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Integration of Weigh-In-Motion and Inductive Signature Data for Truck Body Classification

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil and Environmental Engineering

by

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Dissertation Committee:
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2014

DEDICATION

To

my family, my friends, and my teachers

in recognition of their patience, support, motivation, and trust.

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

LIST OF TABLES

Page

ACKNOWLEDGEMENTS

Former Supreme Court Justice Sandra Day O'Connor says it perfectly, "Whatever happens is the result of the whole tapestry of one's life and all the weavings of individual threads from one to another that creates something." My tapestry has been woven by communities from childhood to academia and it is truly the influences of these communities that have fueled me through my degree.

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Graduate school is an enlightening experience but can be fraught with many personal hurdles. In times of joy my peers have shared and contributed to my success. And in times of struggle my peers have encouraged me to overcome all obstacles. Through their friendship my graduate life was complete. I would especially like to acknowledge Dr. Kang, Dr. You, Dr. Liu, and Dr. Chow for their personal and academic support. For the jovial lunches during which we shared research ideas, movie ratings, and philosophical musings, I have to thank my friends and colleagues- Dr. Ranafier, Dr. Camargo, Daniel Rodriguez, and Ashley Lo. For the coding tips, vocabulary lessons, and feedback on new research ideas I would like to acknowledge my office mates, Dr. Yuan, Gavin Ferguson, and Qijian Gan. Lastly, to the 'inductive signature research team' of Kate Hyun, Dr. Jeng, Dr. Chu, and Jun Park, I owe much gratitude for assistance with data collection and processing, and the various opportunities to collaborate on research.

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Yeon, J., **Hernandez, S.,** and Elefteriadou, L., "Differences in Freeway Capacity by Day of the Week, Time of Day, and Segment Type", *Journal of Transportation Engineering*, Vol. 135, No. 7, pp. 416-426, 2009.

Hernandez, S., Tok, A., and Ritchie, S.G., "Multiple-Classifier Systems for Truck Body Classification at WIM Sites with Inductive Signature Data", Submitted to the 94th Annual Meeting of the Transportation Research Board, Washington, D.C., January, 2015.

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ABSTRACT OF THE DISSERTATION

Integration of Weigh-in-Motion and Inductive Signature Data for Truck Body Classification

By

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Transportation agencies tasked with forecasting freight movements, creating and evaluating policy to mitigate transportation impacts on infrastructure and air quality, and furnishing the data necessary for performance driven investment depend on quality, detailed, and ubiquitous vehicle data. Unfortunately, commercial vehicle data is either missing or expensive to obtain from current resources. To overcome the drawbacks of existing commercial vehicle data collection tools and leverage the already heavy investments into existing sensor systems, a novel approach of integrating two existing data collection devices to gather high resolution truck data – Weigh-in-motion (WIM) systems and advanced inductive loop detectors (ILD) is developed in this dissertation. Each source provides a unique data set that when combined produces a synergistic data source that is particularly useful for truck body class modeling. Modelling truck body class, rather than axle configuration, provides more detailed depictions of commodity and industry level truck movements. Since body class is closely linked to commodity carried, drive and duty cycle, and other operating characteristics, it is inherently useful for each of the above mentioned applications.

In this work the physical integration including hardware and data collection procedures undertaken to develop a series of truck body class models are presented. Approximately 35,000 samples consisting of photo, WIM, and ILD signature data were collected and processed representing a significant achievement over previous ILD signature models which were limited to around 1,500 commercial vehicle records.

Three families of models were developed, each depicting an increasing level of input data and output class resolution. The first uses WIM data to estimate body class volumes of five semi-trailer body types and individual predictions of two tractor body classes for vehicles with five axle tractor trailer configurations. The trailer model produces volume errors of less than 10% while the tractor model resulted in a correct classification rate (CCR) of 92.7%. The second model uses ILD signatures to predict 47 vehicle body classes using a multiple classifier system (MCS) approach coupled with the Synthetic Minority Over-sampling Technique (SMOTE) for preprocessing the training data samples. Tests show the model achieved CCR higher than 70% for 34 of the body classes. The third and most complex model combines WIM and ILD signatures using to produce 63 body class designations, 52 with CCR greater than 70%. To highlight the contributions of this work, several applications using body class data derived from the third model are presented including a time of day analysis, average payload estimation, and gross vehicle weight distribution estimation.

1 Introduction

The newest transportation infrastructure funding and policy act signed into law by President Obama, the Moving Ahead for Progress in the 21st Century Act (MAP-21), represents a substantial shift to ‘performance and outcome oriented’ transportation investment (FHWA, 2013a). Federal highway programs must now provide hard data evidence that provided funds will improve performance along several identified targets including safety, freight movement and economic vitality, and environmental sustainability. MAP-21 also sets forth mandates for identifying and developing a National Freight Network and freight policy such that designation of a highway as part of the National Freight Network can incentivize funding (FHWA, 2013b). While these data-driven approaches will certainly make transportation investments more effective by prioritizing projects which can produce the greatest multi-faceted enhancements to our national highways and on state and regional corridors, the major hurdle becomes finding enough data to be able to evaluate each of the performance goals.

In addition to federal initiatives to increase data driven investment, state agencies have initiated mandates related to air quality and freight transportation that require gathering advanced vehicle data. As a result of California Assembly Bill 32 (the Global Warming Solutions Act of 2006) and California Senate Bill 375, the California Air Resources Board (CARB) has been tasked with developing emissions inventories and models for the State so that achievements in reaching emissions reductions goals can be monitored. Additionally, the California Department of Transportation (Caltrans) in adherence with the federally mandated Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) which requires states and metropolitan planning agencies to incorporate freight travel in their long range plans, is adopting a statewide freight forecasting model. For both emissions models and freight forecasting, highly detailed information about truck travel characteristics is needed.

Commercial vehicles have impacts far more sizeable than what their diminutive volumes might suggest. At the national level, trucks account for around 10% of the annual vehicle distance traveled (Highway Statistics, 2010). Although this represents a small portion of the total travel, the impacts of trucks on the environment, the economy, and infrastructure, are much more substantial than that of passenger vehicles. In fact, according to CARB's Mobile Source Emissions Inventory, heavy-duty diesel trucks are the "single largest source of nitrogen oxide emissions in California" as well as the "largest source of diesel particulate matter" (CARB, 2010). Further, the economic impacts of trucks in regard to freight transport are considerable. The Bureau of Transportation Statistics reported that "trucking as a single mode (including for-hire and private use) was the most frequently used mode, hauling an estimated 70 percent of the total value, 60 percent of the weight, and 34 percent of the overall ton-miles" (BTS, 2006). Given the huge health, safety, and economic impacts of commercial vehicles, many agencies are interested in increasing the amount of and improving the quality of publically available commercial vehicle activity data.

While many states have wide ranging resources for passenger traffic, such as California's Performance Measurement System (PeMS), a significantly smaller set of states collect or measure commercial vehicle traffic at the same level as passenger vehicles. Conventional data sets, although commendable, have various limitations and lack detail, especially regarding truck travel patterns and characteristics beyond basic volume measurement. Due to privacy concerns in the trucking industry, commercial vehicle activity data can be difficult and expensive to obtain, and many times is incomplete due to small sample sizes. To further exacerbate the lack of data, a much used national data set, the Vehicle Inventory and Use Survey, was discontinued over ten years ago, and nothing has been implemented as a replacement. If policies are to be formed which reduce the negative impacts of truck traffic such as temporal shifts or route restrictions, there needs to be a way to assess whether the policy has had any affect, which points to the need for route specific, temporally continuous, up-to-date, and representative truck data.

In this dissertation a more reliable, timely, and detailed classification system of the truck fleet in California is developed. Using weigh-in-motion (WIM) devices to provide axle spacing and weight information and inductive loop detectors equipped with high sampling rate detector cards to provide unique truck signatures, the body-type of a truck can be determined. Truck body class data represents an incredible level of detail regarding the commodity carried and industry served by the truck, the operating characteristics such as time of day travel patterns and spatial range of operations (e.g. long or short haul), and the environmental and infrastructure impacts of the truck. Each of these data elements are missing from current truck data sources which mostly rely on axle or weight based classification of trucks but would be undeniably important for freight forecasting, emissions modeling, and infrastructure management. The proposed work leverages the benefits of both the WIM stations which provide high levels of detail and VDS which are widely deployed throughout CA, and is able to overcome the drawbacks of the traditional truck data collection methods by providing link specific and temporally continuous data. The integration of WIM and inductive signature technologies represents a novel approach that has yet to be investigated by other researchers. Ultimately, considering applications to freight and emissions modeling, the research proposed in this work will assist California, and other States, in meeting the goals set forth by AB 32, ISTEA, and MAP-21 while also opening new doors for research by providing a valuable dataset to study commercial vehicle operations in greater detail.

1.1 Impact and Importance of Commercial Vehicle Activity

Commercial vehicle activity has multi-faceted impacts and benefits. In relation to freight movements, commercial vehicles are the primary mode of transport by both weight and value accounting for 65% and 68% of the market, respectively, as shown in Figure 1.1 (USDOT, 2013).

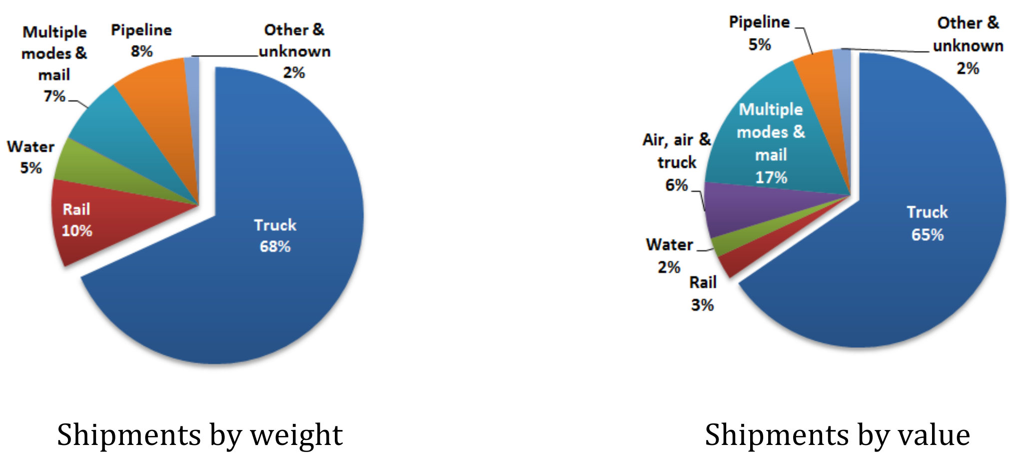


Figure 1.1 Freight shipment weight and value by mode

As a whole, freight transportation is a primary component of economic growth, so there is much to be attributed to commercial vehicle operations. However, with increasing awareness of global warming effects, air pollution concerns, high congestion along freight corridors and around major freight generators, safety concerns, and other effects, it is essential to gain a better understanding of commercial vehicle activity in order to diminish its harmful side-effects. A brief overview of externalities resulting from freight movements provides an apt platform to discuss the impacts and importance of commercial vehicle activity as they relate to the impacts of the research presented in this study.

In economics, *external costs* of an activity are those borne by members of society who may not directly benefit from that activity. In freight transportation, externalities result when one who did not directly benefit from goods movement or other related freight activities has to pay the cost in terms of health impacts, air pollution, and/or congestion, for example (de Palma et al., 2010). Ranaiefar and Regan (2011) categorized freight externalities into economic, ecological, social, and environmental.

While not all externalities depicted by Ranaiefar and Regan (2011) can be attributed directly to commercial vehicles, e.g. they speak more broadly about freight transport including rail, air, port facility operations, etc., several of the externalities are the responsibility of commercial vehicles. Economic externalities include changes in land use, economic growth, efficiency of infrastructures, congestion in terms time away from productive activities, and waste of energy or resources due to empty movements or partial load shipments. Unlike the other three types of externalities, economic externalities can be positive in that growth in freight volumes reflects a growth in the economy, increased employment, and increased revenue. In fact, transportation related goods and services accounted for more than 10% of the US GDP in 2002 according to the Bureau of Transportation Statistics (RITA, 2013).

Environmental externalities of road based freight transportation include air pollution which damages the environment at both the local level (e.g. vegetation and crop damage, endanger nature and animal life) and global levels (e.g. climate change). The environmental effects of different types of air pollutants are shown in Table 1.1 (Ranaiefar et. al, 2011). Lee et. al (2010) analyzed the health impacts of PM and NO_x emissions generated by trucks accessing the Ports of Long Beach and Los Angeles in California and found that, on average, trucks contribute to 50% of PM and 60% of NO_x emissions and more specifically that port trucks contribute 6% of CO, 10% of HC, 35% of NO_x and 21% of PM total emissions.

Table 1.1 Environmental effects of air pollution

Pollutant	Affects
VOC: Volatile Organic Compounds (mainly Hydrocarbons, HC)	• Produces ground-level ozone (O_3) which leads to regional smog production, which impairs visibility and alters the taste and smell of air.
SO_2:Sulfur Dioxide	• Formation of acid rain, which can adversely affect vegetation, buildings, and humans.
NO_x: Nitrogen Oxides	• Produces ground-level Ozone (O_3), which leads to regional smog production. • Formation of Nitric Acid (HNO_3), which causes paint deterioration, corrosion, degradation of buildings, and damage to agricultural crops. • Short term health effects include acute irritation, neurophysiological dysfunction, and respiratory problems. • Long-term health effects are damage to lung tissue and possibly lung cancer.
PM_{10}: Particulate Matter (ten microns)	• Can cause severe health problems. • Increases Greenhouse Gas emissions.
CO: Carbon Monoxide	• CO can form Ozone and has direct effect on global warming when reacting with hydroxyl (OH) radicals.
CO_2: Carbon Dioxide	• Concentration of CO_2 increases GHG effects.

The ecological externalities of freight transportation are the most difficult to measure since they are related to the long term detriment of the environment attributed to global warming. The EPA measures Green House Gas (GHG) emissions as a major contributor to global warming and defines GHG in terms of Carbon Dioxide (CO_2) equivalents. Commercial vehicles are the second largest contributor of GHGs (EPA, 2013) accounting for

28% of the GHG productions in the US. For these reasons, policies related to reducing GHGs through emissions caps, CO_2 feebate programs, CO_2 taxes, and road pricing have been discussed as possible methods for reducing CO_2 output.

Communities near major freight activity centers in urban areas such as intermodal facilities or sea ports benefit from exclusive job market opportunities, economic growth of their region and significant tax revenues. However, freight transportation causes extensive damage to these same populations. Health threats due to air and noise pollution, stressful driving, accidents, death, injuries or property damage, waste of time and energy along congested routes and reduced enjoyment of outdoor activities are some examples of the social externalities of freight transportation.

1.2 Current Data Sources and Their Limitations

The National Cooperative Freight Research Program (NCFRP) Repot 39 reviewed the current state of truck activity data and determined critical gaps in freight data (NCFRP, 2014). Critical information gaps, their basic definition, and the best publically available data sources for each variable are summarized in Table 1.2.

Table 1.2 Data Gaps, Definitions, and Existing Sources for Commercial Vehicle Data

Variable	Definition	Best Publically Available Sources
Vehicle Miles Traveled (VMT)	Measure of the extent of motor vehicle operation within a specific geographic area	Highway Performance Measurement System (HPMS)
Tons/Ton-Miles	Total weight of the entire shipment multiplied by the mileage traveled by the shipment	Commodity Flow Survey (CFS)
Value/Value-Miles	Market value of goods shipped multiplied by the mileage traveled by the shipment	Commodity Flow Survey (CFS)
Origin-Destination (OD) Flows	The start and end points for a particular truck trip	Commodity Flow Survey (CFS) Freight Analysis Framework (FAF)
Vehicle Speed	Velocity of a vehicle	Roadside traffic counters Weigh-in-motion (WIM) GPS traces

The major source for several of these data gaps include the Commodity Flow Survey (CFS) which is a comprehensive survey of businesses, warehouses, and freight managing offices conducted at the national level every five years. In addition to the CFS and HPMS, several other existing data sources were identified in NCFRP Report 39 as sources for commercial vehicle data including the Vehicle Inventory and Use Survey (VIUS), Weigh-in-Motion (WIM) systems, privately owned truck GPS data, and state and federal truck registration records.

Many of these sources lack in their ability to segment each of these variables by: (1) commodity type, (2) vehicle type, (3) vehicle characteristics, and (4) spatial coverage. Unfortunately, no single source addresses each and every data gap with the desired level of detailed segmentation. According to NCFRP Report 39, the CFS and VIUS possess the best ability to cover each of the data gaps at some level of segmentation. Other research highlighted VIUS, GPS, and WIM data as three core data sets which provide truck data stratified across the segmentation categories (ITS, 2010).

1.2.1 Commodity Flow Survey (CFS)

The Commodity Flow Survey (CFS) is often referred to as the most comprehensive tool for understanding freight flows in the US (RITA, 2014). The CFS is a national shipper based survey conducted every five years as part of the Economic Census. It provides information on commodities shipped including value, weight, mode of transport, origin-destination. The survey covers manufacturing, mining, wholesale, and selected retail and service industries. For the 2012 survey, approximately 100,000 establishments were included (NCFRP, 2014). The survey is limited in its coverage of imports and farm based shipments, and due to its coordination with the economic census, is not timely. The CFS is a major input for the Freight Analysis Framework (FAF) which is a national commodity flow model that estimates tonnage, value, and ton-miles for all good shipped to, from, and within the US. FAF estimates are stratified by origin and destination at the regional level, commodity type, and mode. Because the CFS and FAF concentrate on regional commodity flows they are less valuable sources commercial vehicle characteristics at the state and metropolitan levels.

1.2.2 Vehicle Inventory and Use Survey (VIUS)

The widely used Vehicle Inventory and Use Survey (VIUS) formerly the Truck Inventory and Use Survey (TIUS), is a national level survey of registered commercial and private trucks in the US. The survey represents the most extensive data source to capture physical and operational characteristics at the state-level. VIUS provides estimates of distributions of trucks by body type, commodities carried, and vehicle age (VIUS 2002). VIUS is used by state and federal agencies for transportation planning, highway safety studies, emissions estimation, and fuel and energy consumption (NCFRP, 2014). Even though VIUS provides extensive data, these data come with limitations.

First, the VIUS data represents a sample of all vehicles, approximately 2,000 vehicles per state (Cambridge, 2008) and therefore contains sampling biases. Further, VIUS cannot identify truck population statistics at the state level due to discrepancies in how the survey captures in-state and out-of state trucks traveling in each state. For instance, trucks operating on California routes may be registered in California or in any other state, but only trucks which selected California as their home base would be included in the California data sub-set. Thus, only national level characteristics can truly be captured by VIUS which presents a problem if state level characteristics are thought to differ from national level statistics.

Second, VIUS can only capture trucks owned or operated by carriers, which means that intermodal containers and chassis typically owned by shippers are not included in the data. Southern California, which is home to two major US ports, would most likely possess a distribution of vehicle types (intermodal containers, in particular) which would deviate from what national statistics provided by VIUS might suggest or even have the ability of re-porting.

Third, although it is not a goal of VIUS, VIUS is not able to provide route information or OD patterns which are needed for freight and emissions model calibrations. Instead, it is meant to provide more general information about relationships between commodities and truck characteristics (truck types, distance traveled, average weights, etc.) such as payload factors. Commodity-based freight models such as those developed in Florida, Ohio, and California and at the federal level (Freight Analysis Framework, or FAF) require methods of converting tonnage to truck trips and rely on payload factors from the VIUS (Battelle, 2011; Cambridge, 2008; ITS, 2010).

Lastly, VIUS was discontinued in 2002 and can therefore only be used as a source for backcasting validation (backcasting is the process of estimating values for a year prior to the year on which a model was developed and calibrated) in the context of freight models. With the discontinuation of VIUS it has become a challenge to obtain equivalent data for satisfying the various needs of state and local planning agencies. Several suggested re-placements have been identified including survey or mandated data collection programs such as state level truck intercept surveys (Lutsey, 2008), International Registration Plan

(IRP) records, and International Fuel Tax Agreements (IFTA). Further, while IRP and IFTA sources are plausible replacements for VIUS, they are not publically available.

1.2.3 Weigh-in-Motion (WIM)

Weigh-in-motion (WIM) systems and inductive loop detectors are examples of two of the more prevalent passive data collection methods which have the potential to provide detailed truck characteristics data. WIM systems collect weight, axle spacing, and length data without requiring the vehicle to stop, such as would be required at static scales. WIM are sparsely located throughout most states. In California, for example, there are approximately 118 sites (Caltrans, 2014), while in Oregon there are only 22 WIM sites (Monsere et al., 2011). WIM systems are widely used to collect truck data such as axle load spectra for the Mechanical-Empirical Pavement Design Guide (MEPDG) for pavement design and management across many states (Lu and Harvey, 2006; Elkins and Higgins, 2008; Haider et al., 2011; Ishak et al., 2011; Cottrell and Kweon, 2011; Stone et al., 2011; Darter et al., 2013). Additionally, WIM data are used to report traffic classification counts to the HPMS. While these sites provide valuable truck count and weight data, they do not provide detailed characteristics such as commodity carried or trip origin-destination.

1.2.4 Highway Performance Measurement System (HPMS)

The Highway Performance Measurement System (HPMS) was developed in 1978 to provide a central database for the extent, condition, performance, use and operating characteristics of the nation's highways (HPMS, 2003). The main use of HPMS is to allocate funds of the Federal-Aid Highway Program back to states under the TEA-21 legislation. The majority of traffic data reported to HPMS come from short term counts. Annual Average Daily Truck Traffic (AADTT) result from 24 to 48 hour manual traffic counts extrapolated to annual counts by applying adjustment factors. AADTT may possess significant errors, as they depend on short sampling periods which cannot effectively capture the seasonal and diurnal trends of truck travel patterns, even with the use of adjustment factors, due to the heterogeneous disposition of truck travel patterns (Kwon et al., 2003).

In addition to short-count methods, HPMS data also comes from continuous count stations including inductive loop detectors (ILD) and WIM systems. Florida, Illinois, Ohio, Michigan, and Washington use ILD data for highway traffic reporting to HPMS (HPMS, 2014). In California, there are over 25,000 inductive loop detectors grouped among around 8,000 vehicle detection stations (VDS) which report traffic volume, loop occupancy, and, when installed as double loops, speed (PeMS, 2012). Measurements are typically aggregated at 30 second and five minute intervals. Loop detector data from VDS cannot measure truck volumes directly and must rely on estimation algorithms to estimate broad truck classes and can only be used at aggregate levels (Kwon et al., 2003). Although, several researchers have derived algorithms to *predict* truck counts from traditional loop measurements (Wang and Nihan, 2003; Zhang et al., 2006; Coifman and Kim, 2009), loop detector data alone cannot be used to *measure* truck volumes. However, the instrumentation of existing inductive loop sensors with high sample rate detector cards provides significant potential improvements in truck data. Advanced ILD have been shown to be capable of vehicle body classification (Sun and Ritchie, 2000; Sun et al., 2003; Cheung et al., 2005; Ki and Baik, 2006; Jeng and Ritchie, 2008; Meta and Cinsdikici, 2010; Liu et al., 2011; Jeng and Ritchie, 2013). A significant advantage of advanced ILD is their compatibility with existing conventional bivalent ILDs. This allows existing conventional ILDs to be swapped with advanced ILDs without suffering any loss in system functionality.

