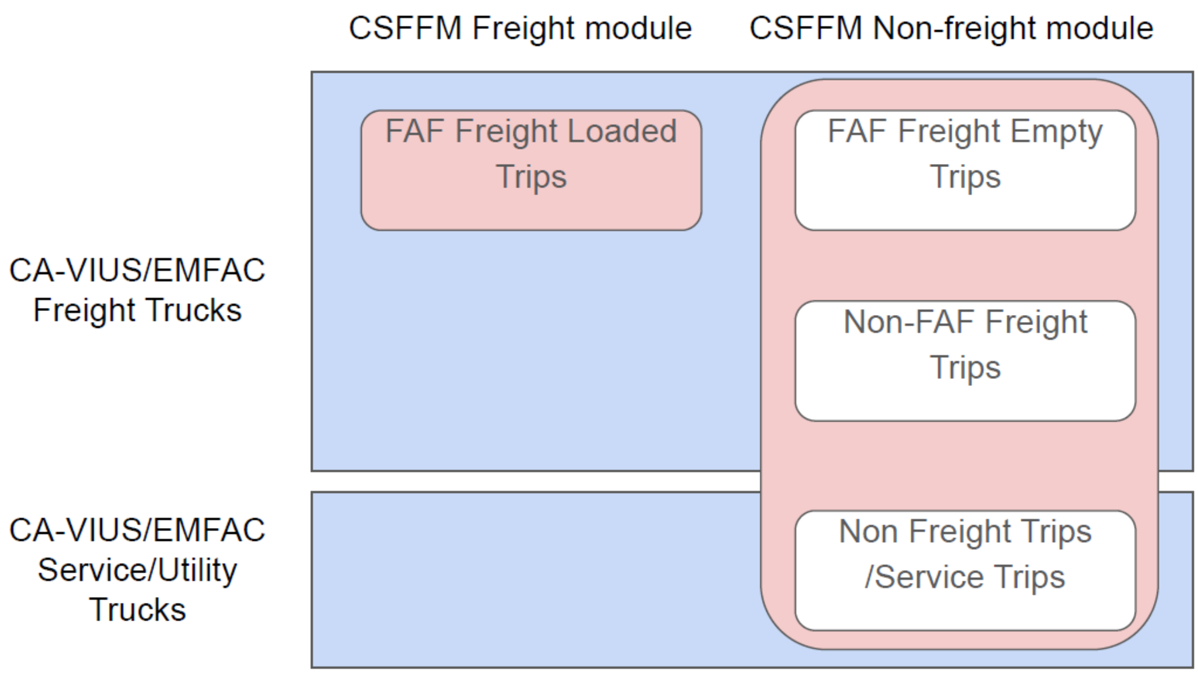

Figure 9- CSF2TDM, CA-VIUS and EMFAC truck activity categorization

One of the outputs of all these models and surveys is VMT and it is the most important measure of travel activity since it provides a metric for travel activity, evaluating the potential impact of travel policies, and shows how VMT across all three datasets compare with each other. CA-VIUS expanded data is a snapshot of the truck population, characteristics and annual mileage for the year 2017-2018. This population and mileage (Annual VMT) were also forecasted by EMFAC and CSF2TDM.

Table 5- 2017 California State Daily VMT forecast comparison (Vehicle-miles)

		Class 2b,3	Class 4,5,6	Class 7	Class 8	Total
CSFFM	Total Freight	363,552	4,891,654	6,533,675	24,364,309	36,153,189
	Non- Freight	3,833,171	6,966,754	1,943,422	3,343,636	16,086,984
	Total	**4,196,723**	**11,858,408**	**8,477,097**	**27,707,945**	**52,240,173**
EMFAC	In State	-	8,279,276	3,226,544	23,945,272	35,451,092
	Out of State	-	47497.38161	207842.3242	16411607.41	16,666,947
	Total	**41,013,342**	**8,326,773**	**3,434,387**	**40,356,879**	**93,131,381**
CA-VIUS	In State	-	8,592,192	3,122,740	24,202,616	35,917,548
	Out of State	-	411,019	275,615	9,414,427	10,101,062
	Total	**-**	**9,003,211**	**3,398,355**	**33,617,044**	**46,018,610**

As seen in the above table, class 8 trucks have more consistent VMT among all these datasets with a small difference between CSFFM and CA-VIUS (less than 18 percent). EMFAC has about 44% more VMT for class 8 compared to CSFFM which implies that the approach of EMFAC in calculating VMT based on truck population and accrual rates results in a higher level of activity than the other two models with focus on freight activity. For class 2B-3 CSFFM has only about 10% activity of EMFAC. As those light heavy-duty trucks are more service trucks than freight trucks and there is a significant population of non-commercial trucks in this category such as recreational trucks, EMFAC captures them more accurately. And for class 4,5,6,7 CA-VIUS and EMFAC have VMT estimates that are in better agreement (less than 8 percent difference), compared to CSFFM with higher VMT numbers. A possible explanation of this discrepancy could be the inaccuracy of payload factors assigned to each truck class in CSFFM. This study picks class 8 truck activity since it has a more robust VMT forecast among all datasets and higher absolute VMT compared to other classes.

3.2 CA-VIUS Insights

One of the CA-VIUS results is having payload factors for each truck class and commodity group. As the CSFFM forecasts the total tonnage of each commodity to be hauled from A to B and then it assigns that to different truck classes and rail, payload factors for each truck class and commodity plays an important role. These payload factors are the same for all commodity groups in CSFFM since the first version of the CSFFM was developed before the CA-VIUS survey and the authors did not have access to this valuable dataset. This study updated the CSFFM with new commodity-based payload factors from CA-VIUS and all runs are based on the updated CSFFM.

CA-VIUS has a question about the home base visit frequency of all trucks. Figure 10 and Figure 11 show the estimated number and percentage of trucks in each category based on in-state (DMV) and Out-of-state trucks (IRP).