1.2.5 Global Positioning Systems (GPS)

Global Positioning System (GPS) data provide speed, location, and directional data necessary for determining origin-destination (McCormack and Hallenbeck, 2006). GPS data is mostly used for real time trucking industry operations and is collected by truck logistics companies (NCFRP, 2014). There are significant privacy concerns that limit the public availability of GPS data. The American Transportation Research Institute (ATRI) collects and sells truck GPS data (Zmud et al., 2014). GPS does not provide truck characteristics such as body configuration or commodity carried and represents only subpopulations. The Ports of Los Angeles and Long Beach also collect GPS data from drayage trucks as part of the Clean Truck Program (You, 2012). The NCFRP Report 39 suggests that a 'near perfect' dataset for understanding truck movements in the US could be created by mandating a national freight GPS network under which all trucks, or a statistically valid sample of trucks, be required to report GPS data of all trips. Major challenges to this potential data source are: (1) the immense amount of data that would require significant amounts of infrastructure for storage (2) creation of a valid sample frame from which to generalize observations, and (3) privacy and proprietary information concerns that limit the number of variables collected (NCFRP, 2014). Several state-level GPS collection programs have been implemented in Oregon using smartphone GPS (Bell and Figliozzi, 2013) and in Washington using GPS (McCormack et al., 2010).

1.3 Defining Commercial Vehicle Body Class

One major hindrance is that data sources which provide commodity information (e.g. CFS, SAS, and VIUS) come from surveys so cannot be linked to links or routes while data sources that provide observed volumes, weights, and vehicle types (e.g. WIM and GPS) do not provide commodity information. This means there is a significant advantage in connecting observed vehicle data to commodity information. Since body configuration is closely linked to commodity carried and other operating characteristics, body class data can provide the link to the desired commodity information currently provided only in CFS or VIUS.

Vehicle configuration generally refers to axle or length based groupings of vehicles and takes different forms depending on the agency using the data. A commonly used scheme, FHWA's Scheme F, shown in Figure 1.2 defines 13 axle based classes. Within each axle based category, vehicles can be further distinguished by body configuration. Examples of body configurations are shown in Figure 1.3 . Semi-tractor trailer body types are classified by their drive unit and trailer unit. Similarly, multi-trailer trucks are defined by drive and trailer units. For example, the body type of a commonly observed five axle semi-tractor trailer listed by the FHWA scheme Figure 1.2 as 'Class 9 single trailer' might have a body configuration of a van, intermodal container, a tank, or a platform.

In California, the California Department of Transportation (Caltrans), the California Air Resources Board (CARB), and the California Energy Commission (CEC) have developed their own classification schemes which represent different levels of detail regarding truck characteristics. For instance, the CEC adopted the U.S. DOT's designation in which trucks with more than 33,000 lbs gross vehicle weight rating are labeled as Class 8. Table 1.3 (excerpt from (CEC, 2012) shows a subset of the CEC truck body classification scheme for USDOT Class 8 vehicles that fall into the FHWA Class 9 category. Clearly, the CEC would benefit from detailed body type data (platforms, tanks, vans, and other) within the Class 8 truck category.

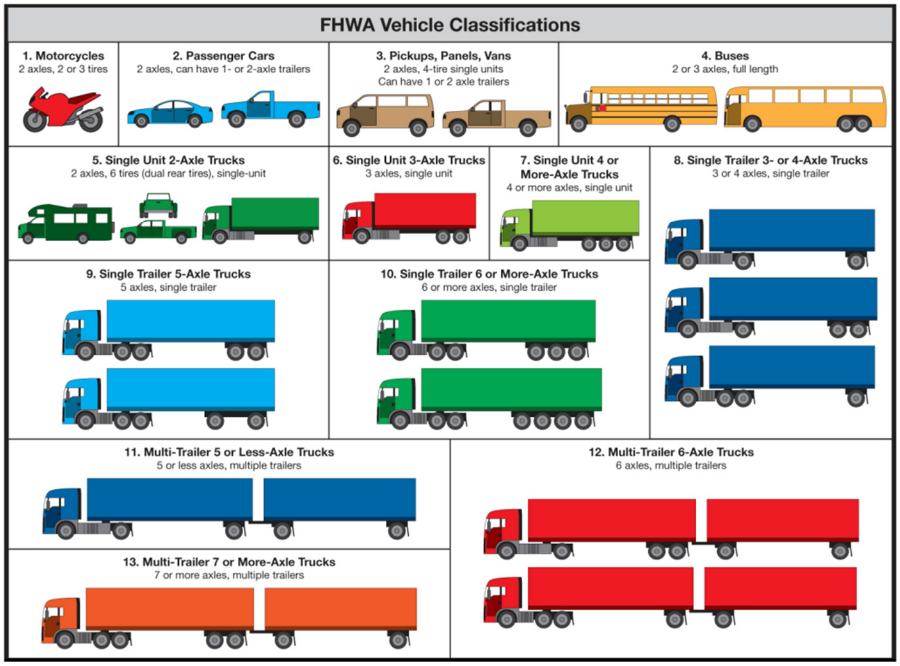


Figure 1.2 FHWA 13 Class Axle Based Classification Scheme

Table 1.3 California Energy Commission Freight Truck Classification Scheme

Class	Description
14	Class 8 (over 33000 lbs.) Cement Mixer
15	Class 8 (over 33000 lbs.) Dump etc.
16	Class 8 (over 33000 lbs.) Other
17	Class 8 (over 33000 lbs.) Platform/Flat
18	Class 8 (over 33000 lbs.) Tank
19	Class 8 (over 33000 lbs.) Van

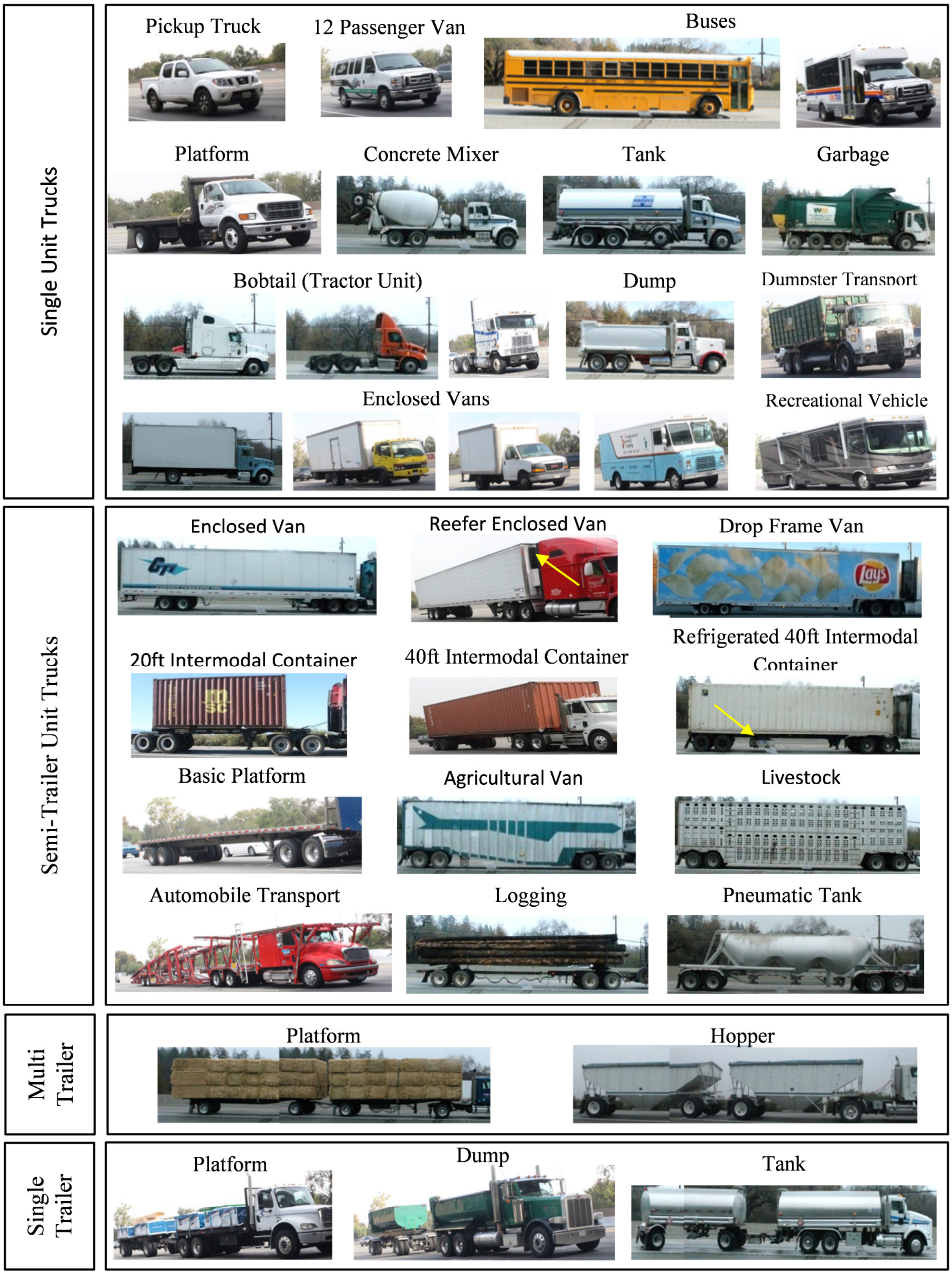
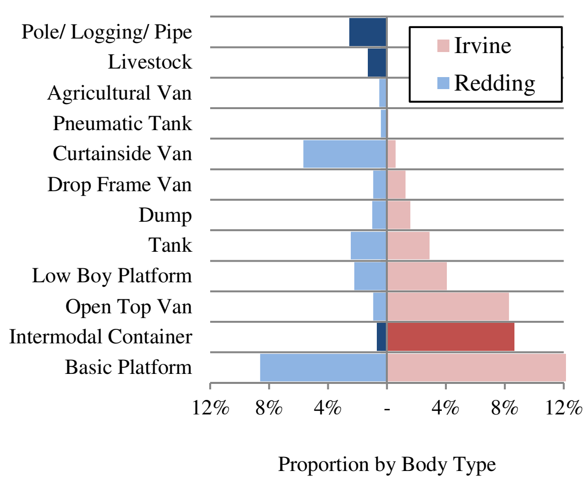


Figure 1.3 Samples of vehicle body configurations

1.4 Needs for Body Classification of Commercial Vehicles

Spatial and temporal trends in truck, trailer, and drive unit body types signal differing activity patterns, industry-specific operating characteristics, regional land uses, and seasonal commodity flow patterns. Figure 1.4(left) shows the variation in minority trailer body classes at two WIM sites in California- an urban location (Irvine) near the Ports of Los Angeles and Long Beach and a rural site (Redding) 120 miles from the Oregon-California border. Although vans represent over 60% of truck traffic, the proportions of industry specific, minority classes contrast significantly between these two sites. In Figure 1.4(right) the volume of enclosed vans observed at a WIM site located in central California (Fresno) peaks in the late afternoon while intermodal container traffic decreases over this same period. Existing data collection methods do not possess the sophistication required to capture the dynamic behavior of commercial vehicle operations illustrated in these figures.



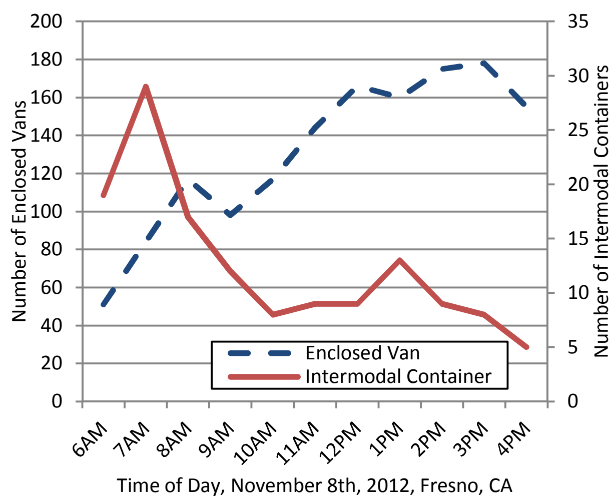


Figure 1.4 Spatial (left) and temporal (right) trends in body class.

The needs for body class data of commercial vehicles are twofold. First, body class data is needed to fill critical gaps for existing transportation programs. Freight transportation planning programs rely heavily on the results of the Vehicle Inventory Use Survey (VIUS), but with the discontinuation of that resource, a critical gap has been opened and a replacement data source is desperately needed. Second, body class data collected at the link and route level presents an increased level of detail that has yet to be captured by any other data source. The previous figures clearly demonstrate that body class varies significantly by location and time of day, so ignoring this level of detail can lead to significant modeling errors.

Body class data can allow agencies to further develop existing models by replacing existing sources that are either inaccurate or lacking in necessary detail or to create new models designed to make full use this new data source. In the end, better models will lead to more effective management of transportation facilities, and improved confidence in estimates of emissions and air quality. In this section, a description of each need is provided.

1.4.1 Transportation Planning

Traditional transportation planning models suffer from the inability to accurately depict commercial vehicle travel (FHWA, 2014). This is because the travel behavior of commercial vehicles differs geographically and temporally from passenger travel, so the same forecasting approaches used for passenger travel do not apply to trucks. For example, passenger vehicles tend to travel shorter distances, concentrate in urban areas, and operate mainly during peak hours, while commercial vehicles exhibit intra-city and interstate travel ranges plus they operate outside of peak hours. In fact, in California, the Ports of Los Angeles and Long Beach implemented the PierPass program in which port-related commercial vehicles are incentivized to operate outside peak periods in an effort to mitigate environmental and social externalities (PierPASS, 2014). Many urban transportation models rely on factoring based approaches to account for truck traffic.

Freight transportation planners are some of the main consumers of truck data specifically related to temporal and geographic body class data. Detailed truck characteristics such as body type which can indicate the commodity transported, can be used in model validation during which estimated and observed truck counts are compared. Knowledge of body configuration data allows validation exercises to compare results closer to the commodity flow level so that rather than comparing aggregate truck counts, commodities can be grouped and compared by truck body configuration. This would allow researchers to better pinpoint modelling errors. Further, the Freight Analysis Framework (FAF), a national level freight forecasting model, presents specific guidelines for converting commodity flows to truck traffic flows by using payload factors from motor carrier surveys (Battelle, 2011).

Beyond model validation and average payload estimation, body class data provided at the link level can assist in understanding travel patterns of commercial vehicles. Point based estimates of body class allow body types to be mapped across a region allowing better depiction of travel patterns. For instance, measuring the volumes of intermodal containers at 100 sites across the state highway system would effectively show the general origin and destination pattern of this class of trucks. Likewise, logging type trucks observed in one region of the state may only be observed in a small bubble around the region thus depicting that short distance trips dominate this particular class. These types of observations provide policy makers a better understanding of truck travel patterns and volumes across the State.

Additional needs relating to freight transportation planning include: (1) truck volumes of freight versus non-freight trucks and long haul versus short haul trucks, (2) proportions of empty hauls to for truck touring models, and (3) seasonal and hourly traffic patterns by commodity type for converting annual flows to daily flows.

1.4.2 Air Quality Monitoring

Although emissions models are currently not designed to harness truck body classification data as input, their inclusion in future models will likely yield significant improvements in emissions estimations due to the improved fidelity of truck characterization. Since trucks can been related to commodity type through body classification, agencies can design programs to reduce emissions that are aimed at specific industries that produce those commodities. Additionally, in line with freight transportation planning data needs, body class information will distinguish between long and short haul movements as well as empty movements. This will lead to improvement in emissions inventory models.

1.4.3 Operations and Maintenance

Truck count and weight data are currently used by state DOTs for pavement studies, highway monitoring and capacity studies, accident rate calculations, and analysis of truck transport practices (Caltrans, 2014). State agencies rely on continuous classifier systems such as Weigh-in-Motion (WIM) or Automatic Vehicle Classifier (AVC) systems to gather truck counts for federal reporting requirements to the Highway Performance Monitoring System (HPMS). Where WIM or AVC systems are not present, manual counts are performed for short time periods. There is a real need to expand not only the geographical scope of measured locations, but also to increase the level of detail in the data that is collected. Pavement maintenance and design, safety, and sensor calibration would each uniquely benefit from higher fidelity truck characterization data.

For pavement studies, many states have implemented the Mechanistic-Empirical Pavement Design Guide, or MEPDG, which at the highest level of detail, requires truck axle load spectra as the main input (Haider et al., 2011; Lu and Harvey, 2006). Agencies that follow the MEPDG must collect site specific truck data (Level 1) or rely on broader regional (Level 2) or even broader state level (Level 3) estimates. Moving away from Level 1 estimates can result in over or under designed pavement structures, resulting in wasteful spending for construction or maintenance and repair. Thus, it would be valuable to be able to obtain estimates of truck volumes and weights as many sites possible.

Body class data can also be a valuable tool for sensor calibration programs. In terms of length-based measurement and load measurement error from the WIM systems, two sources of error relating to load measurements exist: systematic errors due to calibration and random errors due to vehicle dynamics over the sensors (Prozzi et al., 2007). Identifying the cause of measurement errors by relating it to truck body type can be a valuable tool for calibrating WIM sites (Nichols and Bullock, 2004). Nichols and Bullock (2004) comment on liquid tanks causing possible sensor measurement errors due to dynamics of liquid movement while the truck is traversing the sensor, for example. If a site is known to have a high number of tanks, then observed systematic or random errors might not be a result of calibration errors, but rather due to the high concentration of tanks. For state agencies tasked with sensor maintenance this could help prioritize maintenance activities by indicating which sites do not require service as frequently, thus saving time and money.

In terms of safety, body type can serve as a predictor of accident severity and delay time. For instance, a tanker-involved accident may cause more damage, be more dangerous, and cause more delay, then an intermodal container involved accident since a tanker is more likely to be carrying fuel or other corrosive liquid. Figure 1.5 depicts the crash rates by truck body type occurring in 2011 (FMCSA, 2013). Although there appear to be significant differences between the numbers of crashes by body type, the accidents rates are not scaled by observed volumes of each truck type. This is because data such as vehicle-miles-traveled (VMT) by truck body type is not available from existing data sources. Therefore, knowledge of total volumes or VMT by body type would help to provide more informative safety statistics. Moreover, information about body type volumes by location could help decouple accident causes.

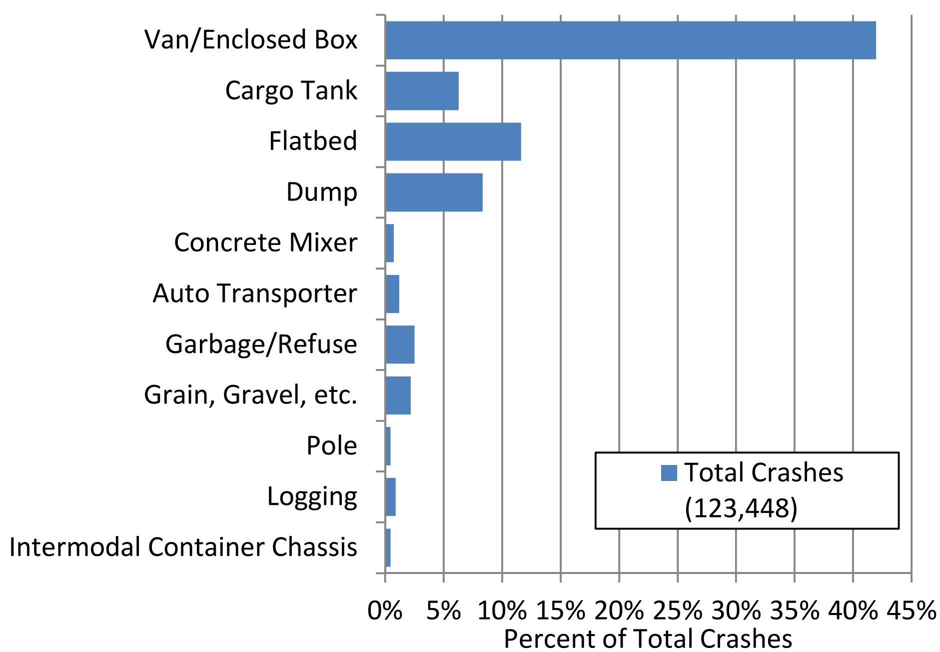


Figure 1.5 Total Crashes by Truck Body Type

1.5 Proposed Solution

Given the many uses of commercial vehicle body class data and the series of drawbacks of current data sources, it is evident that alternative data collection methods are needed. Agencies need a low cost and readily implementable solution to gather data that fulfills the geographical and temporal needs of freight transportation and air quality monitoring. To achieve these goals, a novel approach of integrating WIM and advanced ILDs was developed in this dissertation. WIM and inductive signature data are exceptionally complementary. WIM data provides information on a truck's axle configuration and weights; however, the axle-based information cannot be directly associated with a truck's function or body configuration. On the other hand, ILD signatures have the ability to distinguish trucks by body configuration, although inductive signatures obtained from conventional loop sensors are not suited for obtaining detailed axle configuration information (Jeng and Ritchie, 2008).

As shown on the left side of Figure 1.6, at a typical WIM site the outermost lanes are equipped with bending plates or pressure sensors to measure axle weights while inductive loop detectors straddle the weight sensors to detect vehicle presence. WIM sites measure speed, volume, truck weight, axle spacing, and length, however, axle-based information cannot be directly associated with a truck's function or body configuration. Advanced ILDs produce analog waveform outputs, called inductive signatures, which strongly correlate with vehicle body type. A significant benefit of advanced ILD technology is that it requires no in-pavement infrastructure upgrades thus, implementation costs are minimal. The WIM system can be equipped with advanced ILD technology by simply swapping out detector cards in the WIM controller with advanced signature capable ILDs. Test deployments showed that the modification does not alter the WIM site functionality, so regular data reporting requirements from WIM site are not affected.