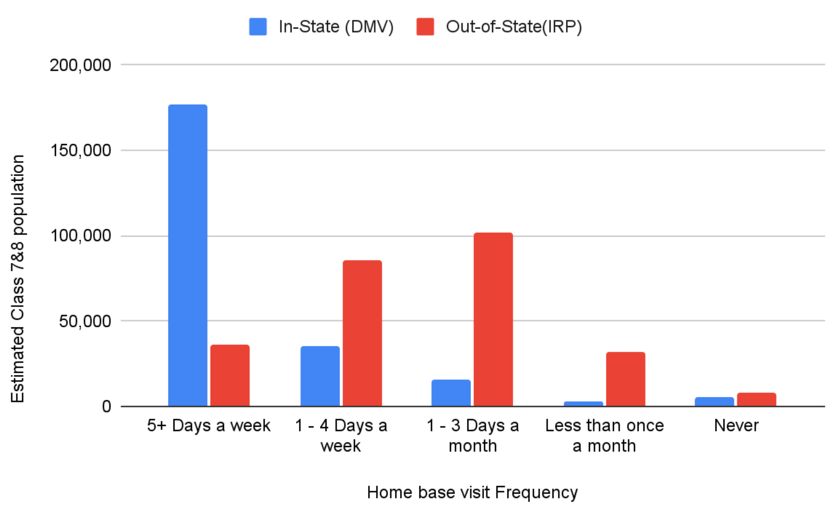

Figure 10- Class 7&8 home base visit frequency

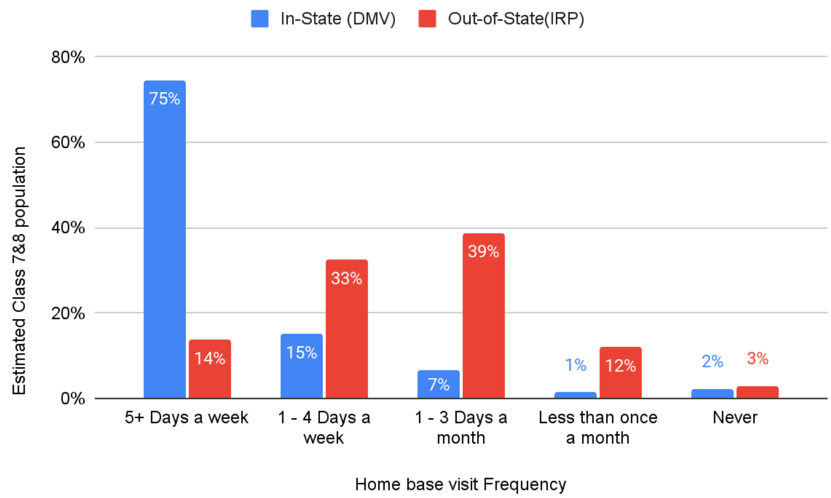

Figure 11-Class 7&8 home base visit frequency percentage

As expected in the above figures, out-of-State (IRP) trucks visit their home base less than in-State (DMV) trucks. This is logical as out-of-State (IRP) trucks have longer trips and cannot go to their home base as often. Another point about the above figures is that trucks that would not go to their home base at all (never) are too little (<3 percent) and there is not much difference between out-of-State (IRP) and in-State (DMV) groups.

To have a better understanding about fleet characteristics in each commodity group (industry), a percentile analysis was performed on the model year of trucks, as shown in Table 6 and Table 7. As truck classes 4,5,6&8 perform more than 80% of all trips in the network and there are some discrepancies in other truck classes, this study analyzed classes 4,5,6&8. In CA-VIUS there are California DMV registered trucks as well as IRP trucks.California DMV trucks were analyzed for percentile analysis. IRP trucks are mostly long-haul class 8 trucks. For example, 36 percent of all class 8 trucks in CA-VIUS are IRP trucks while less than 2 percent of class 4,5&6 are IRP trucks.

Table 6-Class 8 (> 33,000 lbs) model year percentiles

Commodity	Fleet_Size	25% percentile	50% percentile	75% percentile	Number of records	Weight Percentage
Agriculture products	Large 6+	2005	2010	2013	719	12225.7
Agriculture products	Small 1-5	2008	2012	2015	221	34045.7
Chemical Pharmaceutical products	Large 6+	2006	2010	2014	38	650.4
Chemical Pharmaceutical products	Small 1-5	2008	2010	2014	23	4089.1
Coal Metallic minerals	Large 6+	2013	2013	2013	1	17.0
Coal Metallic minerals	Small 1-5	2007	2007	2007	1	197.7
Crude petroleum	Large 6+	2002	2010	2014	13	241.8
Crude petroleum	Small 1-5	2008	2010	2014	13	1884.1
Electronics	Large 6+	2008	2010	2012	247	4606.6
Electronics	Small 1-5	2009	2012	2013	52	9452.0
Food, beverage, tobacco products	Large 6+	2008	2010	2013	622	11205.5
Food, beverage, tobacco products	Small 1-5	2009	2011	2014	198	32545.6
Fuel and oil products	Large 6+	2007	2010	2012	69	1241.6
Fuel and oil products	Small 1-5	2008	2011	2015	51	7155.0
Gravel Sand and nonmetallic minerals	Large 6+	2001	2009	2013	323	5608.9
Gravel Sand and nonmetallic minerals	Small 1-5	2004	2009	2014	99	16621.7
Logs	Large 6+	2004	2009	2014	25	366.7
Logs	Small 1-5	2008	2010	2011	14	1632.8
Manufactured products	Large 6+	2008	2010	2012	792	14398.0
Manufactured products	Small 1-5	2008	2010	2013	227	39899.4
Metal manufactured products	Large 6+	2006	2009	2012	311	5651.0
Metal manufactured products	Small 1-5	2008	2012	2014	92	16353.1
Nonmetal mineral products	Large 6+	2004	2010	2013	64	1179.8
Nonmetal mineral products	Small 1-5	2002	2011	2013	15	2373.7
Transportation equipment	Large 6+	2003	2009	2013	344	6037.3
Transportation equipment	Small 1-5	2007	2011	2014	111	18916.3

Waste material	Large 6+	2002	2009	2012	200	3559.6
Waste material	Small 1-5	2003	2010	2013	104	16672.5
Wood, printed products	Large 6+	2006	2010	2013	374	6642.6
Wood, printed products	Small 1-5	2007	2009	2013	125	20717.7

Table 7-Class 4,5&6 (14,000-26,000 lbs) model year percentiles

Commodity	Fleet Size	25% percentile	50% percentile	75% percentile	Number of records	Weight Percentage
Agriculture products	Small 1-5	2000	2006	2011	548	6203.7
Agriculture products	Large 6+	2003	2006	2012	82	9490.2
Chemical Pharmaceutical products	Small 1-5	2001	2006	2011	64	740.8
Chemical Pharmaceutical products	Large 6+	2004	2009	2015	14	1631.2
Coal Metallic minerals	Small 1-5	2008	2010	2013	4	47.4
Coal Metallic minerals	Large 6+	2007	2007	2007	1	124.9
Crude petroleum	Small 1-5	2001	2001	2009	3	34.6
Crude petroleum	Large 6+	2010	2012	2013	3	375.2
Electronics	Small 1-5	2004	2006	2011	263	3058.6
Electronics	Large 6+	2002	2007	2013	54	6626.1
Food, beverage, tobacco products	Small 1-5	2002	2007	2012	433	4991.9
Food, beverage, tobacco products	Large 6+	2004	2007	2014	57	6426.6
Fuel and oil products	Small 1-5	2002	2007	2014	40	451.2
Fuel and oil products	Large 6+	2005	2008	2008	15	1685.3
Gravel Sand and nonmetallic minerals	Small 1-5	2001	2005	2008	208	2394.7
Gravel Sand and nonmetallic minerals	Large 6+	2000	2004	2007	34	3977.5
Logs	Small 1-5	2002	2006	2011	29	329.0
Logs	Large 6+	2003	2007	2015	9	1095.3

Manufactured products	Small 1-5	2002	2006	2011	1641	19002.7
Manufactured products	Large 6+	2003	2007	2012	223	26883.3
Metal manufactured products	Small 1-5	2002	2006	2011	644	7448.0
Metal manufactured products	Large 6+	2001	2006	2012	116	13793.0
Nonmetal mineral products	Small 1-5	2001	2006	2010	73	838.8
Nonmetal mineral products	Large 6+	2001	2004	2010	14	1632.9
Transportation equipment	Small 1-5	2002	2006	2011	440	4976.4
Transportation equipment	Large 6+	2005	2009	2014	177	20850.3
Waste material	Small 1-5	2000	2005	2008	409	4703.6
Waste material	Large 6+	2004	2007	2013	70	8271.5
Wood, printed products	Small 1-5	2001	2005	2010	534	6155.1
Wood, printed products	Large 6+	2001	2007	2012	77	9369.2

Table 6 and Table 7 show on average small fleets with one to five vehicles have older vehicles compared to large fleets with more than six vehicles. On the other hand, class 4,5&6 trucks are older compared to class 8 trucks.

Among these commodity groups there are some which have older fleets, and that would have higher emission rates as a result. For example, Coal Metallic minerals, Fuel and oil products, Gravel Sand and nonmetallic minerals and Waste material have older fleets in class 8 compared to other commodity groups. Agriculture products, Crude petroleum, Gravel Sand and nonmetallic minerals and Waste material have older fleets in class 4,5&6 trucks.

Analysis of trips based on trip length is another valuable data in CA-VIUS which was studied as shown in Figure 12 and Figure 13.