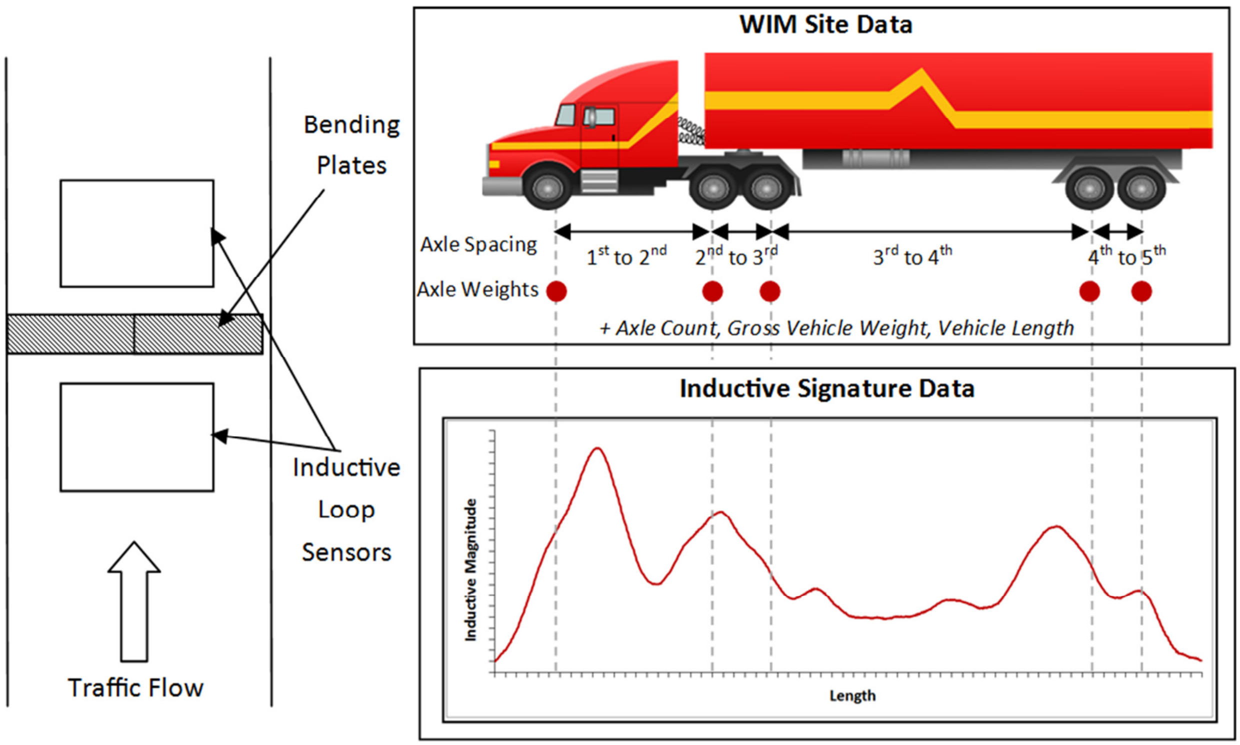


Figure 1.6 WIM Site Configuration with data outputs from Advanced ILDs and WIM

Three models are developed in this dissertation (Table 1.4): (1) WIM based body class volume estimation, (2) ILD signature based body classification, (3) integrated WIM and ILD signature based body classification. Progression from the first to the third model represents increasing levels of input data resolution with the first model using only WIM variables such as length and axle spacing, the second model using only signature data, and the third model fusing WIM variables and signature data. The outputs of each model also vary in the level of detailed truck body classes that are predicted. For simplification purposes, the output classes are shown in Table 1.4 pertain only to semi-trailers which generally correspond to FHWA class 9 five axle single semi-trailer vehicles.

Table 1.4 Summary of Models

Model	Technique	Input Resolution	Output Resultion
WIM Based Body Class Volume Estimation *(Section 5.1)*	Adapted Decision Tree	WIM measurements only	Volume estimates for 5 body class groups for FHWA Class 9 Trailers
Inductive Signature-based Body Classification *(Section 5.2)*	Ensemble of Classifiers	Inductive Signatures	Individual vehicle classifications by vehicle configuration group
WIM and Inductive Signature based Body Classification *(Section 5.3)*	Data integration + Ensemble of Classifiers	WIM measurements + Inductive Signatures	Individual vehicle classifications with weight by axle configuration group

The WIM based Body Class Volume Estimation method outputs truck body class volumes five-axle semi-tractor trailers based solely on WIM data. A modified decision tree model is developed to estimate volumes of five body categories including vans, tanks, platforms, 40ft containers, and an additional ‘other’ category using vehicle length, axle spacing between the third and fourth axles, and a measurement derived from axle spacing and length. This method allows more information to be extracted from axle-based measurement data without any additional equipment or significant resource expenditures. The model is therefore applicable to prior years and is an ideal tool for freight model validation backcasting.

The Inductive Signature-based Body Classification model is formulated in three tiers using features derived from the inductive signature but not using any WIM data. The first tier separates single- and multi-unit vehicle configurations. The second tier employs a multi-layer feed forward neural network to classify vehicles into five broad vehicle configuration categories: passenger car, single unit truck, single unit with trailer, semi-trailer, and multi-trailer. The third tier differentiates body class within the top tier category using a multiple classifier system approach that accounts for class imbalance. The multiple classifier systems (MCS) method was adopted to increase the classification accuracy for minority body classes and to ensure spatial and temporal transferability of the models. Despite their many benefits, MCSs have not been considered in previous work with inductive signatures nor have they been widely used in the broader body of vehicle classification literature. Instead, research in this area has focused on pre-processing of predictive features, or tuning and optimization of individual classifiers used to predict vehicle class. The Signature Only body class model provides truck counts by body class at loop detector sites which have been equipped with advanced ILDs. This model is ideal for pavement management and air quality monitoring because it provides truck counts in regions without WIM detectors.

The integrated WIM and Inductive Signature based Body Classification model represents the highest resolution of input and output data. Like the Inductive Signature only model, the integrated model also follows a tiered approach. However, instead of the first tier relying on inductive signature features to distinguish broad vehicle configuration categories, the integrated model uses WIM axle count, axle spacing, length, and weight measurements to first predict the axle configuration class according to the FHWA classification sieve. The second tier then predicts the body class within each FHWA category using a multiple classifier system approach with correction for class imbalance. Features for the model include WIM variables (length, spacing, etc.) and signature features derived through a fusion of the WIM and signature components. This model is applicable at WIM sites that have been equipped with advanced ILDs. The model suits many of the needs expressed

Section 1.3 including payload factor estimation for freight modeling and time of day analysis.

Together, the unique integrated data source and robust classification framework described in this dissertation represent a significant advancement in detailed truck classification that has not been achieved in previous work. While previous models are able to classify trucks by *either* axle *or* body information, but not both, the methods developed in this research unite the benefits derived from these complementary data sources thus producing the highest possible resolution of truck data from existing sensor technologies. In addition to the body classification models, the large data set resulting from the data collection efforts for this dissertation is itself a valuable and novel resource for truck studies.

1.6 Organization

This dissertation is organized into seven chapters. Following the Introduction in Chapter 1, Chapter 2 presents the necessary background of WIM and ILD signature technologies and summarizes the previous work in using these sources for body classification of commercial vehicles.

Chapter 3 describes the data collection and processing efforts including the development of a user-interface for processing over 35,000 vehicle records which consist of photo, WIM and signature data. Also, the classification scheme developed as part of this dissertation is described and summary statistics are provided for the collected data. The large data set resulting from the data collection efforts for this dissertation is itself a valuable and novel resource for truck studies.

Chapter 4 introduces the machine learning tools used for vehicle classification in the signature only and WIM-signature models. This chapter identifies the reasons for choosing the machine learning tools based on the particular characteristics of the data.

Chapter 5 contains the implementation details and results of each of the three body classification models. The chapter follows the evolution of the models in terms of the resolution of the input and output data, beginning with the WIM based model, continuing with the signature only model for VDS locations, and concluding with the WIM-signature combined model for WIM locations.

Chapter 6 presents the potential applications of body class data including time of day trend analysis, average payload estimation, and gross vehicle weight interpolation.

Finally, Chapter 7 concludes with a synthesis of model results, summary of impacts, and listing of future work.

2 Background

Currently, the main truck data available for emissions and freight models is limited to WIM, ILDs, vehicle registration records, national shipper/carrier surveys, and AADTT counts. The data from these sources is commonly mapped to the FHWA 13 class axle-based scheme, or simplified schemes based on weight classes which divide trucks into medium, heavy, or light duty types. None of the existing sensor based sources (WIM and ILD) are capable of providing body type information, which can be a key indicator of the industry served by the truck as well as the travel patterns of the truck. And while survey data is capable of providing origin-destination information and truck body type, surveys are limited by sample sizes, timeliness, and data lifespan and cannot yet provide individual link or route level data.

As an illustrative example of the lack of detail in axle-based classification, consider the most common truck axle configuration, the five axle tractor trailer corresponding to FHWA class 9. Within class 9, there exists a diverse distribution of trailer body types as shown in Figure 2.1, with the most common being enclosed and refrigerated vans, platforms, and tanks. It is important to know the specific trailer type because each trailer body type may have dissimilar travel patterns, unique emission rates, and distinct effects on congestion and safety. For example, in relation to travel patterns, intermodal containers travel between ports and intermodal facilities whereas enclosed vans might be commercial delivery vehicles traveling between regional distribution centers and businesses. The breakdown of FHWA Class 9 into the wide variety shown in Figure 2.1 clearly illustrates the significant amount of unknown information that exists in existing truck monitoring data.

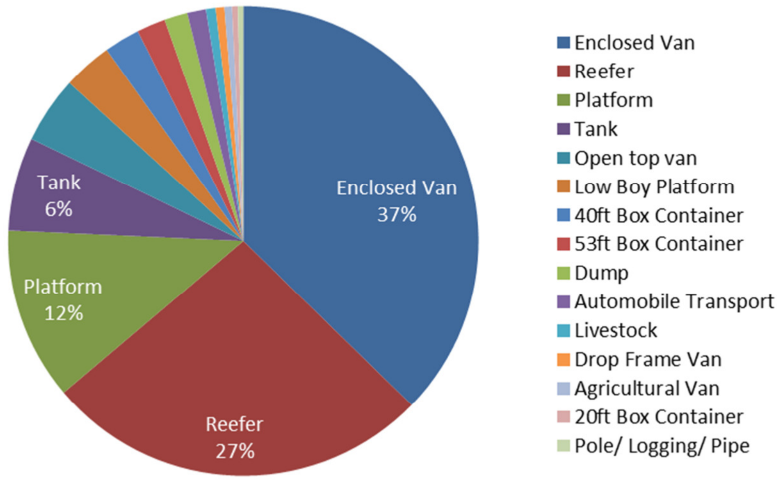


Figure 2.1 Trailer Body Type breakdown of FHWA Class 9 Tractor-Trailers

The integrated data source presented in this dissertation is a result of combining two highly complementary technologies, WIM and inductive signatures, to create a synergistic resource that is highly detailed, link specific, temporally continuous, up-to-date, and representative of the full truck population. In this Chapter, the hardware systems for WIM controllers and advanced ILDs are described and a literature review of classification models which have used these systems is provided.

2.1 Weigh-In-Motion Systems

2.1.1 System Description

Weigh-in-Motion (WIM) devices have been used since the 1980s to collect data for truck routing, pavement management and design, weight enforcement, traffic safety, and transportation policy (Nichols and Bullock, 2004).

There are currently 106 WIM stations in California as shown on the map in Figure 2.4. Two main types of WIM controllers are currently deployed in the State of California: the earlier DOS-based 1060 series controllers and the current Linux based iSinc family of controllers, which include the iSinc WCU-II and iSinc WCU-3 Lite. Of the 106 WIM controllers in California, 17 are WIM iSinc type controllers. The main distinction between the controllers for the purpose of this work is in their built-in ability to log inductive signature data. The loop sensor module (LSM) of the 1060 WIM controllers is designed only to obtain conventional bivalent inductive loop data. On the other hand, the LSM of the iSINC Lite controller has the ability to obtain inductive signature data. The caveat for the iSINC controller however, is that inductive signature data is currently designed only for diagnostic and troubleshooting purposes. Hence, the inductive signature data can only be manually logged when the system is in diagnostic mode, and is not currently available as an operational feature within the system. As WIM controllers become damaged and require replacement, older controllers are replaced with the newest iSinc models. This is a great advantage for the work developed in this dissertation because this essentially means that all WIM controllers will be capable of producing signature outputs.

A typical WIM station, as depicted in Figure 2.3, includes bending plates or pressure sensors straddled by square inductive loop detectors in the outermost lanes and piezoelectric sensors straddled by inductive loops in the innermost lanes. Figure 2.3a depicts a five lane highway sensor site in which the outer three lanes are equipped with bending plates while the inner two lanes, used mostly by passenger vehicles, are equipped with piezoelectric sensors.

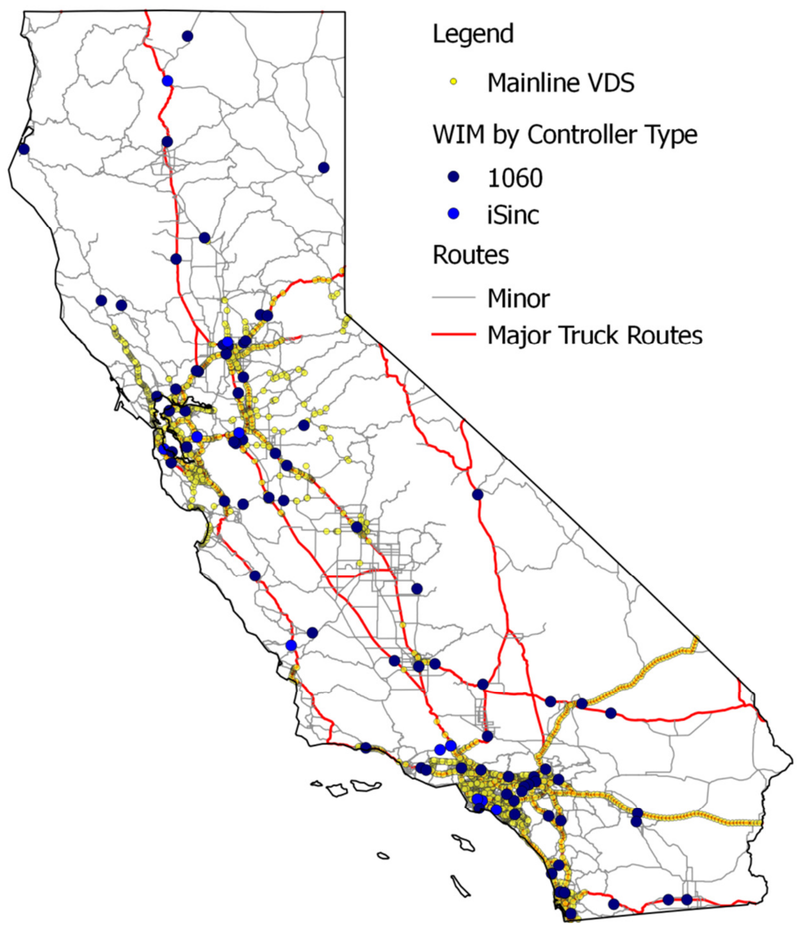
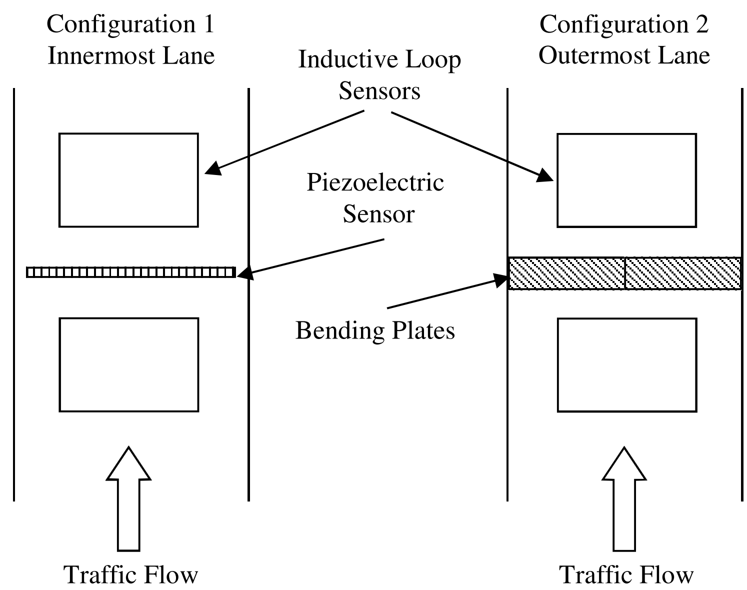
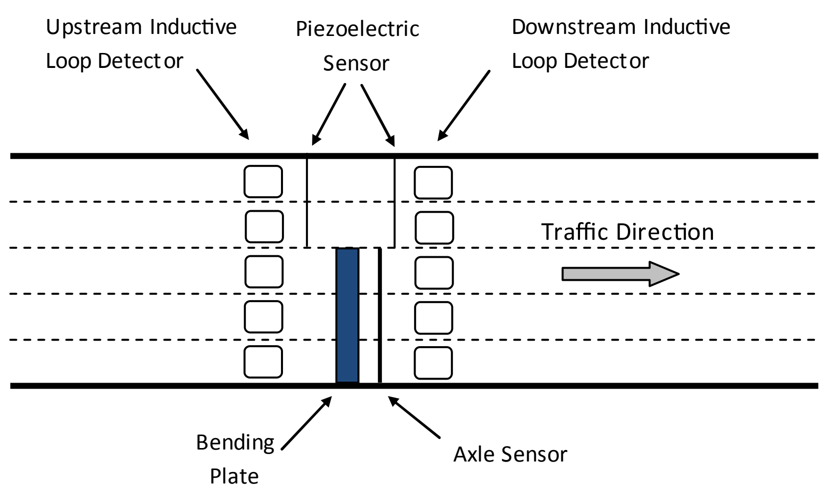


Figure 2.2 WIM and VDS Sites in California



(a) Typical inner and outer lane WIM configurations



(b) Example of site configuration for five lane highway

Figure 2.3 WIM Site Configuration

WIM stations collect vehicle arrival time and date, axle weights and gross weight, axle spacing, and speed (Lu et al., 2002). Vehicle classification is determined from the number of axles, axle spacing, and weight according to the classification sieve for FHWA Scheme F which includes 13 axle-based classes, or for California, the 14 class modified axle-based scheme. A basic decision tree approach divides vehicles into FHWA classes based on number of axles and inter-axle distances. This is approach can lead to classification error for certain vehicle classes since many of the axle counts and distances overlap. Reported errors in classification range have been shown to be as high as 9.5% (Kwigizile et al., 2005). In Chapter 5, improvements to the standard FHWA classification decision tree are made by introducing additional variables such as length and axle spacing ratios to further define certain classes.

Agencies using WIM data are aware that WIM data is prone to accuracy errors in speed, spacing, and weight measurements (FHWA, 2001). The inaccuracies are the result of several possible factors: (1) vehicle dynamics such as speed, acceleration, tire condition, load, and body type; (2) site conditions such as pavement smoothness; (3) environmental factors such as temperature and precipitation (Lee, 1998; NCHRP, 2008). Prozzi et al. (2007) modeled the load errors as systematic and random where random error is a result of statistical fluctuations in estimation which can be over- or under- estimations of the true value. On the other hand, systematic errors are persistent inaccuracies in which the true value is either consistently over- or under-estimated. Through proper calibration procedures such as those outlined in American Society of Testing and Materials (ASTM) Standard E1318-02 (ASTM, 2009) and National Cooperative Highway Research Program Synthesis 386 (NCHRP, 2008), systematic error can be addressed, but random disturbances in the data will persist regardless of calibration.

2.1.2 Previous Work

As was already stated, body-type classification is not available from WIM data. A previous study conducted by the FHWA (FHWA, 1999) attempted to link survey data collected from VIUS to measured truck characteristics from WIM stations in order to better understand truck body configuration characteristics. The study aimed to infer which vehicle configuration variables were indicative of a particular body type so that WIM measurements of those variables could be used to determine body classification over time and across locations. The report deduced the most common body configuration for each of the following vehicle configuration variables:

1. total number of axles,
2. number of lift axles,
3. total vehicle length,
4. average gross vehicle weight (GVW),
5. number of axles on trailers pulled by truck tractors, and
6. number of axles on trailers pulled by straight trucks

Each variable was recorded in VIUS and, except for the average GVW and number of lift axles, is also available from a WIM detector. The report concluded that the 11 distinct body configuration types listed in VIUS could not be distinguished using the above listed variables alone due to significant overlap between axle and weight variables and body configuration categories. For example, weight was found to correlate with body type such that lower weight categories were dominated by platform body types and heavier vehicles tended to be dump trucks, enclosed vans, and tanks. The report concludes that with axle spacing data, it would be possible to further infer body type but without more data connecting vehicle configuration variables to body type available to develop a model, little can be inferred.

2.2 *Inductive Signature Technology*

2.2.1 System Description

Inductive loop detector technology has been used since the 1960s. An inductive loop detector consists of several coils of electrified wire embedded beneath the pavement and connected to a roadside control unit in which loop detector cards process the inductive magnitude changes to measure vehicle presence. The use of inductive loop signature technology for classification was introduced by Pursula and Pikkarainen in 1994.

There are approximately 25,000 inductive loop detectors in California at around 8,000 vehicle detection sites (VDS) as shown in Figure 2.2. VDS are positioned more densely in urban areas.

Conventional loop detectors measure bivalent signals from inductive loops embedded in the pavement and are capable of measuring aggregated volumes and occupancies. The red lines in Figure 2.4 depict the bivalent outputs, e.g. [0,1], of a conventional loop detector. Unlike many other detector systems such as imaging or acoustic sensors, loop detectors are inherently accurate, achieving the best volume count accuracy compared with other common detection technologies, providing a good technology platform to develop the proposed system. Finally, because magnetic inductance is invariant to changes in temperature, lighting, visibility and humidity, ILDs are robust.

Advanced inductive loop detectors measure the inductance change in an inductive loop sensor at rates of up to 1200 samples per second (IST, 2006), producing analog waveform outputs, referred to as inductive signatures, for each traversing vehicle. A significant advantage of advanced inductive loop detectors is that they can replace conventional detectors without altering the system's intended functions (e.g. occupancy and volume measures).

Samples of inductive signatures of various vehicle types are presented in Figure 2.4. The shape of the signature is the result of the ferrous components of the vehicle with the overall duration of the signature related somewhat to the length of the vehicle. Comparing passenger car and semi-tractor trailer signatures, it is easy to distinguish the general shape difference between the signatures. The differences in signature shapes of vehicle within the same axle class are more subtle where spikes and valleys generally relate to the under-carriage or chassis of a trailer but can also be the result of refrigeration tanks or axle placement, for example.

2.2.2 Previous Work

Previous classification methods which use ILDs (Lu et al., 2002; Zhang et al., 2006; Coifman and Kim, 2009; Sun and Ritchie, 2003; Cheung et al., 2005; Ki and Baik, 2006; Jeng and Ritchie, 2008; Liu et al., 2011) have been capable of distinguishing trucks into only a handful of detailed body types. Even the most detailed model by Tok and Ritchie (2008) which focused on commercial vehicles contains only 10 trailer unit types, and this level of detail required an advanced prototype loop detector to be installed in the pavement.

Because of its binary data scale, conventional loop detectors are only capable of providing length-based classification if the speed a vehicle can be obtained. Outputs from conventional ILDs have been used to stratify vehicles into distinct length classes (Reijmers, 1979). But have only been successful in dividing vehicles into no more than five classes with the more successful algorithms obtaining only three defined classes (Coifman, 2007; Coifman and Kim, 2009; Wang and Nihan, 2003).