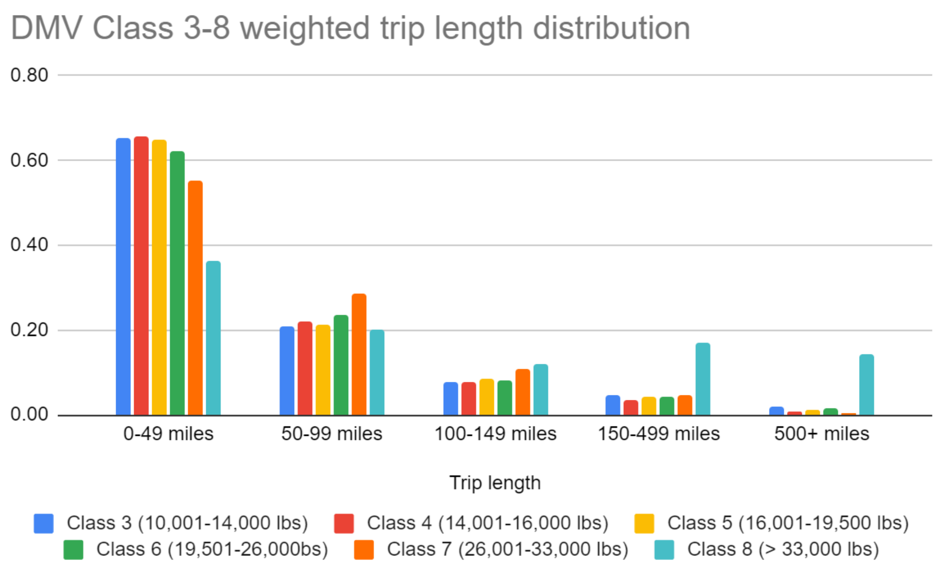

Figure 12-DMV truck weighted trip length based on truck classes

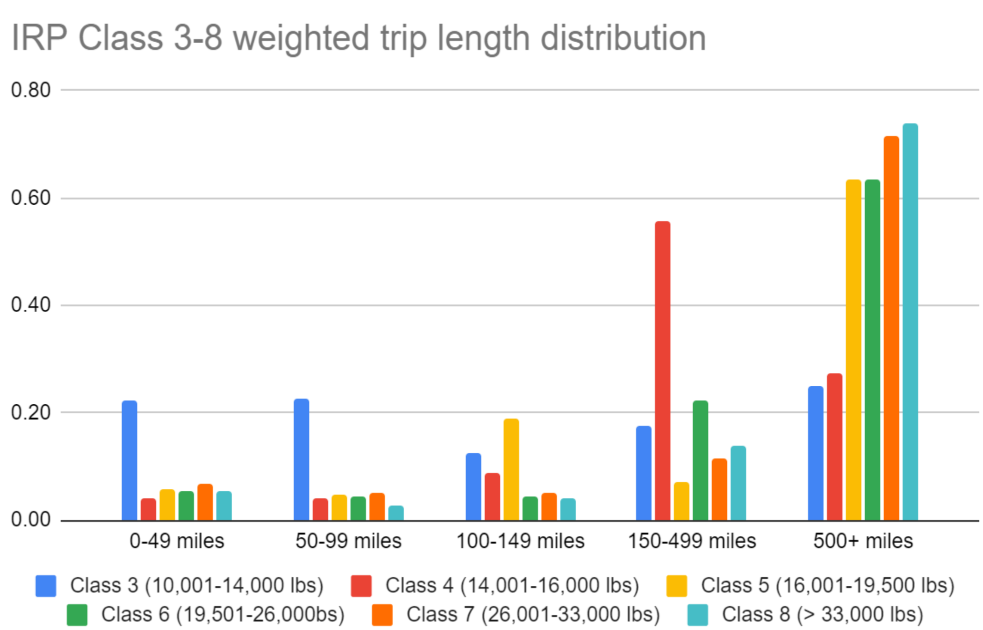

Figure 13-IRP truck weighted trip length based on truck classes

As seen above, DMV trucks make shorter trips compared to IRP trucks and class 8 trucks make longer trips in both the DMV and IRP datasets.

3.3 Limitations and assumptions

In CSFFM there are 15 commodity groups. Commodity groups CG-3 (Crude petroleum) and CG-6 (Metallic minerals) are not included in the CSFFM due to lack of available data (crude petroleum) or lack of activity in the State (metallic ore). These two commodity groups have less than 1% of total VMT in CA-VIUS. This study excluded these two commodity groups as there is no data available in CSFFM.

3.4 Results

3.4.1 VMT Results

CSFFM was run for VMT estimates for 2015 as a base year, and 2020, 2030, 2040 and 2050 as target years. A new commodity-based trip assignment was developed in CSFFM to assign trips by commodity and not the sum of all commodities together. Hence, there are 15 commodity groups and 4 truck classes for a total of 60 origin-destination trip matrices. This study analyzed Class 8 trucks, so there are 15 volumes for commodity groups on the network. Table 8 shows these VMT on the network.

Table 8- Class 8 Commodity-based VMT by CSF2TDM

Class 8 Daily VMT	**2015**	**2017**	**2020**	**2030**	**2040**	**2050**
CG1-Agriculture products	3,508,737	3,618,312	3,782,676	2,913,821	3,530,274	4,831,747
CG2-Wood, printed products	1,246,182	1,295,916	1,370,517	1,544,199	1,773,797	1,774,543
CG3-Crude petroleum	0	0	0	0	0	0
CG4-Fuel and oil products	1,905,304	2,122,937	2,449,386	3,813,458	6,352,152	10,888,487

CG5-Gravel Sand and nonmetallic minerals	1,470,971	1,478,314	1,489,327	1,135,341	1,444,814	3,218,755
CG6-Coal Metallic minerals	0	0	0	0	0	0
CG7-Food, beverage, tobacco products	3,919,928	4,083,457	4,328,751	4,886,349	5,655,003	5,664,259
CG8-Manufactured products	2,980,748	3,142,657	3,385,519	3,886,539	4,862,086	3,890,551
CG9-Chemical Pharmaceutical products	1,834,435	1,855,512	1,887,128	2,082,246	2,442,962	2,197,667
CG10-Nonmetal mineral products	1,449,349	1,498,155	1,571,364	1,926,828	2,479,156	3,362,442
CG11-Metal manufactured products	1,038,834	1,076,950	1,134,123	1,266,409	1,597,842	1,252,991
CG12-Waste material	1,336,825	1,378,526	1,441,077	1,645,688	2,054,915	1,641,644
CG13-Electronics	2,177,293	2,000,088	1,734,280	1,969,598	2,604,890	2,282,056
CG14-Transportation equipment	795,024	739,487	656,182	689,844	767,154	836,396
CG15-Logs	87,694	73,999	53,457	66,167	97,678	121,655
Total	**23,751,323**	**24,364,309**	**25,283,788**	**27,826,488**	**35,662,725**	**41,963,193**

The 2017 estimate is a linear interpolation of 2015 and 2020 estimates. As total VMT is growing through the future constantly, not all commodity groups grow at the same rate. Figure 14 shows this heterogeneity.