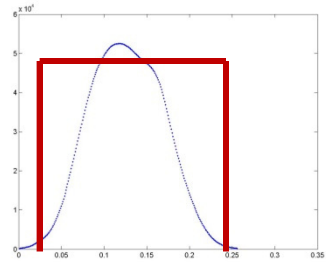
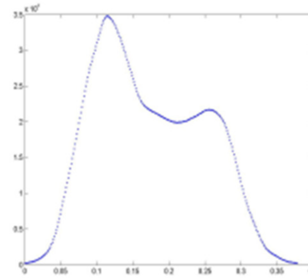
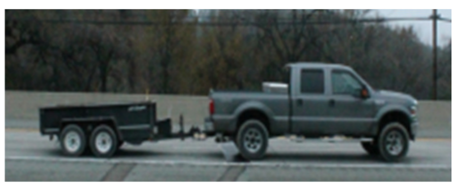
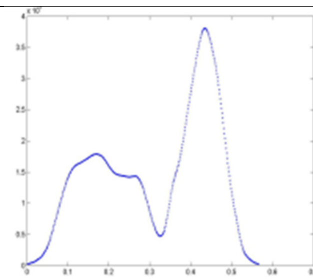
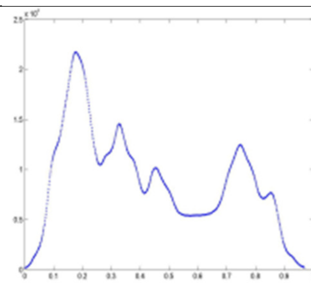
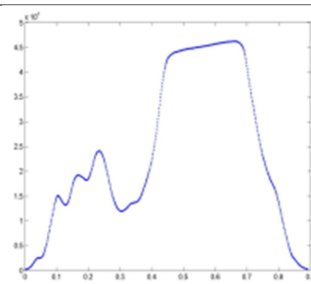
Passenger Car		
Single Unit Truck		
Single Unit Truck with Trailer		
Semi-Tractor Trailer (En-closed Van)		
Semi-Tractor Trailer (Livestock Van)		

Figure 2.4 Examples of Inductive Signatures

This represents only a small portion of the FHWA scheme's 13 axle classes and does not include body classification. These models are therefore not sufficiently detailed to provide accurate emissions estimates or to estimate freight movements. At the more basic level of obtaining truck counts but not classifications, the Caltrans Performance Measurement System (PeMS) estimates truck proportions from inductive loop detectors located in California. Their estimate is taken from five-minute aggregates of volume and occupancy and is based on lane-to-lane speed correlation (Kwon et al., 2003).

Inductive signature based methods of vehicle classification have shown to be better able to stratify vehicles into more detailed classes (Gadja et al., 2001; Ki and Baik, 2006; Sun et al., 2003) than length based classification systems. The signature-based methods are ideal for determining section based travel times, speed, and emissions through vehicle reidentification (Liu et al., 2011; Jeng and Ritchie, 2008), both measures that are needed for accurate determination of air quality. From the summary of the listed classification methods shown in Table 2.1, most emphasis on truck classification is placed on axle or length based classification and most of the models do not focus on commercial vehicle classification. An exception to this is the study by Liu et al. (2011) which stratified vehicles by MOVES emissions model vehicle classes which are based on body classes for trucks such as concrete mixers and dump trucks, therefore this study represents the possibility of signatures to distinguish body types. Although many of these methods demonstrate the ability to stratify vehicles by class with high correct classification rates none have been able to distinguish into detailed body type classes, which is of significant importance for freight analysis and truck movement studies.

Table 2.1 Summary of Vehicle Classification Methods by Inductive Loop Detectors

(A) Inductive Loop Bivalent Outputs

Author	Truck Classifications	Correct Classification Rate
Wang and Nihan (2003)	Two class scheme: (1) short vehicle less than 39 ft, and (2) long vehicles	*Not explicitly provided*
Zhang et. al. (2006)	Four class scheme: (1) cars, pickups, short single unit trucks (less than 26 ft), (2) cars and trucks pulling trailers and long single unit trucks (between 26 and 39ft), (3) combination trucks (between 40 and 65 ft), (4) multi-trailer trucks (greater than 65 ft)	Overall: 91%
Coifman and Kim (2009)	Three class scheme: (1) less than 28 ft, (2) between 28 and 46ft, and (3) greater than 46ft	Overall: 97%, truck classes (2) 93%, (3) 74%

(B) Inductive Loop Signature Outputs

Author	Truck Classifications	Correct Classification Rate
Sun and Ritchie (2000)	Seven vehicle classes: (1) cars, (2) SUV, (3) vans, (4) limos, (5) buses, (6) two axle trucks, (7) trucks with more than two axles	Overall: 81 to 91%, (6) 100%, (7) 75%
Sun et al. (2003)	Of the four schemes evaluated (ranging from four to seven classes), the seven class scheme was: (1) passenger cars, minivans, sports car, and station wagons, (2) vans, SUVs, pickups, and full size pickups, (3) truck, (4) more than two axle truck, (5) bus, (6) vehicle with trailer, and (7) limousine.	Overall: 82-87%, with truck classes (3) 88-100% and (4) 67-75%
Cheung et al. (2005)	Five class scheme: (1)passenger vehicle, (2) SUV, (3) van, (4)bus, (5) Mini-truck (MT) Three class scheme following FHWA classes: (1) FHWA 2, (2) FHWA 3, (3) FHWA 4	Overall: 57%, truck class (5) 28% Overall: 84% (no truck specific class)
Ki and Baik (2006)	Five class scheme: (1) Passenger cars, (2) van, (3) bus, (4) truck, and (5) motorcycle	Overall: 91.5%, for truck class (4) 100%
Jeng and Ritchie (2008)	13 class FHWA Scheme: classes (5) through (13) for trucks 15 class modified FHWA Scheme: (1) passenger cars, (2) two-axel, four tire single units, (3) buses, (4) two axel four tire single unit, (5)three axle six tire single unit, (6) four or less axle single trailer, (7) five axle single trailers, (8) class 1 + trailer, (9) class 2 + trailer, (10) class 4 + trailer, (11) class 5 + trailer, (12) semi-tractor, no trailer, (13) gooseneck trailer or moving van, (14) 30ft busses, and (15) 20 ft busses.	Overall of both schemes: 93%
Meta and Cinsdikici (2010)	Five class scheme: (1) cars, jeep, (2) minbus, van, (3) pickup, truck, (4) bus, articulated bus, (5) motorcycle	Overall: 94%, for class (5) 93%
Liu et al. (2011)	Five class scheme to which MOVES emissions model was applied: (1) passenger car, (2) 4 tire single unit passenger and light commercial trucks, (3) busses, (4) 4 or more single unit truck including refuse trucks, short and long haul trucks, and motorhomes, and (5) multi-unit trucks including combination short and long haul trucks	Overall: 97.6%, for classes (4) 77.1% and (5) 95.0%
Jeng and Ritchie (2013)	13 class FHWA Scheme (same as Jeng and Ritchie, 2008)	Overall: 92.4%; FHWA class 5: 67.0%; FHWA class 9 trucks: 85.5%

2.3 Limitations of Existing Body Classification Models

There have been no published attempts to gather body classification data from WIM systems. The only existing study conducted by the FHWA (FHWA, 1999), performed aggregate analyses to link body type characteristics found in VIUS to axle and weight measurements from WIM systems. In this dissertation, a model for predicting body class volumes from axle spacing and length measurements produced by WIM systems is presented. This model represents the first published attempt to classify commercial vehicles by body type from WIM data. Part of the reason for the lack of predecessor models is the lack of available data to create such models. Likewise one of the main issues with existing body classification models using inductive signature data is the lack of truck data available for model development. Most of the models described above gather data from urban locations for short time periods and consist of mostly passenger car records. For example, Jeng and Ritchie (2008) collected data from the I-405 freeway in Irvine, California for an approximate 30 minute window centered on the morning peak travel period. This dataset used in their analysis consists of less than 3% trucks, due in part to the highway location not being a major truck route and the time period not centered on peak truck travel periods. In fact, only 39 FHWA class 9 trucks were included in the dataset. Tok and Ritchie (2010) collected data from the San Onofre Truck Weigh and Inspection Facility located in Southern California and use approximately 1,000 truck records to build their models. Liu et al. (2011) combined data from both sites used by Jeng and Ritchie (2008) and Tok and Ritchie (2010) to create a more comprehensive dataset for model development, but was only able to separate five classes. By collecting data at WIM sites located along major trucking routes across the state for multi-day periods, the modeling efforts in this dissertation are able to overcome the lack of data problem experienced by predecessor models and to go beyond existing models by using a geographically diverse set of signature records.

While the lack of data for commercial vehicles is corrected for by collecting data over longer time periods and across wider geographic ranges, a second major problem with existing inductive signature models is that they concentrate on sorting vehicles into axle based classes rather than body based categories. This limits the power of prediction of inductive signatures because the true strength of inductive signatures is in depicting the body configuration of vehicles, not the axle configuration or even the axle count. The work in this dissertation corrects this problem by combining WIM data which contains axle spacing and count information with inductive signatures. This fusion of two data sources means that axle-based classification is directly measured and the body class is the only factor being predicted.

Each of the predecessor models discussed in this section are implemented using a single model architecture. For instance, Sun and Ritchie (2000) used heuristic discriminant algorithms and multiobjective optimization, Sun et al. (2003) adopted a self-organizing feature map, Ki and Baik (2006), Tok (2008), Meta and Cinsdikici (2010), and Liu et al. (2011) used neural networks, Oh and Ritchie (2008) used Probabilistic Neural Networks, and Jeng and Ritchie (2008) used decision tree and clustering. However, trucks possess a wider diversity of body types than passenger vehicles and have much more detailed signatures, so more advanced model architectures may be needed. Therefore, in this dissertation, an ensemble approach is adopted for classification.

Dietterich (2000) gives three general reasons why a set of classifiers might be better than a single classifier. First, merging multiple classifiers eliminates the risk of picking an inadequate single classifier and can increase the ability of the model to generalize. Second, for models which rely on optimization approaches including random search or hill-climbing, not all single classifiers will reach global optima. Aggregating multiple classifiers of this type helps to better capture the true optimum. Third, based on classifier formulation, e.g. linear versus non-linear, each single classifier has a varying ability to interpret the feature space to make predictions. By combining classifiers with different inherent assumptions, it is more likely that the true or optimal representation of the feature space is achieved. For these reasons, in this dissertation, pattern recognition is performed via ensembles of classifiers with voting. Chapter 4 provides a more in-depth discussion of ensemble learning approaches.

3 Data Sources

Given the complementary nature of the WIM and inductive signature data, along with the physical embedded configuration of inductive loops within the WIM station, the two are ideally suited for physical integration. There have not been any prior studies which integrate WIM data with inductive loop signatures, thus the integration method described in this dissertation is quite novel. The hardware configuration, data collection procedures, and data groundtruth process are described in this section.

3.1 Hardware Integration

In California, the WIM controllers are fabricated, installed, and maintained by International Road Dynamics (IRD) (Caltrans, 2014 a). Two main types of WIM controllers are currently deployed in California: the earlier DOS-based IRD 1060 series controllers and the current Linux based IRD iSinc family of controllers. For the purposes of this dissertation, the main distinction between the controllers is in their built-in ability to log inductive signature data. The loop sensor module (LSM) of the 1060 WIM controllers is designed to obtain only conventional bivalent inductive loop data whereas the LSM of the iSINC controllers have the ability to obtain inductive signature data. The caveat for the iSINC controller however, is that inductive signature data is currently designed only for diagnostic and troubleshooting purposes and is not currently available as an operational feature within the system. Therefore, the iSinc system could not be readily used for the purposes of this dissertation without further development by the product vendor. Furthermore, 1060 series controllers are currently deployed at about 80% of current WIM sites within the California. Hence, despite their age, a hardware integration solution with the 1060 series controllers would be applicable to a much larger number of candidate sites currently available for deployment consideration.

As part of CARB Contract 11-316 (Ritchie, 2013), a prototype LSM adapter was designed to adapt advanced inductive loop signature detector cards to replace the 1060 WIM LSM. Inductive loop signature data was logged into a field processing unit via the USB port located on the front panel of each signature detector card. Schematic layouts showing a comparison of the hardware setup for a standalone 1060 WIM controller and the proposed integration with an advanced signature detector card are shown in Figure 3.1 (Ritchie, 2013). With this set-up both inductive loop signatures and WIM weight and axle spacing data can be collected at the WIM site.

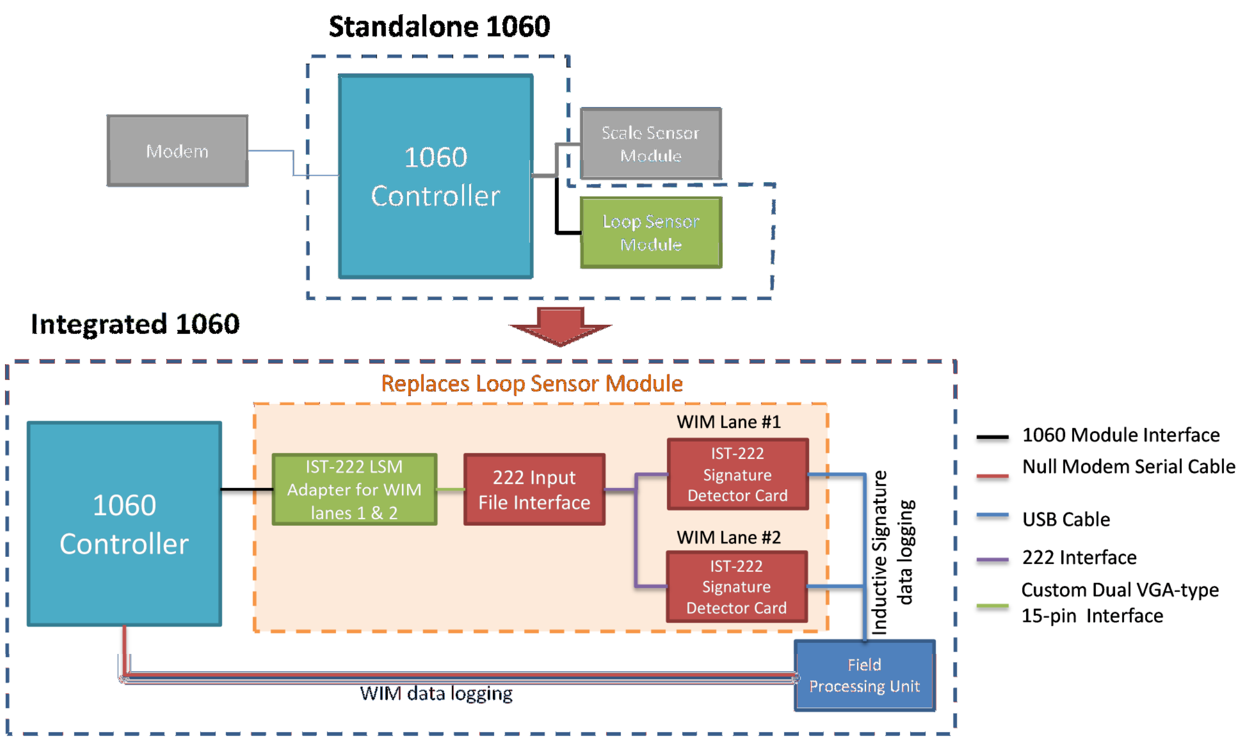


Figure 3.1 Comparison of Hardware for Standalone and Integrated 1060 WIM Controllers

3.2 Data Collection

A major drawback of existing vehicle classification modeling efforts has been lack of data for model training and testing. This is especially true for commercial vehicles which on average account for around 10% of the total highway vehicle population (Caltrans, 2012) thus requiring extended data collection periods or selection of specific truck routes with high volumes of truck traffic to obtain sufficiently large enough samples. An additional complication is that unlike passenger vehicles, commercial vehicle body types vary by location and are influenced by local industry and land uses. For example, intermodal container trailers are more prevalent nearer to port areas while trucks with logging trailers appear in regions tied to the logging industries. Smaller commercial vehicles such as single unit trucks may also vary in body type by location. For instance, service related body types like garbage trucks or firetrucks might be observed in higher volumes near busier urban areas compared to remote rural sites. Significant efforts were made in this dissertation to collect and process an abundant sample of commercial vehicles for model training and testing. This, in part, helped to facilitate more advanced modeling efforts and expand the predictive capabilities of the developed models. Care was taken to select data collection locations and seasonal time periods that would capture the extreme diversity of commercial vehicle body types. In total, around 35,000 vehicle records were captured and processed from four disparate WIM and VDS sites in California over a time period spanning the fall, winter, and spring seasons.

3.2.1 Site Location Description

Truck body types vary by location so to capture the full diversity of the California truck population data was collected at four disparate locations across the State. The sites, from north to south were Redding, Willows, Fresno, and Irvine. Each of the four sites contained a 1060 series WIM controller which was equipped with the data collection equipment described in the previous section. The sites span metropolitan and agricultural regions as shown in Figure 3.2 (adapted from maps.com). Depicted on the map are the major land uses, industries, and cities in California. In the northern portion of the State, forestry dominates while in the central region agriculture is widespread, and further south urban land uses prevail. Each selected site captures a unique set of truck body types related to the region in which it is located. The sites at Redding and Willows were selected to capture logging type trailers; Fresno to capture agricultural land use related body types; and Irvine to capture port related intermodal container and localized service traffic.

The WIM sites at Redding, Willows, and Irvine are located along with Interstate 5 (I-5) freeway that runs longitudinally across the State. The WIM site at Fresno is located on State Road (SR) 99, to the east of I-5. Each of these routes capture inter- and intra-state travel. The WIM sites at Redding, Fresno, and Irvine capture southbound traffic while the site at Willows captures northbound traffic. Table 3.1 provides a summary of the data collection sites including station name, location, a brief description, and number of total and equipped lanes.

Additional data for the signature only body classification model was obtained at a VDS site located 210ft upstream of the WIM controller at the Irvine site. For the data collection the still image camera was placed at the VDS site and both the VDS and WIM sites were equipped with inductive signature cards.

Table 3.1 Summary of Data Collection Sites

Site Name	Irvine	Fresno	Willows	Redding
Location	I-5 Southbound Southern California	SR-99 Southbound Central California	I-5 Northbound Northern California	I-5 Southbound Northern California
Description	Urban, Approx. 45mi from San Pedro Bay Ports	Semi-Urban, Agricultural	Rural	Rural, Approx. 120mi from OR-CA border
WIM Site Number	15	10	108	2
Controller Type	1060	1060	1060	1060
California Postmile	R25.8	25	R10.9	R24.9
Total Lanes	5 SB	3 NB, 3 SB	2 NB, 2 SB	2 NB, 2 SB
No. Lanes for data	2 SB	2 SB	2 NB	2 SB
Approximate Total Truck Percentage[1]	5%	22%	25%	25%

1 Percent of total trucks, Source: Caltrans Traffic Counts for AADTT (Caltrans, 2012)

3.2.2 Site Configuration

The Irvine WIM and VDS site configuration is shown in Figure 3.3. There are a total of five mainline lanes plus a high occupancy vehicle (HOV) lane. At the Irvine WIM site, weight sensors (i.e. bending plates) are installed in the outermost three lanes and an axle sensor (e.g. piezoelectric sensor) is installed in the inner three lanes. At the Fresno site, there are a total of three lanes as shown in Figure 3.4. The outer two lanes are equipped with weight sensors and the innermost lane with an axle sensor. The Willows and Redding sites each consist of two lanes equipped with weight sensors as shown in Figure 3.5.

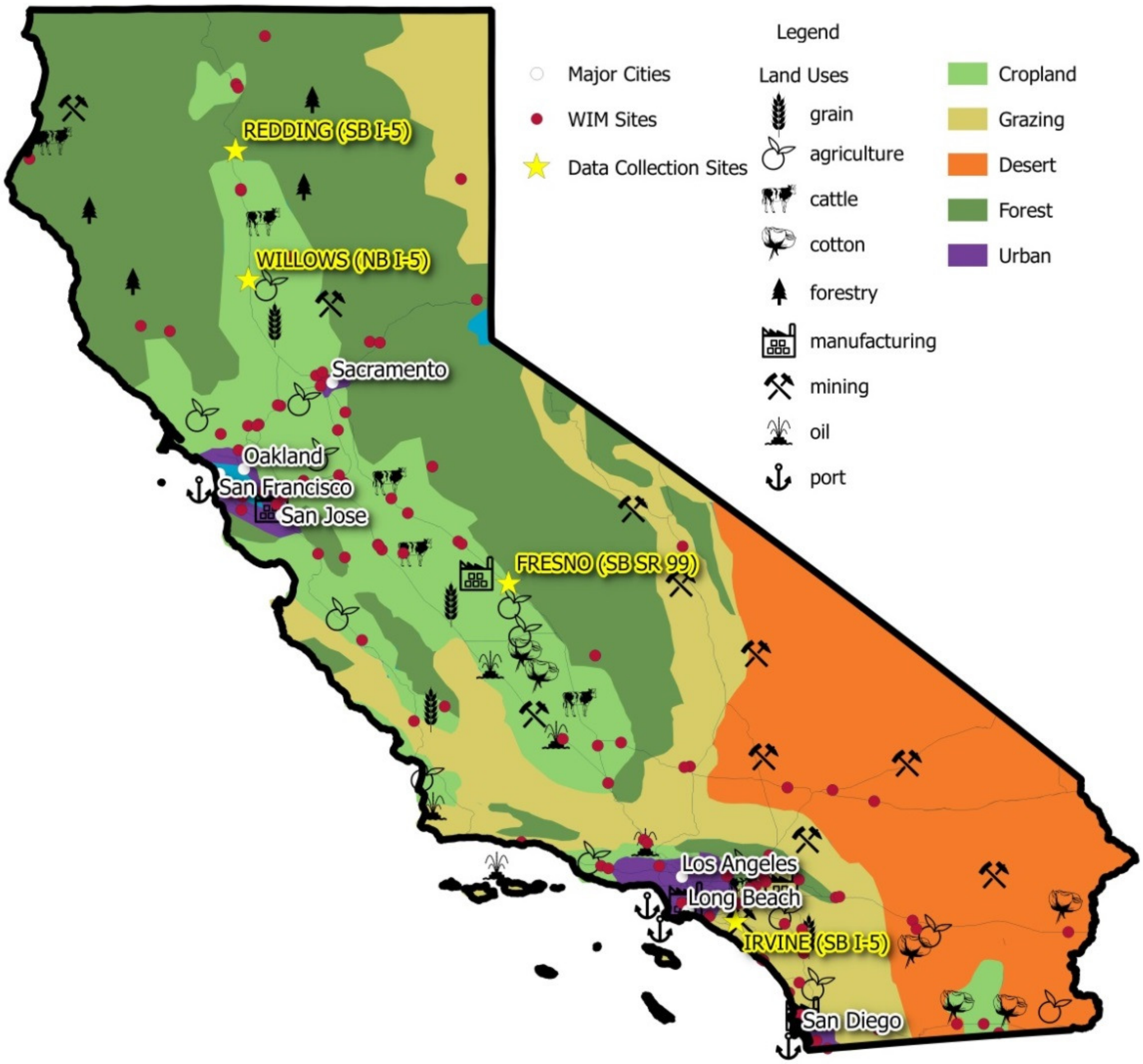


Figure 3.2 Data collection sites used for model development and testing

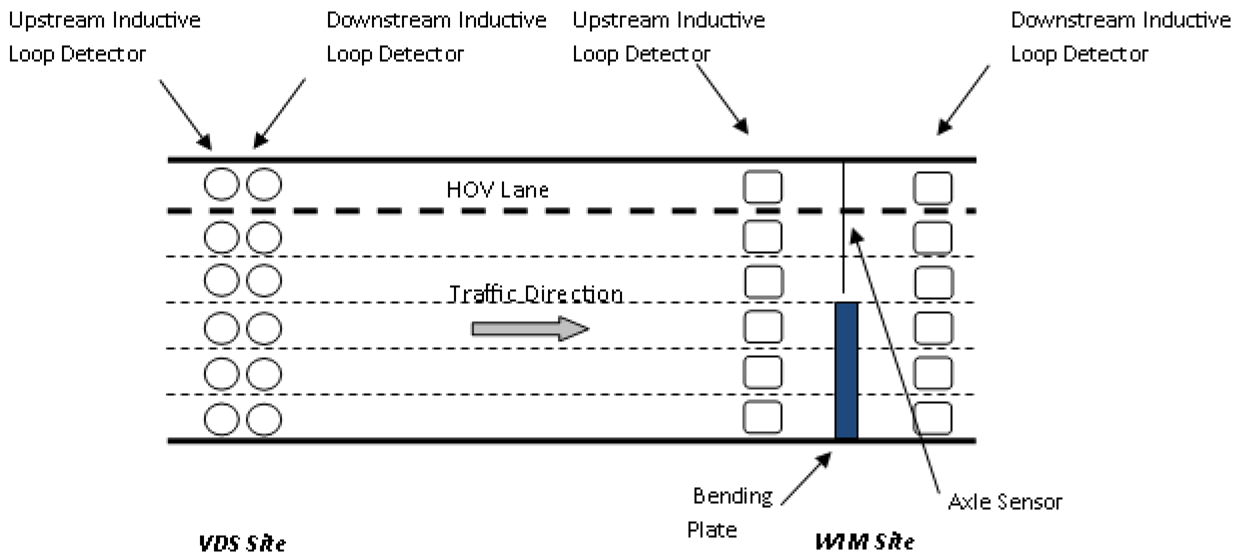


Figure 3.3 Irvine Site Configuration

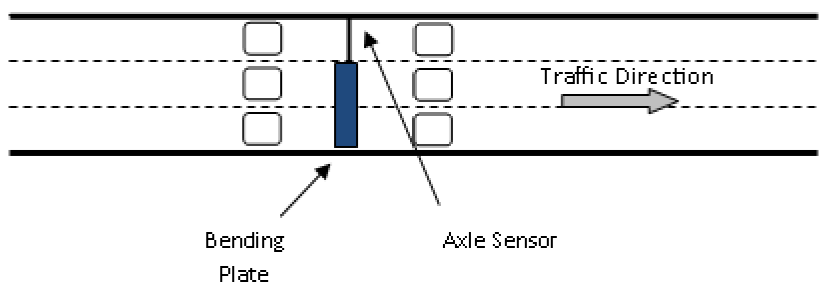


Figure 3.4 Fresno Site Configuration

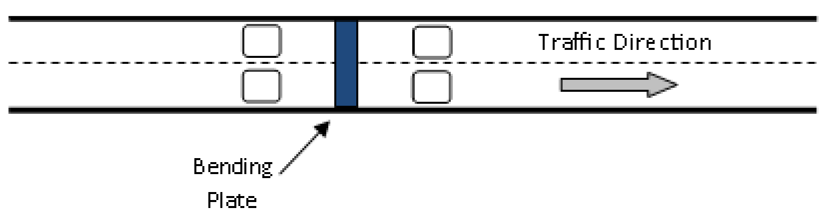


Figure 3.5 Willows and Redding Site Configuration

3.2.3 Data Collection Time Periods

Data was collected at the four sites over several two to three day periods during the fall, winter, and spring seasons between 2012 and 2013 as summarized in Table 3.2. The data collection covered 13 weekdays spanning a total of 97.25 hours.

The posted speed limits for I-5 and SR-99 are 65 mph. However, in California trucks must obey the statewide laws for speed limits and lane usage. In California, large trucks must drive in the right hand lane or in a lane specially marked for slower vehicles and follow reduced speeds of 55mph (CA DMV, 2014 a and b). It is important to note that during congested conditions the quality of inductive signature and WIM data diminishes (Tok, 2010; Nichols and Bullock, 2004) due to vehicle dynamics over the sensors. The majority of the data were collected during uncongested conditions as shown in the box plots in Figure 3.6. The box and whisker plots show the median, upper and lower quartile, minimum and maximum, and outliers. The median speeds are between 50 to 55 miles per hour across all sites. The Irvine site experienced a brief period of minor congestion on October 3rd with speeds below 50 mph. The Fresno site also experienced a brief period of congestion during the November 8th time period.

Table 3.2 Summary of Data Collection Time Periods

Site Name	Date	Day of Week	Season	Time Period	Total Hours	Average Speed (mph)
Irvine	Sept. 21, 2012	F	Fall	10:45AM – 6:00PM	7.25	56.4
	Oct. 2nd, 2012	T	Fall	1:00PM – 6:45PM	5.75	57.7
	Oct. 3rd, 2012	W		6:30AM – 9:15AM	2.75	48.2
	March 20th , 2013	W	Spring	6:30AM – 7:45PM	12.25	61.9
	March 25th, 2013	M		7:30AM – 4:15PM	8.75	59.1
Fresno	Nov. 7th, 2012	W	Fall	10:15AM -5:15PM	7.0	57.6
	Nov. 8th, 2012	T		6:15 AM – 4:45PM	10.5	56.8
Willows	Dec. 10th 2012	M	Winter	10:30AM – 4:45PM	6.25	62.1
	Dec. 11th,2012	T		7:15AM - 4:45PM	9.5	59.0
	Dec. 12th,2012	W		7:00 AM – 3:00 PM	8.0	61.9
Redding	Dec. 10th 2012	M	Winter	1:30 PM – 5:00 PM	3.5	57.8
	Dec. 11th,2012	T		7:00 AM – 4:45PM	9.75	57.7
	Dec. 12th,2012	W		7:00 AM – 1:00PM	6.0	58.8
Total	*13 days*				*97.25*	*58.5*

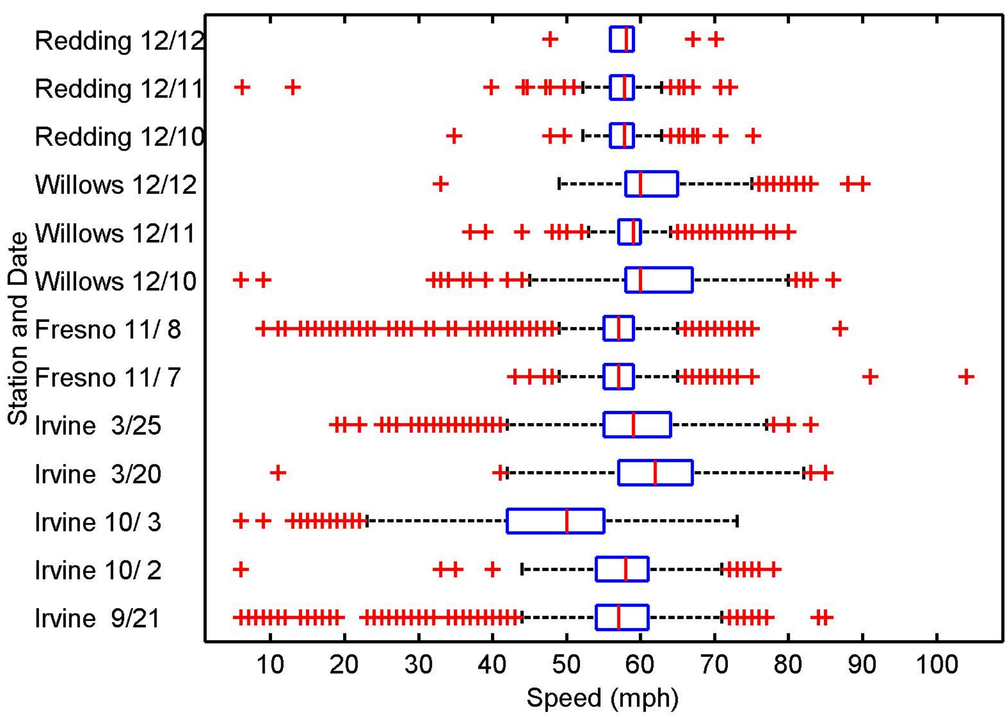


Figure 3.6 Box and whisker plots of speed for data collection time periods

3.2.4 Photo Data Collection

In addition to inductive loop signature and WIM data, still image data was collected for each passing vehicle by connecting a digital camera with a remote trigger to the ILD detector card. Figure 3.7 (Ritchie, 2013) depicts the hardware configuration including the still image camera connected to the inductive signature cards. With this configuration, the loop activation triggered the camera and a series of still images were captured for each passing vehicle at a rate of three frames per second while the vehicle was over the loop. Figure 3.8 (Ritchie, 2013) shows a typical data collection hardware setup at WIM site. The traffic cabinet on the right contains the WIM controller and ILD signature cards. The still image camera shown to the left of the cabinet connects to the ILD signature detector cards within the cabinet. The field PC clock which set the timestamps for the ILD signature and photo data was synchronized against the WIM controller clock in order to ease the data groundtruth process that required the processor to link the WIM record, inductive signature, and photo together.

For each passing vehicle, the number of still images is proportion to the vehicle's length. For example, a passenger vehicle covers the inductive loop sensor for approximately 0.2 seconds during uncongested conditions which results in a single still image. Longer vehicles, like FHWA class 9 tractor-trailer combination trucks have durations nearer to 1.0 second in uncongested conditions which result in a series of around 2 to 4 still images. The camera was set back from the traveled lanes and angled in such a way that the series of still images capture the full side view of the truck or car. Figure 3.9 shows examples of still images captured for longer combination trucks and a passenger vehicle.

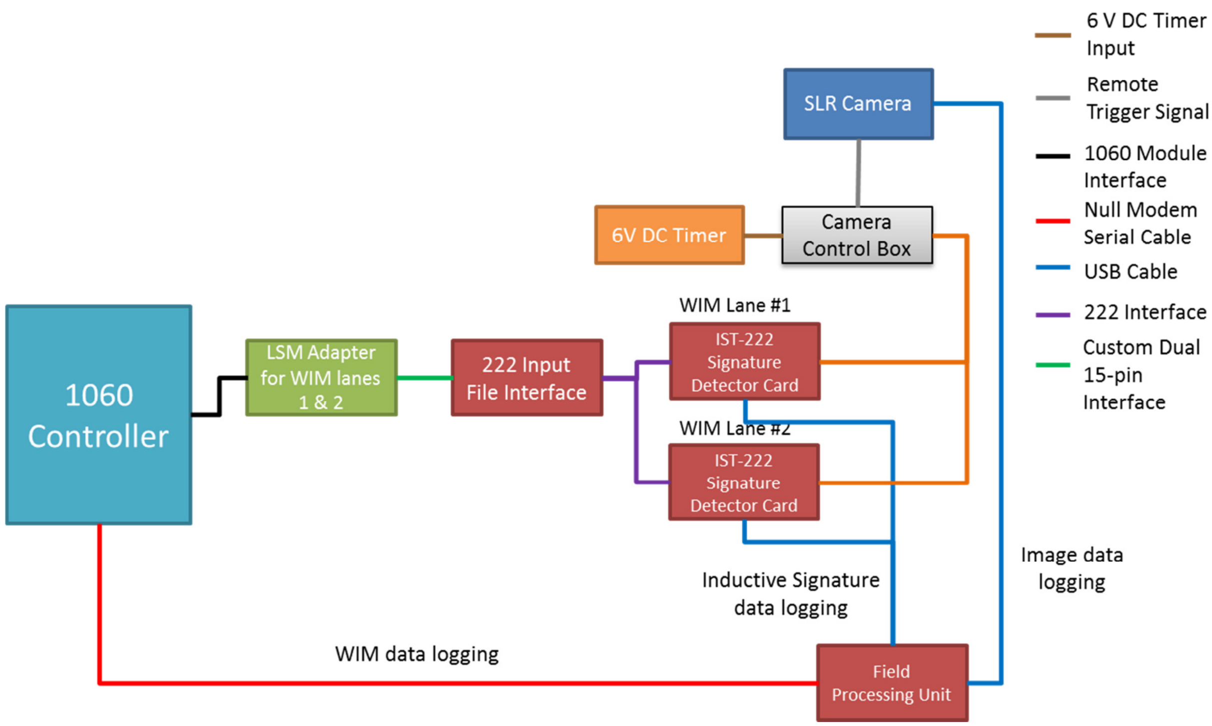


Figure 3.7 Data Collection System Architecture with SLR Still Image Camera

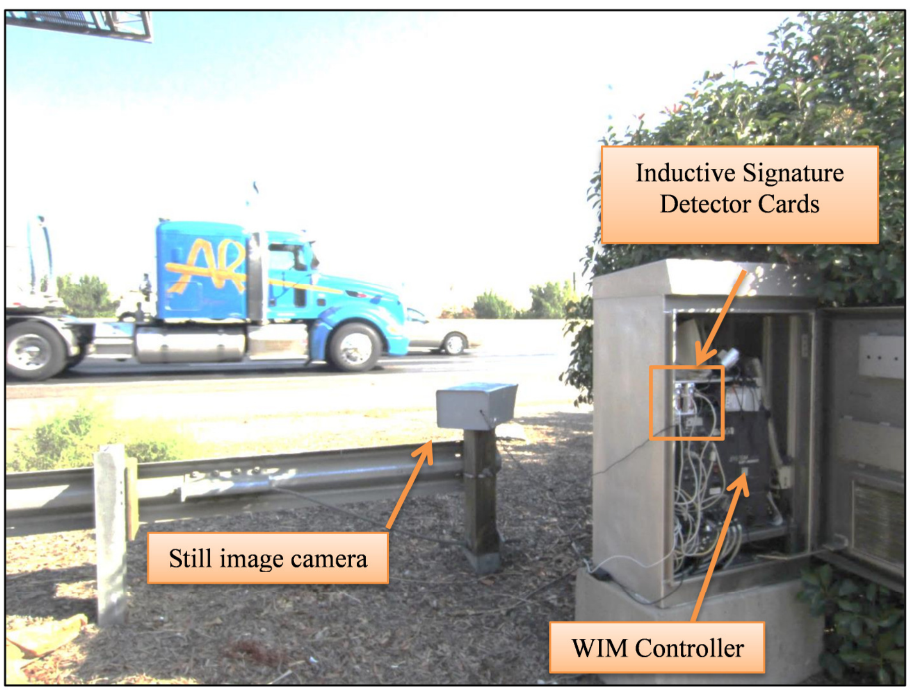


Figure 3.8 Data collection setup at WIM site

(a) Tractor-Trailer Combination truck in two still images

(b) Tractor-Trailer Combination truck in three still images

(c) Pickup trucks in single still images

(d) Single unit truck in two still images

Figure 3.9 Examples of still images collected for various truck types

3.3 Data Groundtruth Process

The data groundtruth procedure involved preprocessing the WIM, inductive signature, and photo data, linking the three data types, and identifying the vehicle configuration and body type from each photo record.

3.3.1 Preprocessing

All WIM record, inductive loop signature, and photo data was stored in a relational database powered by PostgreSQL. Currently, the 1060 WIM controller output (Table 3.3) is captured as a text file which is processed and stored as individual vehicle records according to a unique vehicle identification number in the PostgreSQL database.

In addition to the fields shown in Table 3.3, the day, year, hour, minute, and second time fields were combined into a single timestamp and the vehicle length and speed were used to determine an approximate loop occupancy value (i.e. the time over which the loop was occupied by the vehicle). These two additional fields were used to link the WIM record to the photo and inductive signature data.

Table 3.3 WIM Data record fields

Field	Data Type By Field	Field	Data Type By Field
1	Lane	16	Axle 2 Right Side weight (kips)
2	Month	17	Axle 2 Left Side weight (kips)
3	Day	18	Spacing between Axles 1 and 2 (feet)
4	Year	19	Axle 3 Right Side weight (kips)
5	Hour	20	Axle 3 Left Side weight (kips)
6	Minute	21	Spacing between Axles 2 and 3 (feet)
7	Second	21	Axle 4 Right Side weight (kips)
8	Vehicle Number	22	Axle 4 Left Side weight (kips)
9	Type	23	Spacing between Axles 3 and 4 (feet)
10	Gross Weight (kips)	24	Axle 5 Right Side weight (kips)
11	Overall Length (feet)	25	Axle 5 Left Side weight (kips)
12	Speed (mph)	26	Spacing between Axles 4 and 5 (feet)
13	Violation code	28 - 39	*Remaining axle spacing and weights*
14	Axle 1 Right Side weight (kips)	40	Direction
15	Axle 1 Left Side weight (kips)	41	Axle Count

Inductive loop signature data was collected through proprietary software provided by Inductive Signature Technologies (IST), the manufacturer of the signature cards. The proprietary software converts the binary outputs from the detector cards to a continuous stream of inductive magnitude changes. The continuous stream of data was parsed into separate individual signature records by applying magnitude cutoff and smoothing criteria. The smoothing procedure reduced the effects of noise from dropped data.

To ease the data groundtruth procedure each inductive signature was then plotted and stored as an image referenced by a unique identification number. Along with the image of the inductive signature, the timestamp and duration (i.e. time occupancy of the loop detector) were also stored in the database for later reference against the WIM data.

Each vehicle traversing the loop produced a series of photos. The shutter speed of three frames per second was used to group the photos by vehicle such that a group of photos corresponding to one vehicle consists of photos with timestamps separated by less than 1/3 seconds. The photos were stored in the PostgreSQL databased referenced by a unique identification number, labeled as the 'vehicle identification number' or 'VehicleID'.

3.3.2 Customized User Interface

A software user interface was developed in Visual Basic to efficiently integrate the WIM, signature, and photo data. The user interface is linked to the database. The user can scroll through photos and select the vehicle class parameters while also linking inductive loop signature and WIM records to the photo. The rightmost image of Figure 3.10 is the inductive loop signature and the table below the signature is the list of vehicle signature records within the user-designated time window. The center FHWA image based on the FHWA class predicted by the WIM controller and the table below is the list of WIM vehicle records with the user-designated time window for the WIM data. The largest table in the upper right is the list of vehicle records derived from the set of photos taken by the still camera. The photo series corresponding to the vehicle record is show at the left. Since this interface was developed to provide groundtruth truck body classification data, below the photo there is a selection region where the user designates the axle and body configuration of the vehicle. Figure 3.11 shows an example of the customized user interface for the Irvine site with WIM and VDS signature data. The leftmost signature image is from the VDS site and the rightmost signature image is from the WIM site.

For each vehicle record, the user should scroll through the list of inductive signatures and WIM records comparing the timestamp, duration, and other characteristics such as the shape of the signature or the designated FHWA vehicle class in order to find the corresponding signature and WIM records. Then, the user must designate the total axle count, truck axle configuration, truck body configuration, trailer axle configuration, truck body configuration, and may optionally select the commodity type transported by the vehicle. Once all the fields are selected and the WIM and signature data have been identified, the user 'appends all' of the data to the vehicle record. This links the unique identification numbers of the photo, WIM record, signature record, and body classification data to the vehicle record in the PostgreSQL database.

Figure 3.12 presents an example of the database structure to link the inductive signature, WIM records, and photo data with the vehicle records. The uppermost table summarizes the user inputs for body class, while the middle three tables contain identification numbers. The 'wimsigid' is the unique identification number for each inductive signature record, 'wimid' for the WIM records, and 'photoid' for the photo records. The unique identifier for each vehicle record, 'vehid', provides the link between each data source. The table at the bottom of Figure 3.12 shows how the three data sources are referenced for each vehicle record.