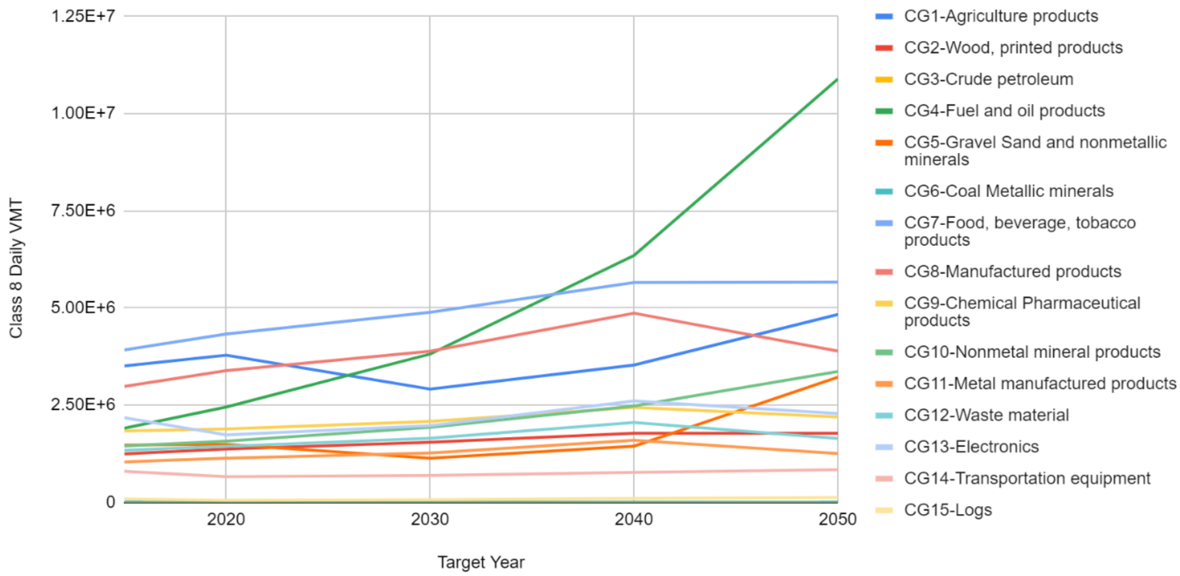

Figure 14- Class 8 Commodity-based VMT by CSF2TDM

3.4.1 Population Results

EMFAC and CA-VIUS have California truck population estimates. EMFAC has estimates for future years while CA-VIUS has only a snapshot of the population in 2017. Truck populations based on each class and out of state activity are shown in Table 9.

Table 9- 2017 Truck population estimates (excluding gasohol)

2017 Population		**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**	**Class 8**
	DMV	69,723	34,382	39,569	68,529	43,912	192,297
	IRP	5,129	2,167	6,655	10,644	18,707	243,965
CA-VIUS	**Total**	**74,852**	**36,549**	**46,224**	**79,173**	**62,619**	**436,262**
	DMV	205,091	50,468	65,494	91,437	65,322	186,362
	IRP	-	322	397	1,046	2,696	98,896
EMFAC	**Total**	**205,091**	**50,790**	**65,891**	**92,483**	**68,017**	**285,257**

There is a huge difference in class 8 numbers above between these two models, which can be explained by the way each database works. The number of class 8 DMV trucks in the two databases is close while the number of IRP trucks are far away from each other. IRP expansion rates are based on each stratum and for IRP trucks there are a few trucks in some of those strata which makes the expansion rates on that stratum big and estimates less dependable based on that expansion rate. This study believes an expansion rate problem is the reason for the class 8 IRP trucks estimates, and that EMFAC has more reliable estimates for IRP trucks. Hence, IRP trucks in CA-VIUS were scaled to the EMFAC total, as shown in Table 10.

Table 10- Scaled 2017 Truck population estimates (excluding gasohol)

2017 Population		**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**	**Class 8**
	DMV	69,723	34,382	39,569	68,529	43,912	192,297
	IRP	-	322	397	1,046	2,696	98,896
CA-VIUS	**Total**	**69,723**	**34,704**	**39,966**	**69,575**	**46,608**	**291,192**
	DMV	205,091	50,468	65,494	91,437	65,322	186,362
	IRP	-	322	397	1,046	2,696	98,896
EMFAC	**Total**	**205,091**	**50,790**	**65,891**	**92,483**	**68,017**	**285,257**

Based on the VMT discussion for class 8 trucks, other classes are not discussed in this study. Also, service trucks are not included in this study since there is no exclusive VMT estimate for them in CSF2TDM. Based on CA-VIUS, class 8 trucks that are not service trucks are as shown in Table 11. CG3 and CG6 are excluded in this study as those are not included in CSF2TDM and, they only contribute less than1 percent to the total state VMT. The IRP truck populations as discussed earlier are scaled to match EMFAC numbers.

Table 11- 2017 CA-VIUS class 8 truck population (No service trucks)

	DMV	Scaled IRP	Total
CG1-Agriculture products	38,341	18,165	56,506
CG2-Wood, printed products	13,319	5,684	19,003
CG3-Crude petroleum	1,549	4	1,553
CG4-Fuel and oil products	7,278	784	8,063
CG5-Gravel Sand and nonmetallic minerals	22,231	857	23,088
CG6-Coal Metallic minerals	215	139	354
CG7-Food, beverage, tobacco products	22,746	20,699	43,445
CG8-Manufactured products	29,386	22,799	52,185
CG9-Chemical Pharmaceutical products	4,739	2,187	6,926
CG10-Nonmetal mineral products	1,585	1,249	2,834
CG11-Metal manufactured products	11,486	10,757	22,244
CG12-Waste material	11,628	1,687	13,315
CG13-Electronics	3,525	2,480	6,004
CG14-Transportation equipment	15,226	11,061	26,287
CG15-Logs	1,677	115	1,792
N/A	304	228	532
Total	**185,235**	**98,896**	**284,131**

Table 11 is the seed truck population in 2017. Future truck population is based on the seed and VMT estimates of the CSF2TDM freight module in Table 8 as below.

Table 12- CA class 8 freight truck population forecast (No service trucks)

	2020	2030	2040	2050
CG1-Agriculture products	59,072	45,504	55,131	75,455
CG2-Wood, printed products	20,097	22,644	26,011	26,022
CG3-Crude petroleum	0	0	0	0
CG4-Fuel and oil products	9,302	14,483	24,124	41,352
CG5-Gravel Sand and nonmetallic minerals	23,260	17,732	22,565	50,270
CG6-Coal Metallic minerals	0	0	0	0

CG7-Food, beverage, tobacco products	46,055	51,987	60,165	60,264
CG8-Manufactured products	56,218	64,537	80,737	64,604
CG9-Chemical Pharmaceutical products	7,044	7,772	9,119	8,203
CG10-Nonmetal mineral products	2,973	3,645	4,690	6,361
CG11-Metal manufactured products	23,424	26,157	33,002	25,880
CG12-Waste material	13,920	15,896	19,849	15,857
CG13-Electronics	5,206	5,913	7,820	6,851
CG14-Transportation equipment	23,326	24,523	27,271	29,732
CG15-Logs	1,294	1,602	2,365	2,946
Total	**291,192**	**302,394**	**372,848**	**413,796**

Table 12 shows total DMV and IRP freight class 8 truck forecasts for each commodity. As the seed truck population of CA-VIUS has all characteristics of fleet, truck and commodity, they can be populated for future truck populations.

The agriculture products (CG1) truck population fluctuates from 2020 to 2050 from about 45,000 class 8 trucks to 75,000 trucks. This fluctuation in truck population is due to VMT fluctuation and socio-economic variables such as harvest land and employment changes over time. CG1 also has older trucks based on 25th percentile Table 6. As a result, CG1 is one of the targets for zero emission policy push due to rising VMT, population and relatively older trucks. Gravel Sand and nonmetallic minerals (CG5) has almost the same characteristics with fewer trucks compared to CG1 but still significant number of trucks needed. So, CG5 is another target for zero emission policy push. Nonmetal mineral products (CG10) and Logs (CG15) have smaller population of trucks with steady growth from 2020 to 2050 in population and older trucks relatively based on 25th percentile Table 6. So, they could be the next target for zero emission policies. The footprint of these truck populations in disadvantaged communities would also be valuable for policy purposes and should be analyzed in future research.

Table 13- CA class 8 Truck population comparison (No service trucks)

	2017	2020	2030	2040	2050
EMFAC	268,340	270,785	362,440	456,905	561,496
CA-VIUS & CSF2TDM	284,131	291,192	302,394	372,848	413,796

Table 13 compares DMV and IRP freight class 8 truck forecasts for the approach developed in this study compared to EMFAC results. For 2017 and 2020, the results are close to each other (less than 10 percent difference) while for 2030, 2040 and 2050 EMFAC results are much higher. This difference is based on future growth forecasts of the CSF2TDM and EMFAC. EMFAC forecasts a steeper growth for the freight truck population in the future compared to CSF2TDM. EMFAC technical documents state that results are normalized by CSFFM VMT growth rates but apparently, they are not. Unfortunately, there is no open-source EMFAC to track down this problem.

Some of these policy questions that can be answered by this tool are:

- Which industries are making the highest air pollution per mile? Based on truck characteristics such as make, model, age.
- Which industries are making the highest air pollution in certain areas such as disadvantaged communities? Based on geographical resolution of CSF2TDM and truck characteristics of CA-VIUS
- Which areas are hit the most by old trucks (more emission per mile)?

- What would be the optimal industry, area and fleet size to incentivize for zero emission freight activity? This can be analyzed under different objective functions or a mix of all:
    - Minimize pollution in disadvantaged communities
    - Minimize dollars spent per unit emission eliminated

Policy makers have a lot of interest these days in zero emission vehicles and how to get to 100 percent zero emission vehicles. Recently there have been some incentives to buy and operate electric trucks. Heavy-duty trucks, as one of the main contributors of transportation emissions, have different emission rates per mile based on truck characterization. Incentivizing zero emission trucks based on these characteristics would make the transition more effective by replacing trucks with higher emissions per mile. For example, by the CA-VIUS analysis it was shown that small fleets (less than five vehicles) have older trucks in some industries. By targeting those industries and small fleets the transition could be more effective compared to giving all fleets the same opportunity to receive the incentive. Another important topic is the air quality impact of heavy duty trucks on disadvantaged communities. This question also can be answered by the geographical resolution of CSF2TDM of heavy-duty truck movements and truck characteristics from CA-VIUS.

Chapter4: Electric truck demand analysis

California mandates zero emission trucks from 2024. By 2035, 55 percent of delivery vans and large pickups sold in California must be zero emission. [14] For this purpose, fuel-cell and battery electric trucks have been in researchers' interest. For battery electric trucks there are some challenges such as charging demand from the grid network infrastructure, battery weight, payload limitations and charging duration constraints. This exploratory study investigated a framework for the power demand in each geographical area based on forecasted truck trips in California.

Charging location is one of the important aspects of truck electrification. Trucks have to get charged at the origin, destination or in between. CSF2TDM provides forecast truck trips with origin, destination and assigned path for each OD. Based on CSF2TDM, truck trips can be analyzed, and power demand be estimated based on travel demand. Inputs to this analysis are forecasted trips with origin, destination and path from CSF2TDM and truck stop locations as candidates for truck charging stations. The process analyzes trips and selects some of the truck stops through an optimization problem for charging stations first; it then analyzes trips that can be served by those charging locations. Next, it assumes all truck trips (that can be served by those charging stations) will be electric and estimates how much power in each of those stations and zones is needed. Here are the steps for power demand analysis:

1- Nature of electric trucks and range of activity

2- Analyzing trips

4.1 Electric trucks nature

Three important characteristics of electric trucks are weight of the battery, time needed to charge the battery and range of activity, which are intercorrelated. Battery electric truck (BEV) tractors usually need about 100 kWh of energy for fifty miles of range which the battery right now weighs about 1,375 pounds. Other battery sizes and ranges are as below: [15]

- 235 miles (480 kWh) = 6,600 lbs.
- 275 miles (565 kWh) = 7,768 lbs.
- 350 miles (750 kWh) = 10,300 lbs.