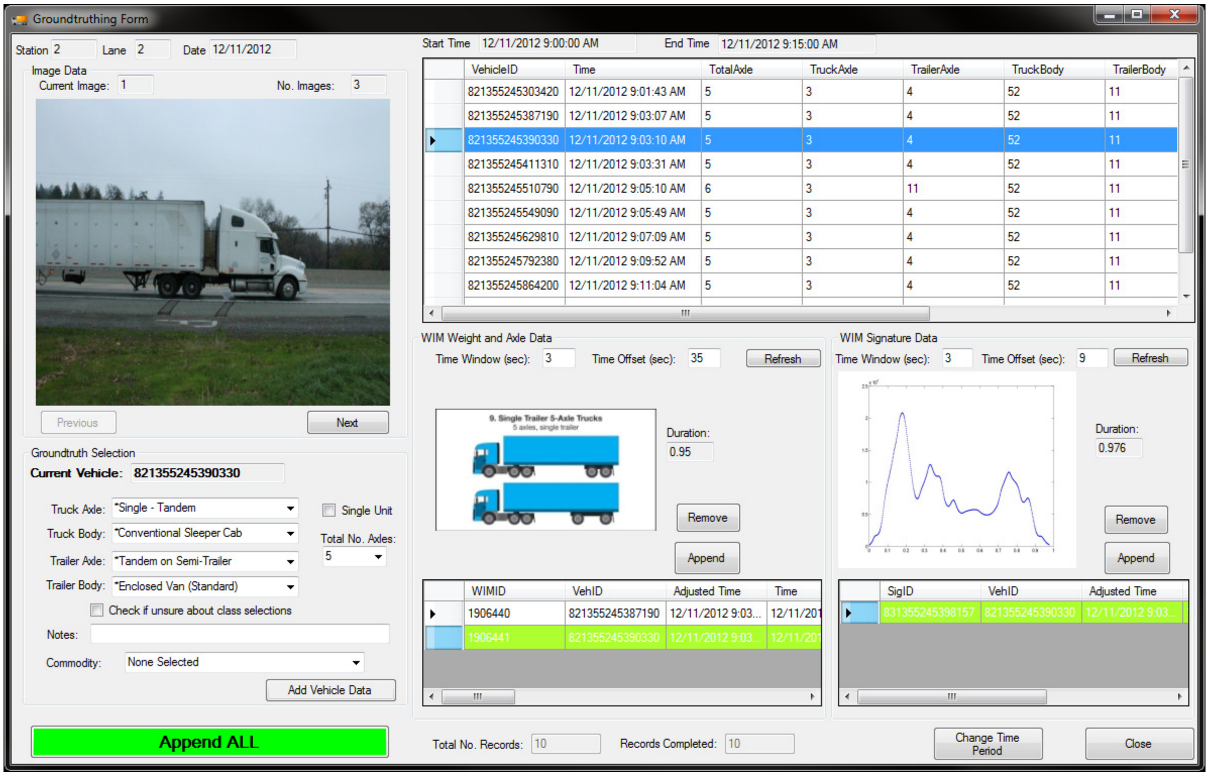


Figure 3.10 Customized User Interface for Vehicle Classification Example 1

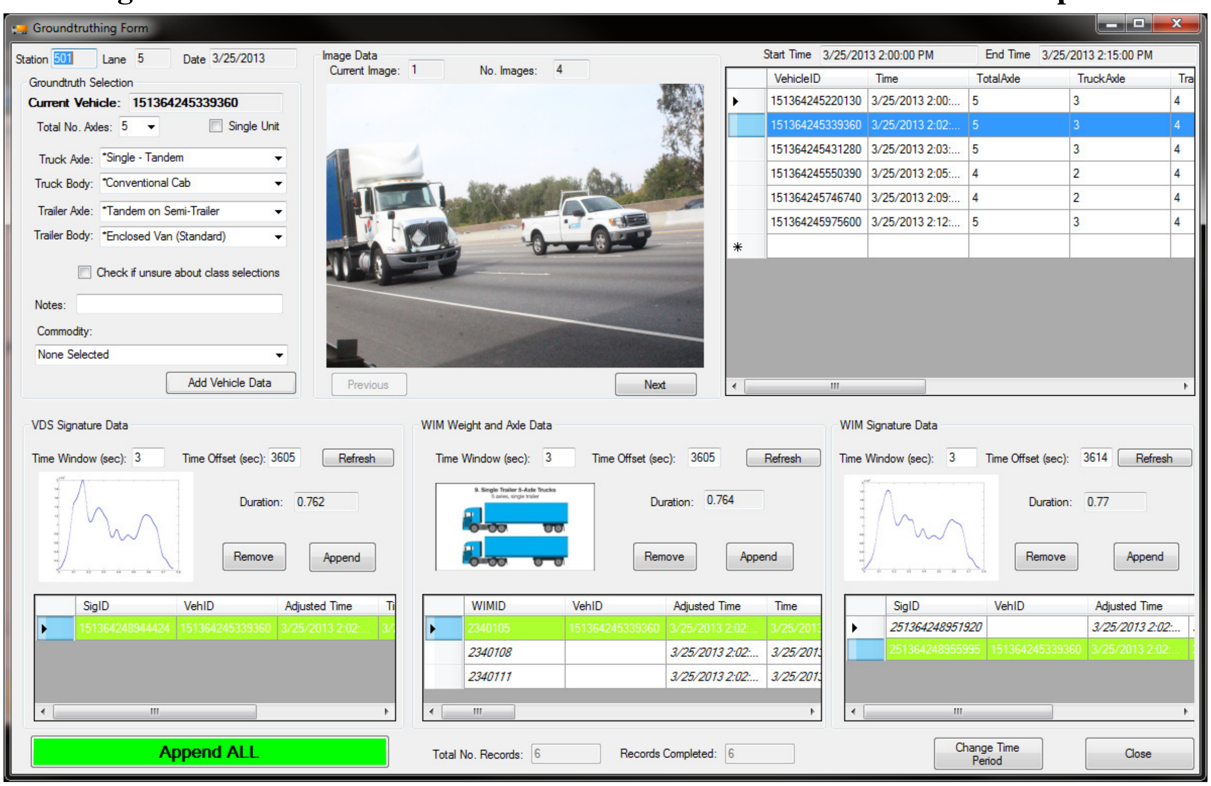
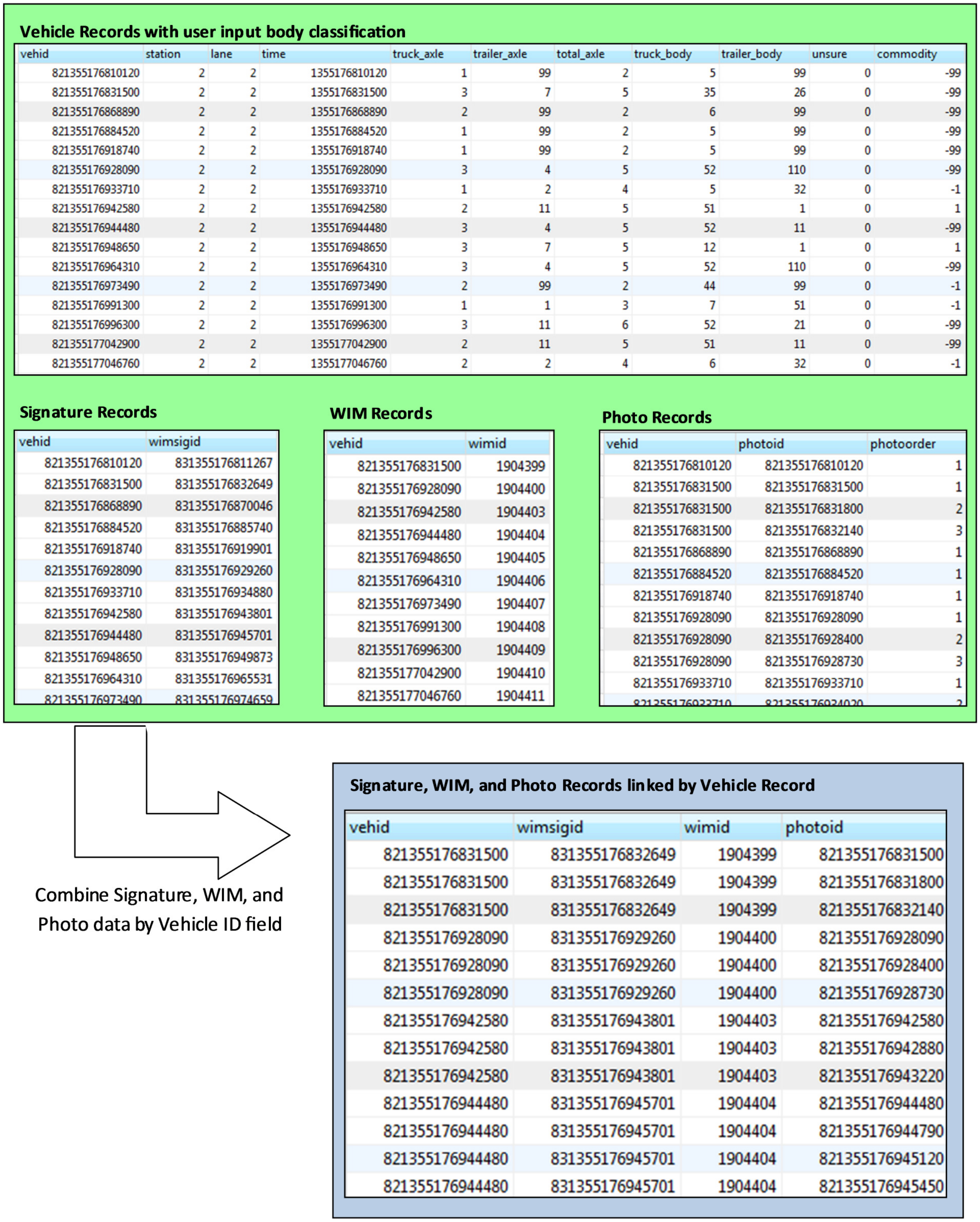


Figure 3.11 Customized User Interface for Vehicle Classification Example 2



Vehicle Records with user input body classification

vehid	station	lane	time	truck_axle	trailer_axle	total_axle	truck_body	trailer_body	unsure	commodity
821355176810120	2	2	1355176810120	1	99	2	5	99	0	-99
821355176831500	2	2	1355176831500	3	7	5	35	26	0	-99
821355176868890	2	2	1355176868890	2	99	2	6	99	0	-99
821355176884520	2	2	1355176884520	1	99	2	5	99	0	-99
821355176918740	2	2	1355176918740	1	99	2	5	99	0	-99
821355176928090	2	2	1355176928090	3	4	5	52	110	0	-99
821355176933710	2	2	1355176933710	1	2	4	5	32	0	-1
821355176942580	2	2	1355176942580	2	11	5	51	1	0	1
821355176944480	2	2	1355176944480	3	4	5	52	11	0	-99
821355176948650	2	2	1355176948650	3	7	5	12	1	0	1
821355176964310	2	2	1355176964310	3	4	5	52	110	0	-99
821355176973490	2	2	1355176973490	2	99	2	44	99	0	-1
821355176991300	2	2	1355176991300	1	1	3	7	51	0	-1
821355176996300	2	2	1355176996300	3	11	6	52	21	0	-99
821355177042900	2	2	1355177042900	2	11	5	51	11	0	-99
821355177046760	2	2	1355177046760	2	2	4	6	32	0	-1

Signature Records

vehid	wimsigid
821355176810120	831355176811267
821355176831500	831355176832649
821355176868890	831355176870046
821355176884520	831355176885740
821355176918740	831355176919901
821355176928090	831355176929260
821355176933710	831355176934880
821355176942580	831355176943801
821355176944480	831355176945701
821355176948650	831355176949873
821355176964310	831355176965531
821355176973490	831355176974659

WIM Records

vehid	wimid
821355176831500	1904399
821355176928090	1904400
821355176942580	1904403
821355176944480	1904404
821355176948650	1904405
821355176964310	1904406
821355176973490	1904407
821355176991300	1904408
821355176996300	1904409
821355177042900	1904410
821355177046760	1904411

Photo Records

vehid	photoid	photoorder
821355176810120	821355176810120	1
821355176831500	821355176831500	1
821355176831500	821355176831800	2
821355176831500	821355176832140	3
821355176868890	821355176868890	1
821355176884520	821355176884520	1
821355176918740	821355176918740	1
821355176928090	821355176928090	1
821355176928090	821355176928400	2
821355176928090	821355176928730	3
821355176933710	821355176933710	1
821355176933710	821355176934020	2

Signature, WIM, and Photo Records linked by Vehicle Record

vehid	wimsigid	wimid	photoid
821355176831500	831355176832649	1904399	821355176831500
821355176831500	831355176832649	1904399	821355176831800
821355176831500	831355176832649	1904399	821355176832140
821355176928090	831355176929260	1904400	821355176928090
821355176928090	831355176929260	1904400	821355176928400
821355176928090	831355176929260	1904400	821355176928730
821355176942580	831355176943801	1904403	821355176942580
821355176942580	831355176943801	1904403	821355176942880
821355176942580	831355176943801	1904403	821355176943220
821355176944480	831355176945701	1904404	821355176944480
821355176944480	831355176945701	1904404	821355176944790
821355176944480	831355176945701	1904404	821355176945120
821355176944480	831355176945701	1904404	821355176945450

Figure 3.12 Database Structure for Data Groundtruth

3.4 Classification Scheme Development

A key component in the development of the body classification model was the creation of a classification scheme that captured the diversity of truck bodies found in the data. The initial body classes were based on the VIUS defined body types (VIUS, 2002). VIUS was selected as it provided the highest level of detail regarding body classification. VIUS separates trucks into three vehicle configuration groups: Passenger vehicles, single unit trucks, and semi-tractor trailer combination trucks. Body classes corresponding to trucks were further expanded based on observed field data.

3.4.1 Single Unit Trucks

Single unit trucks are defined by VIUS as any truck with or without a trailer that is not a truck or road tractor. Figure 3.13 illustrates examples of single unit trucks without trailers (a and b) and with small trailers (c). VIUS defines 22 single unit body classes.

Table 3.4 summarizes the five main body class groups: vans, platforms, tanks, service, and specialty vehicles. The VIUS classes were separated into 28 body classes for modeling in this dissertation. The VIUS body class, 'Vans, insulated, non-refrigerated' are not visually distinguishable and therefore grouped together with VIUS category for basic enclosed vans and separated across four body class for modeling. The VIUS body class for 'Concrete pumpers' were not found in the data and thus not included in model development. Body classes identified the data but not defined in VIUS include pneumatic tanks, livestock trucks, and firetrucks. Additionally, the three body classes including buses and recreational vehicles (RV) are not included in the VIUS classification scheme so these were added to the model classification scheme. In total there are 31 body classes for single unit truck included in the model.

(a) Enclosed van

(b) Trash, Garbage, or Recycling

(c) Enclosed Van with small trailer

Figure 3.13 Examples of Single Unit Trucks

Table 3.4 VIUS and Model Single Unit Trucks Body Classification

Body Category	VIUS Body Class	Model Body Class
Van	Van, basic enclosed (dry cargo) Van, insulated non-refrigerated	Conventional Enclosed Van
		Light Duty Enclosed Van
		Low Loading Enclosed Van
		Cab-Over Engine Enclosed Van
	Van insulated refrigerated	Conventional Reefer Enclosed Van
		Cab-Over Reefer Enclosed Van
	Van, open top (including low-side grain, fruit, potato bed, etc.)	Open Top Van
	Van, step, walk-in, or multistep (including hi-cube or cutaway)	Multi-Stop or Step Van
Tank	Tank, dry bulk	Tank
	Tank, liquids or gases	
	Vacuum	
	*	Pneumatic Tank
Platform	Flatbed (including any with added devices), stake, platform, etc.	Basic Platform
		Low Boy Platform
Service	Service, utility (telephone line, cable, pipe-line, etc.)	Utility
	Service, other (mobile workshop, crafts-man's vehicle", etc.)	
Specialty	Armored	Armored
	Beverage	Beverage
	Concrete mixer	Concrete Mixer
	Concrete pumper	**
	Crane	Winch or crane truck
	Curtainside	Curtainside Van
	Dump (including belly or bottom dump)	End Dump
		Bottom Dump
		Dumpster Transport
	Pole, logging, pulpwood, or pipe	Pole, logging, pulpwood, or pipe
	Street sweeper	Street sweeper
	Tow/Wrecker (including flatbed)	Platform for auto transport
		Wrecker
	Trash, garbage, or recycling	Garbage
	*	Livestock
	*	Firetruck
Other	Other	Other
Bus	*	Recreational Vehicle (RV)
	*	30ft Bus
	*	20ft Bus

* Not included in model body classification scheme

** Not included in VIUS

3.4.2 Combination Trucks

Combination trucks refer to multi-unit trucks including single unit trucks pulling single or small trailers (Figure 3.14 a and b) and semi-tractor trailer trucks with semi-trailers or multiple trailers (Figure 3.14 c and d). A single unit truck pulling a trailer is defined by the drive unit body type as defined in the previous section and a trailer body type. Similarly, a semi-tractor trailer combination truck whether for a single semi-trailer or multiple trailer combination is defined in two parts: the tractor unit and trailer unit(s).

(a) Single unit truck with single trailer

(b) Single unit truck with small trailer (recreational vehicle)

(d) Enclosed Van Semi Trailer

(d) Belly Dump Multi-Semi Trailer

Figure 3.14 Examples of Combination Truck Trailer Body Classes

3.4.2.1 *Tractor Units*

The tractor refers to the cab of the truck as shown in Figure 3.15 and is divided by VIUS into four standard engine configuration types described in Table 3.5. Conventional and cab-over engine configurations are further specified as sleeper (Figure 3.15 a and b) or non-sleeper (Figure 3.15 c and d). 'Cab forward engine' and 'cab beside engine' body classes defined in VIUS were not found in the data and are thus not included in the model scheme. Lastly, two specialty cab types were found in the data including cabs with attached cranes and cabs for auto transport (Figure 3.15 e) and included in the body classification scheme for model development. In total there are six drive unit body classes included in the model classification scheme.

(a) Conventional drive unit without sleeper

(b) Cab over drive unit without sleeper

(c) Conventional drive unit with sleeper

(d) Cab over drive unit with sleeper

(e) Specialty cab with crane

Figure 3.15 Examples of Semi-Tractor Trailer Drive Units

Table 3.5 VIUS and Model Drive Unit Body Classification

Body Category	VIUS Body Class	Model Body Class
Standard Drive Units	Conventional cab with or without sleeper	Conventional cab
		Conventional sleeper cab
	Cab over engine with or without sleeper	Cab over cab
		Cab over sleeper cab
	Cab forward engine	*
	Cab beside engine	*
Specialty Drive units	**	Cab with attached crane
	**	Cab for auto transport

* Not included in model body classification scheme
** Not included in VIUS

3.4.2.2 ***Trailer Units***

As shown in Table 3.6, VIUS defines 17 trailer body types which can be categorized into four groups: van, tank, platform, and specialty. The 17 body classes were redefined into 27 body types for the model classification scheme as shown in the rightmost column of Table 3.6. VIUS classes for basic enclosed vans and insulated non-refrigerated vans were combined because they could not be visually distinguished. For model purposes, this group was divided into vans with and without side skirts (e.g. 'skirted enclosed van') which are aerodynamic panels attached to the bottom sides of the trailer to decrease airflow through the trailer undercarriage. Skirted panels cause disturbances in the inductive signature and must be separately categorized to avoid model confusion. Further added categories include hoppers and agricultural vans.

Major additions to the VIUS body classification scheme include intermodal containers and smaller trailers. Intermodal container trailers are not included in VIUS since these belong to shippers rather than carriers or operators who participated in the VIUS survey. Additional body classes include container chassis, 20ft, 40ft, and 53ft intermodal containers, and 40ft intermodal refrigerated containers. Inclusion of these specific categories greatly expands the applicability of the models to freight activity analysis. As for small trailers, for the purpose of this dissertation, the trailer units are considered to be any unit pulled by a drive unit which can be a single unit truck or a tractor. Therefore, the VIUS trailer body classes were expanded to include small trailer body types such as RV trailers, towed vehicles, and small dolly trailers.

Table 3.6 VIUS and Model Body Classification for Semi-Trailers for Existing VIUS Classes

Category	VIUS Body Class	Model Body Class
Van	Van, basic enclosed (dry cargo) Van, insulated non-refrigerated	Enclosed van
		Skirted enclosed van
	Van, drop frame (excluding livestock)	Drop frame van
	Van, insulated refrigerated	Reefer enclosed van
Tank	Tank, dry bulk Tank, liquids or gases	Hot product tank
		Deep drop tank
		Food grade tank
		Petroleum tank
		Chemical tank
		Crude oil tank
		Air compression tank
		Propane tank
		Pneumatic Tank
Platform	Flatbed, platform, etc.	Basic platform
		Platform with devices
	Low boy (platform with depressed center)	Low boy platform
Specialty	Dump (including belly or bottom dump)	Bottom/Belly dump
		Bulk waste transport
		End dump
	Livestock (including livestock dropframe)	Livestock
	Curtainside	Curtainside van
	Mobile home toter	*
	Open tops (vans, low side grain, fruit, etc.)	Open top van
	Pole, logging, pulpwood, or pipe	Pole, logging, pulpwood, or pipe
	Automobile Carrier	Automobile transport
	Beverage	Beverage
	Trailer mounted equipment	*
	**	Hopper
	**	Agricultural van
Intermodal Containers	**	Container chassis
	**	40ft container
	**	40ft refrigerated container
	**	20ft container
	**	20ft container on 40ft chassis
	**	53ft container
Small Trailers	**	Recreational vehicle trailer
	**	Towed vehicle
	**	Small trailer/dolly

* Not included in model body classification scheme
** Not included in VIUS

3.5 Summary of Data

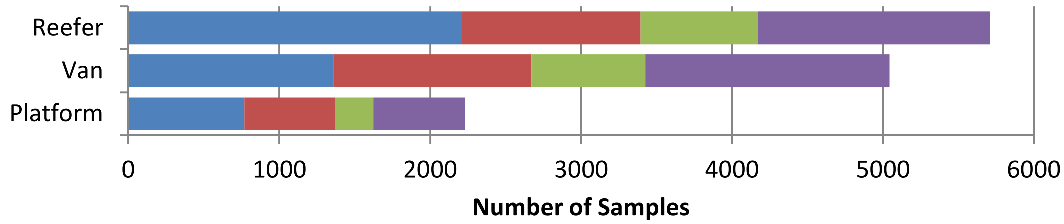
Single unit trucks in FHWA class 5 and semi-tractor trailer combination trucks in FHWA class 9 were the most prevalent across all four data collection sites as summarized Table 3.7. It should be noted that Table 3.7 reports lower than observed volumes of passenger vehicles. For more efficient data groundtruth processing, passenger vehicles not considered to be larger pick-up trucks or 12 passenger vans were not processed for the Fresno, Willows, or Redding data collection sites, or for the September and October data collection periods at Irvine. Passenger vehicles, including sedans, SUVs, minivans, etc. are included in the March 20 and 25th data sets at the Irvine site.

Semi-tractor trailer combination trucks (FHWA class 9) exhibit one of the most diverse sets of body types. Therefore the summaries provided in this section focus on semi-trailer body types. There are a total of 12,681 processed vehicle records for semi-tractor trailer vehicle configurations in FHWA class 9. The most prevalent trailer body type is the enclosed van which comprises 65.1% of the data across all sites. Within the enclosed van body category, non-refrigerated vans represent 28.6%, refrigerated (e.g. reefer) vans represent 26.1%, and non-refrigerated skirted vans represent 10.4% of the total data. The second most populous semi-trailer body type is the basic platform which accounts for 9.5%, followed by tanks representing 4.8% of the total data. Figure 3.16 shows the number of samples for each semi-trailer body class across all four sites.