For the complete tractor, a typical diesel day-cab weighs about 15,600 pounds. If battery weight is added to the cab, it would be somewhere between 22,000 and 29,000 lbs based on battery capacity without a driver and without a trailer. [15]

This study assumed each class 8 truck has a range of 300 miles and ignores the battery weight effect on maximum truck weight allowed on highways. In this scenario the battery would be about 8,600 lbs and 627 kWh. Based on that, class 8 trucks consume about 2 kWh per mile. The charging time of the battery depends on type of the charger as below: [16]

- Level 1: 1kW
- Level 2: 7-19kW
- DC Fast Charging: 50-350 kW

Based on the above numbers, a 627 kWh battery gets charged in about 2-12.5 hours with DC fast charging.

4.2 Trip Analysis

The CSFFM inside CSF2TDM models truck activity in California. To be more precise, it models the freight activity in the whole US and with finer resolution in California based on FAF data, and utilizing Cube software. Cube is a transportation model software which can assign an OD matrix to a network and calculate link volumes. Paths for each of the ODs are needed to be able to analyze the truck range and possible charging station needed. CSF2TDM was manipulated to create path results along the stochastic assignment of class 7 ad 8 trucks to the free-flow-speed network. Cube stores path characteristics as below:

- Origin and destination node
- List of network nodes on the path
- Volumes on the path
- Costs of the path

For analyzing the path, path length in miles plays a key role for an electric truck to see if it needs charging before arriving to the destination or not. This cutoff path length (distance threshold) was assumed to be 300 miles based on battery capacity. For paths less than 300 miles, trucks get charged either at the origin or destination. For paths more than 300 miles, trucks need to get charged somewhere in between as well as origin and destination. An optimization problem was run to find the best spots to capture most of the truck flows with more than 300 miles path length on the network. Station candidates are truck stops which there are 147 locations in California[17]. The optimization formula is based on Jung's study on optimal sensor location for truck activity monitoring system. [18]

Max Σ_i ($f_i \times y_i$)

S.t. Σ_j $\boldsymbol{\partial}_{ji} \times x_j \geq y_i$, $\forall$ i $\in$ I

Σ_j x_j = P

$\boldsymbol{\partial}_{ji}$ =1, if location j is a valid charging station for path i; 0, otherwise

x_j; 1 if truck stop location is selected; 0, otherwise

y_i; 1 if path i is covered by a truck stop; 0, otherwise

f_i ; Class 8 volume on the path

I; all truck travel paths more than 300 miles

J; Truck stop locations (147 locations)

P; Maximum number of charging station out of truck stops

The above formulation maximizes class 8 truck volumes that can be served with a determined number of charging stations (P) in California for paths more than 300 miles. $\boldsymbol{\partial}_{ji}$ is a key value in this optimization which is a 0,1 matrix. 1 if truck stop j is a valid charging station for path i and 0 otherwise. Truck stop j is valid charging station for path i if it splits the path into two legs both less than 300 miles. In this case only paths with origin and destination inside California and only one charging station per path were analyzed. Meaning $\boldsymbol{\partial}$ is 1 if and only if a path can be served by only one truck stop. By this assumption, paths more than 600 miles cannot be served by only one charging station and

∂ will be zero for them. This will not be a limit since most of paths inside California are less than 600 miles. San Diego to the Oregon border is about 870 miles.

The optimization will select truck stops to be charging stations and the analysis for power demand of each, can be done afterward.

As the ODs are single pairs in CSF2TDM and there is no tour behavior of trucks, charging behavior is based on single trips. It would be a more accurate way to define tours and home base for each truck and assign charging points based on those locations but due to lack of such data this could not be addressed in this study. Hence, power demand calculation could be either of these scenarios:

1- Charge at origin: Truck gets charged at origin only for the trip. For example, for a trip from A to B which is 150 miles the truck gets charged for 150 miles* 2kWh/mile=300 kWh at A.
2- Charge at destination: Truck is full at origin and is charged at the destination to top off charge spent on the route. For example, for a trip from A to B which is 150 miles the truck is fully charged at A and gets charged for 300 kWh at B to top off the charge and get ready for the next trip.

If a path is more than 300 miles and the truck has to get charged at a charging location, for the first scenario the truck gets charged for the second leg at a charging station and for the second scenario the truck gets charged for the first leg at a charging station. For example, for a trip from C to D which is 450 miles and charging station is at E. C to E is 300 miles and E to D is 150 miles:

1- Charge at origin: Truck gets charged for 300 miles* 2kWh/mile=600 kWh at C and 150 miles* 2kWh/mile=300 kWh at E.
2- Charge at destination: Truck is fully charged at C and gets charged for 300 miles* 2kWh/mile=600 kWh at E to top off the charge and get 150 miles* 2kWh/mile=300 kWh at D.

Based on path results from CSF2TDM, VMT associated with each path can be converted to kWh (2 kWh/mile) and assigned to origin, destination and charging stations as below:

1- Charge at origin
    a. Paths less than 300 miles: Power demand would be the VMT (volume*path distance) multiplied by 2 kWh/mile at origin
    b. Paths more than 300 miles:
        i. Paths covered by a charging station: Power demand would be the first leg VMT multiplied by 2 kWh/mile at origin and second leg VMT multiplied by 2 kWh/mile at charging station
        ii. Uncovered paths: electric trucks are not feasible for these paths, and this study ignores them in power analysis
2- Charge at destination:
    a. Paths less than 300 miles: Power demand would be the VMT multiplied by 2 kWh/mile at destination
    b. Paths more than 300 miles:

i. Paths covered by a charging station: Power demand would be the first leg VMT multiply by 2 kWh/mile at charging station and second leg VMT multiplied by 2 kWh/mile at destination

ii. Uncovered paths: electric trucks are not feasible for these paths, and this study ignores them in power analysis

Under the assumptions above, there are two types of paths that would not be covered by defined power characteristics of 300 miles range and one charging station along the path. These paths are either between 300 and 600 miles with no access to truck stops along the path, or paths more than 600 miles. This study considers these types of trips not suitable for electrification and puts them into a matrix for further analysis later.