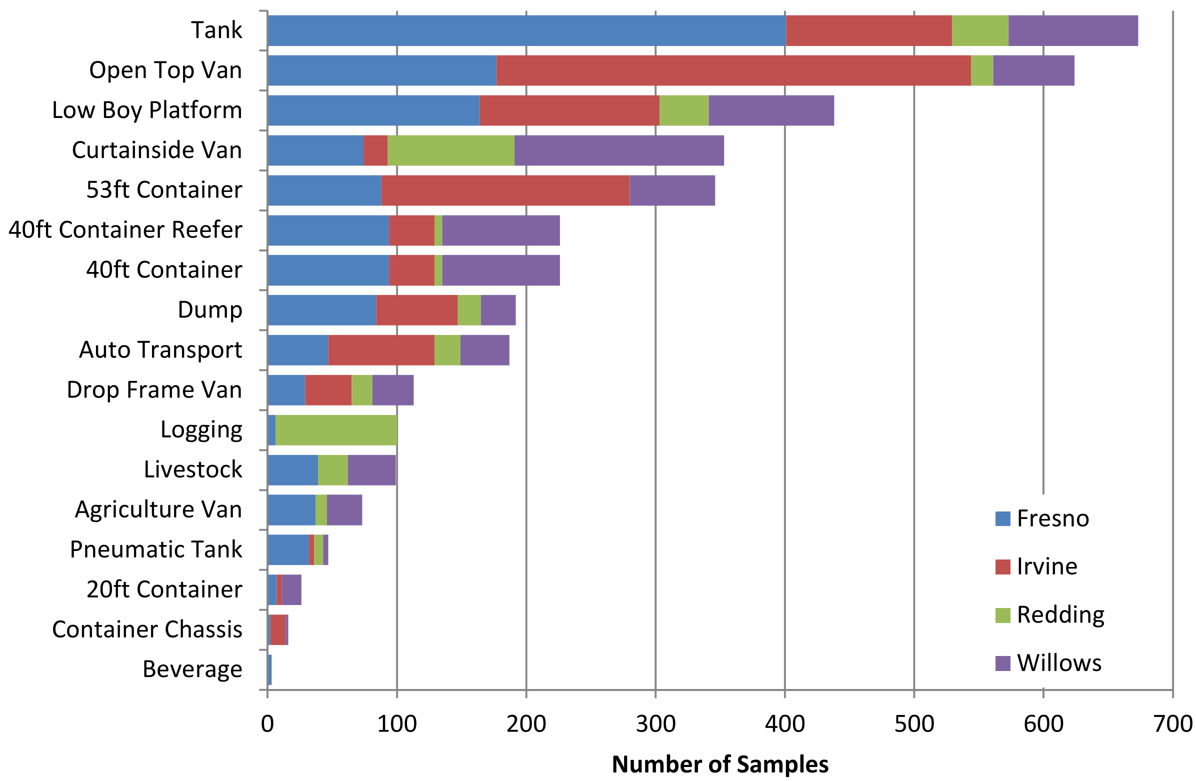
Enclosed vans, refrigerated enclosed vans, and platform semi-trailer body classes dominate the population across all four sites. Notable differences by site are observed in the number of tanks, open top vans, curtainside vans, 53ft containers, 40ft containers, and pole/logging/pipe trailers. These trailer body types are more industry specific and thus possess greater spatial variability due to diverse land uses among the four sites. For example, logging trucks are observed in higher proportion at the Redding site which is located in a region with forestry related industries. At the site in Irvine, open top vans which transport garbage, refuse, and construction debris are observed in greater numbers as a result of the more urban land uses.

Table 3.7 Volume by site and FHWA class

FHWA Class		Irvine	Fresno	Willows	Redding	Total
Passenger Vehicles	**2**	1,649	47	127	1	**1,824**
	3	4,345	745	1,187	22	**6,299**
Single Unit	**4**	176	58	11	8	**253**
	5	2,843	842	145	77	**3,907**
	6	515	238	64	64	**881**
	7	149	14	0	1	**164**
Single Trailer	**8**	455	261	82	112	**910**
	9	3,077	4,200	3,693	1,711	**12,681**
	10	11	20	7	7	**45**
	14	225	119	43	96	**483**
Multi Trailer	**11**	232	477	251	125	**1,085**
	12	12	63	65	44	**184**
	13	2	0	1	0	**3**
Other	**15**	148	422	88	88	**746**
Total		**13,839**	**7,506**	**5,764**	**2,356**	**29,465**



(a) Majority Class Samples by Site



(b) Minority Class Samples by Site

Figure 3.16 Number of semi-trailer truck samples by body type across all sites

4 Machine learning methods for Vehicle Classification

The body classification schemes for single unit, semi-tractor trailer, and multi-unit trucks defined in Chapter 3 show the wide diversity of truck body types that exist on our highways. For instance, five axle semi-tractor trailers, which represent the majority of the trucks by vehicle configuration, were divided into 27 trailer body types ranging from commonly observed enclosed vans to rarer types such as 20ft intermodal shipping containers. Not only is there a wide diversity of body types within each vehicle configuration group, but observed volumes of trucks by body type at the four data collection sites showed that each site contains a different distribution of truck body types, especially for minority body classes such as those that carry seasonal commodities like agricultural vans, or vehicle classes with unique travel characteristics such as intermodal containers. In light of these observations, the body classification models developed in this dissertation have the complicated task of producing accurate classifications across a large array of body classes and generalizing across locations with varying distributions of those classes. Furthermore, because many of the vehicle configuration groups are dominated by a particular class even the most naive model would be relatively accurate if it simply assigned all vehicles to the dominate class. For example, for the case of five axle semi-tractor trailers, enclosed vans represent about 71% of the observations at the Irvine data collection site. Therefore, in addition to addressing multiple classes and spatially related proportions of body classes, the classification model development tasks developed in this dissertation also address the class imbalance problem.

In this Chapter, the scope of the vehicle classification problem including selection of applicable tools from the machine learning literature are discussed (Section 4.1), an overview of the classification model development procedure is given (Section 4.2), and details concerning model selection and implementation are presented (Sections 4.3 and 4.4). Lastly, the proposed model is summarized (Section 4.5).

4.1 Overview of Classification Methods from a Machine Learning framework

Classification is the task of assigning labels to objects represented by a set of measurements called features. Features can be any qualitative or quantitative representation of the object. For example, a photo image could be discretized by pixel so that each pixel would be feature. A 'classifier', also called a 'learner' or 'machine', is defined as a set of algorithmic rules which map an object's features to its class label.

A classification problem has two phases: training and prediction. In the training phase, a classifier learns to model the relationship between features and labels. This form of model training is called 'supervised learning' because each object in the dataset has a predefined class label. Supervised learning involves presenting learning examples to the classifier which then derives the particulars of the set of algorithmic rules. The algorithmic rules can be parametric distributions, linear or more complex decision boundaries, or nearest neighbor patterns. In the prediction phase, unlabeled examples are presented to the trained classifier which uses the set of learned rules to assign a label to the example.

There are a wide variety of classifiers available for supervised learning and several taxonomies for defining categories of classifier methods. Lippmann (1991) categorizes five types of classifiers by the form of the decision rule and the computing element:

1. Probabilistic- model the likelihood distributions of classes using parametric functions (e.g. Naïve Bayes classifiers)
2. Rule-forming- partition the input space into labeled regions using threshold-logic nodes or rules (e.g. decision trees)
3. Local- form discriminant functions using Gaussian or radially symmetric functions (e.g. radial basis function neural networks)
4. Global- form discriminant functions using sigmoidal or polynomial functions (e.g. multilayer perceptron neural networks)
5. Nearest neighbor type- estimate distance between unknown samples and stored patterns (e.g. k-nearest neighbors)

Each type of classifier listed above may be equally applicable to a dataset and result in equally acceptable performance. Studies comparing the performance of a variety of classifiers across a variety of datasets show that although some classifiers can be labeled as the best or worst classifier based on average performance, there is significant, data dependent variability in classifier performance (King et al., 1995; LeCun et al., 1995; Cooper et al., 1997; Lim et al., 2000; Caruana and Niculescu-Mizil, 2006). The expansive StatLog project (King et al., 1995) compared the performance of 17 learning algorithms representing statistical (e.g. Naïve Bayes), symbolic (e.g. decision trees), and neural network formulations across twelve real-world, noisy, complex classification datasets. The author's main conclusion is that there is no single best classifier and that the best algorithm is highly dependent on the features of the dataset. Furthermore, the authors found that even the worst models based on average performance across multiple datasets occasionally performed exceptionally well. Therefore, a major consideration in classifier development, in addition to feature extraction and selection, is the selection of an appropriate classifier for the particular data used in this dissertation.

4.2 Machine Learning Methods for Body Type Classification with Inductive Signatures

It is clear from the diverse set of classification algorithms that have been employed in previous studies using inductive signatures for vehicle classification and the conclusions drawn from the comprehensive comparison studies described in Section 4.1 (King et al., 1995; Caruana and Niculescu-Mizil, 2006), that that no single classifier has been shown to produce more accurate classifications than another. As summarized in Table 4.1, Sun and Ritchie (2000) used heuristic discriminant algorithms and multiobjective optimization, Sun et al. (2003) adopted a self-organizing feature map, Ki and Baik (2006), Tok (2008), Meta and Cinsdikici (2010), and Liu et al. (2011) used neural networks, Oh and Ritchie (2008) used Probabilistic Neural Networks, Jeng and Ritchie (2008) used decision tree and clustering, and Jeng et al. (2013) used a K-Nearest Neighbor approach with wavelet features of the inductive signatures. It should be noted that each of the studies summarized in Table 4.1 worked with a very limited number of commercial vehicle samples so it is difficult to conclude the ability of any of these models to accurately predict commercial vehicle classes. Also, each study used a different feature set and classification scheme, so direct comparisons are not possible. However, the general observation intended by Table 4.1 is that there is no single 'best' classifier for inductive signature data.

Table 4.1 Summary of inductive signature based vehicle classification methods

Model	Classifier	Approx. accuracy (number of classes)**
Sun et al. (2003)	Self-organizing feature map	87% (7 body classes)
Ki and Baik (2006)	Neural Networks	92% (4 body classes)
Tok (2008)*	Neural Networks	84% (9 semi-trailer body classes)
Meta and Cinsdikici (2010)	Neural Networks	93% (5 body classes)
Liu et al. (2011)	Neural Networks	98% (5 body classes)
Oh and Ritchie (2008)*	Probabilistic Neural Networks	71% (4 body classes)
Jeng and Ritchie (2008)	Decision tree	93% (13 axle classes)
Jeng et al. (2013)	K-Nearest Neighbor	92% (13 axle classes)

*Inductive signatures were obtained from experimental Blade inductive loop detectors
** Body classes include passenger vehicle body types and truck body types

Selection of the classifier is of utmost importance as it has immediate effects on the predictive abilities of the classification model. More specifically, the predictive abilities of the body classification model relate to the model's ability to generalize from imbalanced class distributions and noisy features- two prevailing issues in the vehicle classification problem with inductive signatures.

Firstly, class imbalance is highly apparent in the observed body class data across the four data collection sites as was shown in Chapter 3. This is important for vehicle classification since the rarer minority classes can be related to seasonal activities such as agricultural shipments, or trucks with unique travel characteristics such as intermodal container movements. Observations of unique trucks such as these would give great insight that is otherwise not available through existing data collection programs. Class imbalance causes classifiers to be overwhelmed by the majority class and ignore the minority classes leading to poor classification accuracy of minority classes. Weiss (2004) categorized the problems arising in learning from imbalanced data:

1. improper evaluation metrics such as overall classification accuracy which do not capture minority case classification accuracy,
2. lack of total number of minority samples (absolute) and proportion of minority samples (relative) leading to difficulties in defining distinct decision boundaries,
3. inductive bias in the classifier in favor of class priors such that in the face of uncertainty, the classifier preferences the majority class
4. noise has a greater impact on minority cases since minority samples many be interpreted as noisy samples of the majority class

Previous vehicle classification research using inductive signatures have not explicitly addressed the class imbalance problem in model development. Instead, research in this area has focused on pre-processing of inductive signatures and tuning and optimization of individual models. No attempts have been made to account for dominant majority classes during training.

Secondly, inductive signature and WIM data are prone to measurement noise. Measurement noise in inductive signature and WIM data are the result of several possible factors: (i) vehicle dynamics such as speed, acceleration, tire condition, load, and body configuration; (ii) site conditions such as pavement smoothness or sensor calibration issues; (iii) environmental factors such as temperature and precipitation (Nichols and Bullock, 2004; Papagiannakis et al., 2008). An effective classification model should be able to perform well given noisy features. Furthermore, in relation to the class imbalance problem, noise in minority class samples can have significant effects on classification performance.

Several tools in the machine learning domain address the issues related to the body classification problem with inductive signature as described above. When many models are available for classification and little prior knowledge does not point to which classifier is best, the first attempt is to try many different models on the data and select the model which achieves highest performance. Alternatively, rather than selecting a single classifier, much can be gained from combining multiple classifiers. This method of combining the predictions of a set of classifiers is referred to as Multiple Classifier Systems (MCS), also called ensemble learning methods, committees, or mixtures of experts. MCS have been found to increase overall classification performance, ensure generalization, and reduce the effects of class imbalance (Kuncheva, 2004). Additionally, MCS are more likely to approximate the optimal classifier by removing the risk of selecting a single sub-par classifier. This well-suited approach has not been considered in previous work with inductive signatures nor has it been used in the broader body of vehicle classification problems.

Dietterich (2000) gives three general reasons why a set of classifiers might be better than a single classifier: statistical, computational, and representational. Dietterich (2000) defines the goal of a learning algorithm is to find the best hypothesis in the search space of all possible hypotheses. From a statistical perspective, when the amount of training data is too small, the learning algorithm can produce many different hypotheses. But if multiple learners are averaged, the combined hypothesis might be closer to the most accurate hypothesis. From a computational perspective, learners which rely on hill climbing or random search algorithms are subject to getting stuck in local optima. Thus, an ensemble approach where local search is started from varying points can have a better chance of approximating the global optimum. Lastly, from a representational perspective, it is possible that the true relationship between inputs and outputs cannot be represented by any of the learners. In this case, the true classifier lies outside the scope of the individual leaners, so combining learners can help expand the space of representable functions. For these three reasons, multiple classifier systems exceed the capability of standard learning algorithms.

Kuncheva (2004) defines four levels at which we can develop a MCS. The approaches range from methods to combine predictions of independent classifiers to methods to train different classifiers that constitute the ensemble. These are:

1. Combination level
2. Classifier level
3. Feature level
4. Data level

The combination level is the capstone to the MCS. Given a set of independent predictions from the set of classifiers that constitute the ensemble, the combination level looks at different methods in which the set of predictions can be combined into a single prediction. For example, majority voting or weighted voting can be used to combine the predictions. The next tier of MCS development is the classifier level. At this level, the set of constituent classifiers is selected. The constituent classifiers are commonly referred to as base classifiers. Base classifiers can be variations of the same classifier or widely different classifier formulations. The goal in selecting the base classifiers is to ensure as much diversity in the scope of the ensemble as possible. For example, a classifier from each of the five classifier categories listed in Section 4.1 could be selected to as a base classifier in the ensemble. Following the selection of base classifiers, the feature set used as input to each model has to be selected. Kuncheva (2004) refers to this as the feature level. Different feature subsets can be used for the base classifiers. Lastly, the data level focuses on selecting subsets of the dataset on which to train each base classifier. Each classifier could be trained on different subsets of the data, or the data could be subsampled to correct for class imbalance, for example. In this dissertation, attention is placed on the combination, classifier, and data levels and each are discussed in the following sections.

4.2.1 Combination Level

At the combination level, individual base classifier predictions are combined. Combination can be done in two ways: (1) fusing label outputs through voting or averaging, or (2) selecting a label output from a single classifier in the ensemble based on each classifier's confidence it its prediction (e.g. posterior probability). Based on the findings by Kuncheva (2004) there is no significant difference between the simplest and most complex combination methods in terms of prediction accuracy. So, two voting methods were selected and evaluated in this work: majority voting and Naïve Bayes Combination. Majority vote was selected due to its simple interpretability and ease of implementation. Naïve Bayes Combination was selected due to its popularity and reported success and efficiency in experimental studies summarized in Kuncheva (2004). Majority voting simply assumes each model is equivalent in terms of prediction accuracy whereas Naïve Bayes Combination places weight on base model predictions as part of the voting scheme.

4.2.1.1 ***Majority Vote***

Each base classifier produces a class label independent from the class labels predicted by the other base classifiers. At the most basic level, if no information is assumed about the accuracy of each base classifier, than the individual predictions can be combined by simple majority voting. Following the notation used by Kuncheva (2004), in which label outputs are assumed to be c-dimensional binary vectors $[d_{i,1}, ..., d_{i,c}] \in \{0,1\}^c$, i = 1, ..., L, where c is the number of classes, L is the number of base classifiers, and $d_{i,j} = 1$ if D_i labels a sample as w_j and 0 otherwise, the majority vote is formulated as:

$$\sum_{i=1}^{L} d_{i,k} = max_{j=1}^{c} \sum_{i=1}^{L} d_{i,j}$$

This results in a simple majority, or plurality vote, where ties are broken arbitrarily. The majority vote is proven to give an accurate class label if at least L/2 + 1 classifiers give correct answers and the following assumptions hold true: (1) the number of classifiers is odd, (2) the accuracy of individual classifiers is greater than 0.5, and (3) the classifier outputs are independent. While this is a widely used concept in combining classifiers, it does not make full use of the known accuracies of each base classifier on the dataset. For the vehicle classification problem, even weighting the majority vote by the accuracy of the model might not be useful since even the weakest model can be at least 80% correct if the majority class is predicted for each and every vehicle.

4.2.1.2 *Naïve Bayes Combination*

Majority voting simply fuses base classifier labels without regard for known class specific accuracies of a given base classifier. A more informed approach, Naïve Bayes Combination, weights base classifier predictions following from Bayes theory (Kuncheva, 2004; Stefano et al., 2012). Following the notation used by Kuncheva (2004), where $P(s_j)$ is the probability that classifier D_j labels a sample as class s_j and w_k is the correct class label, conditional independence (probability of assigning to class s, given the true class is w_k) assumed among base classifiers is represented as:

$$P(s|w_k) = P(s_1, s_2, \ldots, s_L|w_k) = \prod_{i=1}^{L} P(s_i|w_k)$$

The posterior probability (probability of the true class w_k given the assigned class s), which is used as the weight in the Naïve Bayes Combination voting scheme, is a follows:

$$P(w_k|s) = \frac{P(w_k)P(s|w_k)}{P(s)} = \frac{P(w_k)\prod_{i=1}^{L} P(s_i|w_k)}{P(s)}$$

Ignoring the denominator, P(s), which does not depend on the true class, w_k, the support for class w_k is:

$$\mu_k \propto P(w_k)\prod_{i=1}^{L} P(s_i|w_k)$$

$P(w_k)$ is the prior distribution of each class and can easily be estimated from the training or validation data as the number of samples in class k, N_k, divided by the total number of samples, N. The latter half of the formulation, termed 'modal evidence', can be represented by the confusion matrix, cm^i, resulting from application of each classifier, i, on the training or validation data. Each entry, (k, s), of $cm_{k,s}^{i}$ represents the number of samples with true class k (w_k) and assigned class s (w_s). Further, the formulation is adapted to account for zero values of $P(s_i|w_k)$ which would equate μ_k to zero regardless of the remaining classifier estimates. The final formulation from Titterington et al. (1981) for the Naïve Bayes Combination is:

$$\mu_k = P(s|w_k) \propto \left\{\prod_{i=1}^{L} \frac{cm_{k,s_i}^{i} + 1/c}{N_k + 1}\right\}^B$$

Where B is a tunable constant suggested by Titterington et al. (1981) to be {1, 0.8, 0.5}. The class, w_k, with the highest value of support, $\boldsymbol{\mu_k}$, is the assigned class label. Kuncheva (2004) concludes that Bayes Combination has been found to be accurate and efficient even when classifiers are not independent in their predictions.

4.2.2 Classifier Level

At the classifier level, the set of constituent classifiers is selected for the MCS. The set of base classifiers included in the MCS can be modifications of the same classifier or a combination of different classifiers. For example, a set of neural networks with different number of hidden layers constitutes an ensemble, as does a set of three different classifiers consisting of a neural network, decision tree, and support vector machine. The question becomes how to ensure the optimal set of base models is selected.

An important consideration in selecting base classifiers for MCS is to ensure "error diversity" among the classifiers used (Brown, 2005). Error diversity means that the base models should exhibit different error on different instances. To ensure diversity, entirely different classifiers such as neural networks, support vector machines, decision trees, etc., can be combined. Brown (2005) refers to ensembles of different learners as 'hybrid ensembles' and draws conclusions about their effectiveness in providing 'error diversity' from the following studies: Wang (2000) combined decision trees with neural networks; Langdon (2002) combined decision trees with neural networks; Woods (1997) combined neural networks, k-nearest neighbors, decision trees, and Bayes classifiers. Brown (2005) concluded that hybrid ensembles *"produce estimators with differing specialties and accuracies in different regions of the space- it seems sensible that two systems which represent a problem and search the space in radically different ways may show different strengths, and* *therefore different patterns of generalization"* (p.18). In this dissertation, a hybrid ensemble is adopted to best ensure diversity among classifiers.

The ensemble of classifiers used for the body classification model spans the five categories outlined by Lippman (1991) and within each category, the chosen model has shown to have good performance for a variety of datasets (King et al., 1995; Caruana and Niculescu-Mizil, 2006). The ensemble consists of:

1. *Probabilistic*: Naïve Bayes Classifier (NB)
2. *Rule forming*: Decision Tree (DT)
3. *Global:* Support Vector Machine (SVM)
4. *Global:* Multilayer Feed Forward Neural Network (MLFF)
5. *Probabilistic, Local, or Nearest neighbor:* Probabilistic Neural Network (PNN)

Several classifiers selected for the ensemble can be considered in multiple categories. For instance, a Probabilistic Neural Network (PNN) is a variant of radial basis function networks that approximate Bayesian statistical techniques. According to the taxonomy by Lipmann (1991) PNNs fall into the probabilistic, local, or nearest neighbor categories. The purpose of organizing the ensemble constituents into the classifier categories is to illustrate the diversity that exists in this particular set of classifiers. This diversity is captured in the varying assumptions and implementations captured by each classifier.

4.2.2.1 ***Naïve Bayes Classifier (NB)***

The Naïve Bayes classifier (NB) is a simple statistical approach which makes use of an underlying probability model based on Bayes Theorem. The method relies on the assumption of conditional independence among features. NB assumes the value of a particular feature of a class is unrelated to the presence of any other feature. Parameter estimation for NB is conducted using maximum likelihood estimation. Using Bayes Theorem the probability model is formulated as:

$$P(\mathrm{C}|f_1, f_2, \dots, f_n) = \frac{P(\mathrm{C})P(f_1, f_2, \dots, f_n|\mathrm{C})}{P(f_1, f_2, \dots, f_n)} = P(C)\prod_{i=1}^{n} P(f_i|C)$$

where $(f_1, f_2, \dots, f_n)$ is the set of n sample features and C is the dependent class variable. The conditional independence assumption between features implies that the likelihood, $P(f_1, f_2, \dots, f_n|\mathrm{C})$, can be rewritten as the product of terms, $\mathrm{P}(f_i|C)$, as shown on the right hand side of the equation.

The posterior probability model is translated to the NB classifier using the training data to calculate the class priors, P(C), and maximum likelihood estimation to determine the feature probability distributions, $\mathrm{P}(f_i|C)$. The feature distribution is assumed to follow a statistical distribution, most commonly Gaussian, $N(\mu,\sigma)$.

The advantages are short computational time for training and high accuracy given its simple formulation. The main limitation is linked to the conditional independence assumption of features, however, even though this assumption is violated, studies show good results using NB.

4.2.2.2 ***Decision Tree Classifier***

Tree based supervised learning models are simple but common tools for classification. Classification and Regression Trees (CART) recursively partition the feature space into sub-regions beginning at the root of the tree and traversing down binary branches until a leaf node is reached at which point the sample is assigned to a class. Figure 4.1 depicts a decision tree. Each node (light grey circle) represents a split in the data, x_i, by feature value, O_i. The terminal nodes, or leaves, (dark grey circles) indicate the final class assignment.

To train the tree, the feature that best divides the training data is set as the root node of the tree. A common method for determining which feature to split at each node is the information gain criterion (Hunt et al., 1966). The tree grows by adding branches according to the information gain criteria until the tree meets a specified stopping criterion preventing the tree from over fitting the training data. Pruning of the tree is accomplished most commonly using the Grini Impurity Index which encourages the formation of regions which cover a high proportion of the data, thus allowing unnecessary branches to be trimmed from the tree.