Forecasting power demand under two scenarios 1 and 2 and would enable one to compare and assess the differences.

The Stochastic assignment of class 8 trucks to free flow speed is done by CSF2TDM on Cube for 5 iterations and creates about 92 million paths. Analyzing 92M paths into two categories based on path length (distance), creating VMT and $\boldsymbol{\partial}$ matrices and running the optimization for charging stations was developed in Python. However, analyzing 92M paths on Python takes about 5-10 days on the computer facilities available to the author at the time this report was written. Unfortunately, these results could not be included in this thesis, but the framework developed provides a valuable approach for further research into optimal locations of charging stations and their impact on grid infrastructure.

Chapter 5: Summary and Conclusion

5.1 Summary

Travel supply and demand statewide models are developed by state agencies for different purposes such as forecasting network congestion, fuel consumption and air pollution. But in the end, they are modeling the same activity (travels) from different perspectives. Comparing these models and their results gives a good view of each model and how the model works.

This study focused on California Statewide Freight Forecasting and Travel Demand Model (CSF2TDM) and the California Vehicle Inventory and Use Survey (CA-VIUS) from Caltrans and compared them to the Emission Factor model (EMFAC) from the California Air Resource Board (CARB). There are some aggregate results such as vehicle population and VMT that are different in these models. This study tried to find these differences and address them based on inputs and process of each model. Moreover, this study connected the commodity-based activity of CSF2TDM to CA-VIUS class 8 truck inventory and forecasted this population for future years. CSF2TDM and CA-VIUS forecasted 17, 19 and 27 percent less class 8 trucks for 2030, 2040 and 2050 target years compared to the EMFAC model. This could be explained by different procedures in EMFAC for forecasting future year populations. EMFAC is based on truck inventory and vehicle sales forecasts normalized by fuel sales and VMT forecasts while CSF2TDM is purely based on socio-economic variables and network characteristics. Basically, EMFAC is based on supply of trips (vehicles) and CSF2TDM is based on demand (trip production based on socio-economic variables). EMFAC is good at capturing all truck activity while lacking in detailed characteristics such as geographical resolution. CSF2TDM provides a detailed profile of truck activity on the network but it does not capture all the truck activity due to insufficient input data of transporting goods and does not have truck inventory associated with truck activity.

The other use of statewide models is to answer some of the new policy questions such as the infrastructure impact of zero emission vehicles and electrification of vehicles. The second part of this thesis developed a framework for investigating the feasibility of electric class 8 trucks in California by analyzing the optimal locations of charging stations and their impact on grid infrastructure based on forecasted travel demand on CSF2TDM. Through the analysis only a small fraction of truck trips was found to be unfeasible for electrification under the assumptions of 300-mile effective range and optimum charging station locations. Other trips that are feasible for electrification were analyzed under two scenarios: charge at origin and charge at destination. Charge at origin means a truck is charged for the trip at the origin and charge at destination means a truck is fully charged at the origin, makes the trip, and then is charged at destination to get the battery full. Since the OD matrix is not symmetrical, there would be a difference in charging demand on grid network under these two scenarios.

5.2 Suggestions for Future Research

Truck population inventory forecasts based on CSF2TDM and CA-VIUS were developed in this study for class 8 trucks in California. There is an opportunity to do the same for other truck classes 2b,3 through 7 and compare them to the EMFAC model to examine how those numbers are close or different than each other. A passenger car inventory could be done the same way with Department of Motor Vehicles (DMV) data instead of CA-VIUS. Analyzing truck classes 2b, 3-7 needs more attention due to greatly different VMT numbers in the CSF2TDM and EMFAC models. As discussed in Chapter 3, there are a lot of discrepancies in the definition of activity of those trucks studied in each of those models and researchers should be aware and be cautious about them.

This study assumed fixed VMT per truck in each commodity-group. As this assumption could be limiting in far future with electric and self-driving trucks, it can be released by some VMT rates per truck per year for future target year truck inventory forecast.

This study compared CSF2TDM, EMFAC and CA-VIUS. EMFAC is the only model that is not open-source and all info about the model is from the technical documents. As there are some vague points in the process of this model, it would be informative to study the process if the source code of EMFAC was released to the public. In addition, there is another statewide model called DynaSim from the California Energy Commission (CEC) which forecasts vehicle activity and fuel consumption in California. There is an opportunity to compare DynaSim results and procedures to EMFAC and CSF2TDM.

On truck electrification and charging demand from the grid network there are many future research opportunities as this field is largely uncovered for trucks. This study focused on class 8 trucks, and it can be done for other truck classes with some considerations about total VMT of those trucks in CSF2TDM. The assumption of one charging station along the trip can be relaxed to multiple charging stations, for example. In addition, charging station attractions, meaning electric trucks would be more interested to choose routes with more accessible charging stations, was captured in this study and could be studied in the future. Another assumption was only trips with origin and destination inside California which can be released to trips with origin or destination in California as CSF2TDM has a national network and those trips can be captured from the model. These trips need more consideration as they might not be feasible with a 300-mile range and only California truck stops available for charging. Payload reduction due to battery weight on trucks is another important concern about battery electric vehicles which can be analyzed by CSF2TDM as the model has a payload module that can be modified.

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