The main advantages of decision trees are easy interpretation and implementation. Limitations include: (1) lack of generalization ability if pruning method is not properly adjusted, (2) inability to efficiently represent non-linear decision boundaries (Kotsiantis, 2007), and (3) training approach does not guarantee global optimal solution.

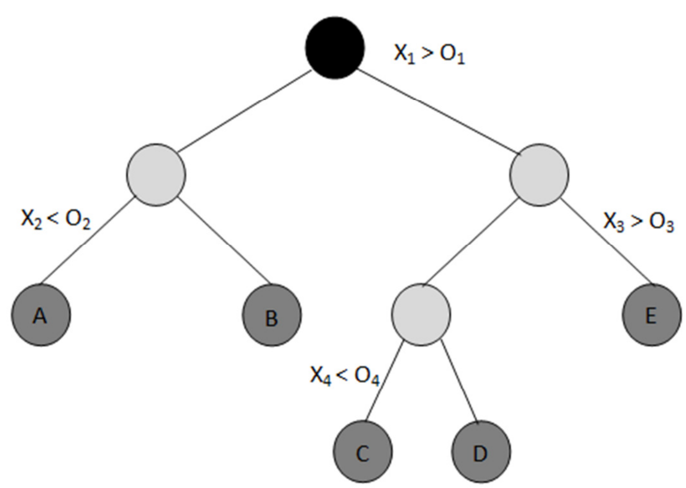


Figure 4.1 A Decision Tree

4.2.2.3 ***Support Vector Machines***

Support Vector Machines (SVM) estimate a margin around a hyperplane separating two classes. The model maximizes the margin to create the largest possible distance between the separating hyperplane and instances surrounding it. Once the separating hyperplane is found, data points that lie on its margin are known as support vector points, and the model is represented as a linear combination of these points. Figure 4.2 depicts the main concept of SVMs for the two class problem.

The following formulations follow from Bishop (2006). The hyperplane for a binary classification problem is represented as a linear model of the form $y(x) = w^T x + b$, where w is the weight vector and b is the intercept. Data points, x_n, are classified according to the sign of $y(x_n)$ such that the class of point x_n, labeled $t_n = +1$ when $y(x_n) > 0$ and $t_n = -1$ when $y(x_n) < 0$.

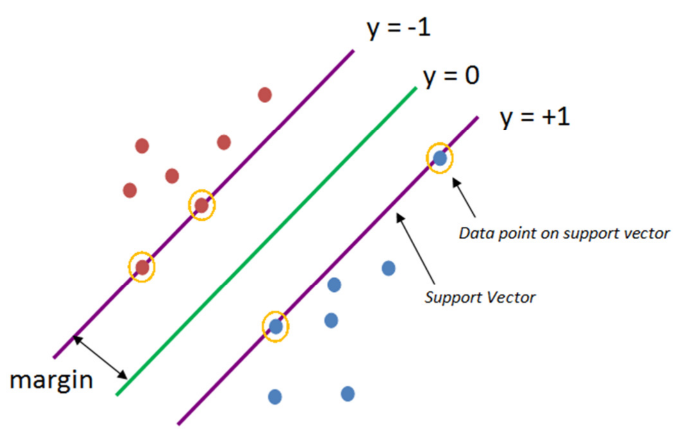


Figure 4.2 Support Vector Machine

Among many possible hyperplanes, the optimal plane will produce the lowest misclassification risk which is the hyperplane with the maximum margin. Given that the perpendicular distance from a point, x, to a hyperplane, y(x) =0, is |y(x)|/||w||, the maximum margin solution is given by:

$$\arg\max_{w,b}\left\{\frac{1}{||w||}\min_n[t_n(w^Tx_n+b)]\right\}$$

The solution to this equation is complex, so an equivalent constrained optimization problem is formulated as:

$$\arg\min_{w,b}\frac{1}{2}||w||^2$$

$$\text{Subject to: } t_n(w^Tx_n+b) \geq 1$$

The formulation above requires the feature space to be perfectly separable, which is not feasible for most datasets. The correction is to allow for 'soft margins' which allow data points to be misclassified but subject to some penalty term. Slack variables, ξ_n, are introduced for each training data point such that $\xi_n = 0$ for points on the correct side of the margin, and $\xi_n = |t_n - y(x_n)|$ for those on the wrong side of the margin, i.e. a distance based penalty. Thus, the objective function becomes:

$$\arg\min_{w,b,\xi}\frac{1}{2}||w||^2 + C\sum_{n=1}^{N}\xi_n$$

$$\text{Subject to:} \quad t_n(w^Tx_n+b) \geq 1-\xi_n$$

$$\xi_n \geq 0$$

Solution to the minimization is performed using the corresponding dual Lagrangian formulation and Karush-Kuhn-Tucker (KKT) conditions. Finally, the solution derived above is for the two class problem, but can be extended to multi-class problems. A commonly used approach constructs K separate SVMs in which the kth model is separates class k from all other classes in a one-versus-the-reset approach. Lastly, many machine learning software packages implement the Sequential Minimal Optimization (SMO) method of Platt (1998) to speed up training of SVMs.

The advantages of SVMs are: (1) well suited to deal with large number of features, (2) training procedure reaches a global optimum so SVM is not subject to local optimum (Kotsiantis, 2007). Limitations are: (1) SVM was originally proposed for binary classification and the adaptation to multi-class problems leads to weaker outcomes (Bishop, 2006) and (2) larger training data sets are required to achieve maximum accuracy features (Kotsiantis, 2007).

4.2.2.4 ***Neural Networks***

Artificial Neural Networks (NNs) derive their name from the biological central nervous system functions from which they were inspired. The use of NNs is extensive across many fields of study with well-established abilities to perform accurately on real-world classification tasks (Lippman, 1989). The main structure of a NN is shown in Figure 4.3 and consists of an input layer, hidden layer, and output layer made up of neurons. The basic neural network model can be described as a series of functional transformations (Bishop, 2006). Two NN architectures are described in this section, the commonly used Multilayer Feedforward Neural Network and the Bayesian interpretation of NN called the Probabilistic Neural Network.

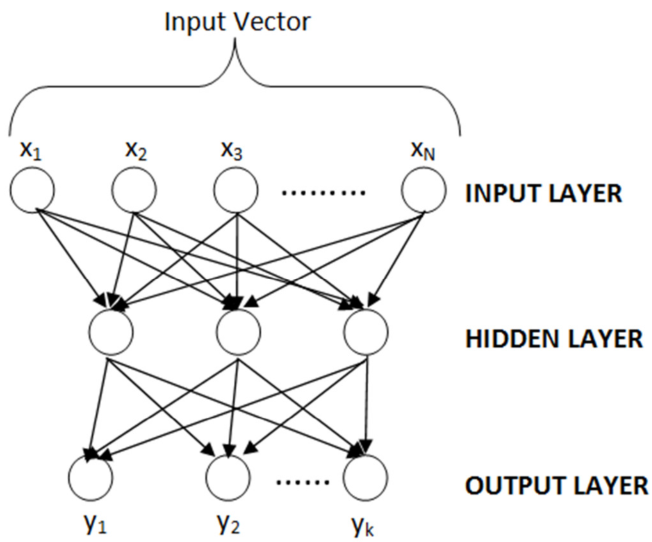


Figure 4.3 Artificial Neural Network

4.2.2.5 *Multilayer Feedforward Neural Network*

The Multilayer Feedforward (MLF) Neural Network follows the same principle as described above. The input layer constructs linear combinations of the input variables, $x_1,\ldots, x_N$, using weights and biases. The summed quantities of the input layer are then fed to an activation function on the hidden layer, usually a sigmoidal function. Output unit activations are linearly transformed using another set of weight and bias values to give the final set of network outputs. The model is termed feedfoward because the output of each layer is passed only to the higher layer, from input to output. The number of input neurons corresponds to the size of the feature set and the number of output neurons corresponds to the number of classes. The number of hidden layers and number of hidden neurons must be set as part of the network architecture and can be determined through sensitivity testing.

The training procedure for a MLF involves adjusting the weights and biases of the transformation and activation functions as labeled training samples are introduced. A common training method is called the backpropagation training algorithm. Essentially, this algorithm adjusts weights at each neuron by first calculating the error of a training sample at the output node and then carrying that error back through each layer and neuron (Bishop, 2006). For each neuron, the weights are adjusted so that the local error is reduced. The local error is passed to the connecting neurons and used to assess their local error. The process continues until a stopping criterion, such as an error measure on an independent validation dataset, is reached.

The advantages of MLF are: (1) ability to adapt to noise and distorted patterns, (2) ability to perform well with dependent feature inputs, and (3) proved capability in real-world problem sets. Limitations include: (1) high variance and unsteadiness due to back-propagation training reaching local minima in determining weights, (2) long training times, (3) lack of interpretability, and (3) sensitivity testing required to determine network architecture.

4.2.2.6 ***Probabilistic Neural Network***

The Probabilistic Neural Network (PNN) is a computationally efficient pattern classification algorithm for implementing Bayesian decision theory. It differs from MLFs in that the sigmoid activation function is replaced by a statistically derived function. The PNN has four layers: input, pattern, summation, and output (Figure 4.4). The input layer normalizes then distributes the input features to the pattern layer. The pattern layer compares the features to training patterns by calculating the dot product of the input pattern and the weight/training vector and then uses the dot product as input to the activation function. The summation layer sums of the activation outputs of the pattern layer as shown below which is essentially a Gaussian mixture smoothed by σ as follows:

$$f_A(X) = \frac{1}{(2\pi)^{p/2}\sigma^p}\frac{1}{m}\sum_{i=1}^{m} exp\left[-\frac{(X-X_{Ai})^T(X-X_{Ai})}{2\sigma^2}\right]$$

The output layer compares the estimated posterior probabilities and determines the final class to which the vehicle belongs. The network is trained by making a pattern neuron for each training vector and then finding the connections between pattern units and summation units. Also, the smoothing parameter has to be determined through sensitivity analysis.

Advantages of PNN are: (1) fast training process, (2) guaranteed convergence to an optimal classifier as the size of the training set increases, and (3) training samples can be added and removed without extensive re-training. Limitations include: (1) large memory requirement to store all training samples, (2) slow running time for new data due to the requirement to compare new data to all training samples, and (3) requires a representative training set.

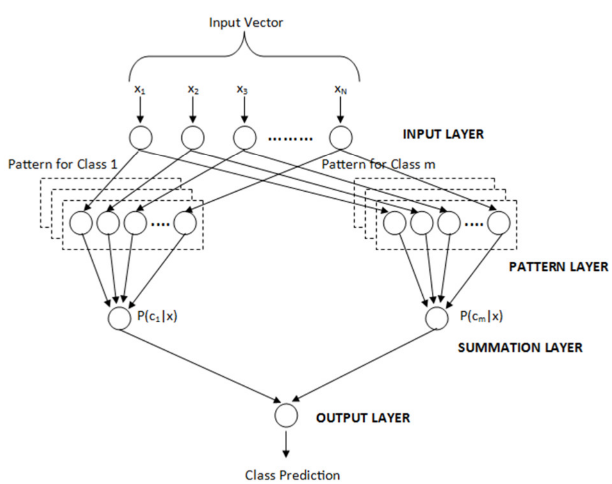


Figure 4.4 PNN structure consists of input, pattern, summation, and output layers

The large data storage requirement and resulting lengthy running time have been addressed by the Constructive PNN (CPNN) adaptation of the PNN (Berthold and Diamond, 1998). CPNN introduces new pattern layer neurons (i.e. training data samples) only when they will contribute positively to the overall classification rate and adjusts the shape of the already existing pattern neurons individually to minimize the risk of misclassification. Essentially, CPNN reduces the number of training samples stored in the pattern layer which reduces running time.

4.2.3 Data Level

To build a successful vehicle body classification model, not only is it important to select the right classifier or set of classifiers, but the model should also address the problem of class imbalance when training the classifiers. Key problems in learning from imbalanced datasets are due to small sample sizes and overlapping class features. When the number of samples is small or no sample is available for a particular class the estimated decision boundary can be very far from the true boundary (Kotsiantis et al., 2006). Overlapping class features make discriminative rules hard to learn so more general rules are created which more likely misclassify minority instances (Kotsiantis et al., 2006). As the degree of data complexity increases, the class imbalance factor (e.g. ratio of majority samples to total samples) starts to affect the generalization ability of the classifier (Kotsiantis et al., 2006).

If the class imbalance problem is not addressed, classification models contain bias toward classes with greater numbers of instances. Galar et al. (2011) illustrate an extreme case where the imbalance ratio is 100:1. They state that a classifier which tries to maximize accuracy can obtain 99% accuracy just by ignoring the single instance of the minority class. Ignoring this aspect will reduce the models spatial transferability to sites which may not be dominated by the majority class such as sites near Ports with heavy intermodal container traffic or farming regions with high proportions of agricultural type trucks, for example, thus reducing the usefulness of the model in studying unique freight patterns.

Several methods have been developed for handling the class imbalance problem. The methods can be synthesized into three main areas based on reviews by Kotsiantis et al. (2006) and Galar et al. (2011): (1) data preprocessing techniques, (2) classifier modification techniques, and (3) hybrid approaches. Additionally, MCS are also considered to be methods to handle class imbalance when the set of classifiers in the ensemble are diverse enough.

4.2.3.1 ***Data preprocessing techniques***

Data preprocessing techniques balance the class distributions prior to classifier training by under sampling the majority class, over sampling the minority class, or combining both. Under-sampling refers to random sub-selection of the majority class. Under-sampling methods have three branches: completely random selection from the majority class (e.g. random under-sampling RUS), selecting of majority examples near the classification boundary, or selection of majority examples with lots of neighbors. Examples of these methods include the Condensed Nearest Neighbor rule (CNN), Edited Nearest Neighbor (ENN), Neighborhood Cleaning Rule (NCL), and Tomek Link method (Kotsiantis et al. (2006)). Kotsiantis et al. (2006) comment that these methods are difficult for large datasets since for any example in the dataset nearest neighbors of the sample must be found and also that potentially useful data is discarded. Rather than reduce the majority class, an alternative is to increase the number of samples in the minority classes. This is called oversampling. Oversampling can be performed by replication (sampling with replacement) or introduction of synthetic samples. A much used method for sample generation is Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al., 2002).

SMOTE generates synthetic minority examples by finding *k* minority class nearest neighbors and then randomly interpolating between the line segments connecting the sample to the nearest neighbor. If there are many nearest neighbors, a random subset is chosen. The authors suggest using five nearest neighbors. This procedure in effect creates 'noise' in the features of the minority samples. This is beneficial for inductive signature data because signatures naturally contain fluctuations caused by vehicle dynamics over the sensors or other environmental considerations, but the basic shape of the inductive signature is maintained. In other words, the SMOTE method would mimic the noise that would occur naturally. Chawla et al. (2002) suggest that in addition to SMOTE, under-sampling of the majority class should also be applied to the training data. Under-sampling the majority class is done by randomly selecting samples from the majority class.

SMOTE improves minority classification accuracy by causing the classifier to create larger and less specific decision regions which better capture minority classes. The main limitation is over-fitting since modified copies of minority class examples may come from a small set of nearest neighbors and thus not provide enough feature diversity to create different enough samples allowing for generalization. Comparison of SMOTE, oversampling alone, and under-sampling alone, across multiple datasets of varying complexity and levels of imbalance shows that SMOTE improved the accuracy of minority classification better than either of the other approaches (Chawla et al., 2002).

4.2.3.2 ***Classifier modification techniques***

Rather than preprocessing data prior to classifier training, class imbalance in the training sample can be compensated for without actually altering class distributions and instead manipulating classifiers internally. Although there are many forms this can take, depending on the classifier, the general idea is to internally bias the learning procedure by applying weights to the training samples. Classifier level methods include: cost sensitive learning in which the objective is to minimize the cost of misclassification by incorporating a cost matrix into the learning algorithm; one class learning in which only the minority class samples are used in training and defaulting to the majority class if a threshold on the similarity value is surpassed; and ensemble methods which train multiple or successive learners and combine results.

Ensemble methods, specifically bagging and boosting, have been used extensively to solve class imbalance problems at the classifier level. Bagging, i.e. bootstrap aggregating, was introduced by Breiman (1996) to construct ensembles. Bagging involves independently training multiple classifiers on separate, randomly sampled, bootstrap sub-samples of the training data and then combining the classifiers through majority voting. Boosting, introduced by Freund and Schapire (1997), is an iterative algorithm that places different weights on training samples at each iteration. After each iteration weights on incorrectly classified examples are increased while weights on correctly classified examples are decreased. This forces the learner to focus more on the incorrectly classified examples in the next iteration. Each trained classifier is then combined via a weighted vote where the weight is derived from overall classification accuracy of each classifier. AdaBoost, or Adaptive Boosting, is the most representative implementation of boosting. Boosting based approaches can also be modified to incorporate misclassification costs into the weights, rather than placing arbitrary valued weights on the iterative training phases. The most common algorithm is called AdaCost.

4.2.3.3 *Hybrid approaches*

Hybrid approaches combine some form of data preprocessing with classifier modification through ensemble methods. For example, SMOTEBoost introduces synthetic examples from the minority class during the iterative boosting process weighting phase. SMOTEBagging combines SMOTE preprocessing with bagging. RUSBoost removes instances from the majority class by random under-sampling the dataset during each boosting iteration.

4.2.3.4 *Comparison of Class Imbalance Methods*

Galar et al. (2011) compare approximately 35 different class imbalance methods including both data preprocessing methods such as SMOTE and classifier modification techniques including boosting and bagging based ensembles across 44 datasets. Statistical results show that a hybrid form of data preprocessing and bagging, SMOTEBagging, outperformed the other methods of class imbalance correction and is the computationally least complex among the best performing methods. The authors conclude that more complex methods such as AdaBoost and AdaCost do not perform better than simpler methods such as SMOTE. Furthermore, the authors comment that the collective approach of random under-sampling of the majority class, synthetically oversampling the minority class, and applying an ensemble approach such as Bagging "stood out" in the experimental analysis.

4.3 *Proposed Classification Model Framework*

4.3.1 Model Development Framework

The proposed classification model development framework shown in Figure 4.5 can be applied for body classification using inputs of inductive signatures only and inductive signatures and WIM data. The framework incorporates the MCS and class imbalance tools described in the previous sections.

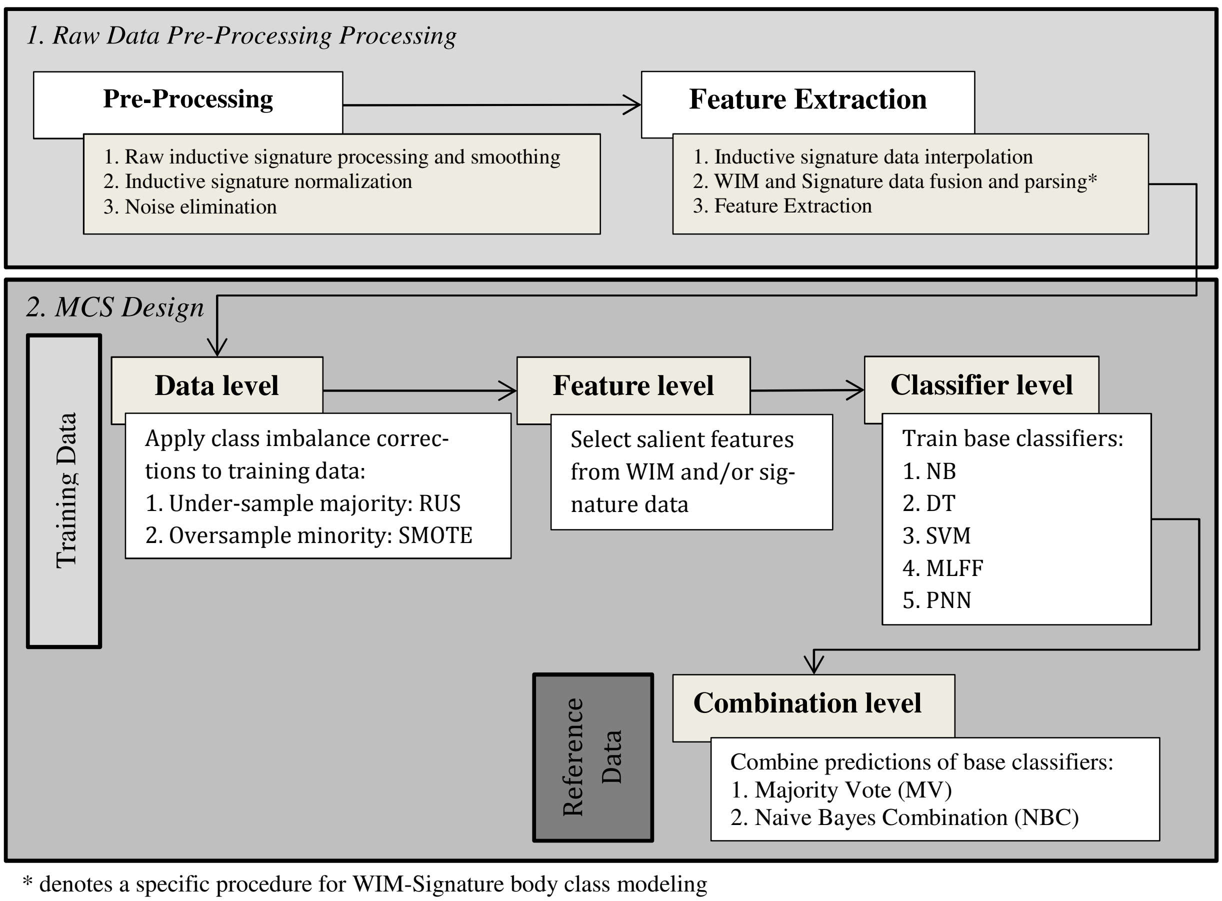


Figure 4.5 Framework for Classification Model Development

The first stage of the model development process deals with the raw input data from the WIM controllers and inductive signature detectors. Data pre-processing entails cleaning of the raw inductive signatures and WIM data so that effects of lane changing, off center vehicles, and sensor calibration are corrected. This step results in noise-reduced, normalized, spatially insensitive inductive signature data. The second procedure pertains to feature extraction in which the pre-processed inductive signature is converted to features that are representative of the signature. This is necessary because an inductive signature can contain between 200 to 1400 data points depending on the length of the vehicle and traffic conditions. Using all of the data points would be too computationally intensive for any classifier, so the inductive signature is reduced to between 30 to 60 representative data points through interpolation methods such as cubic spline interpolation (Jeng and Ritchie, 2008). Next, the WIM data including axle count, spacing and weight and vehicle length, is paired to the inductive signature. The WIM data can then be used to parse the signature into components representing different portions of the vehicle.

The second stage of model development deals with classifier design. The MCS approach is adopted and follows the four levels discussed in Section 4.2: data level, feature level, classifier level, and combination level. At the data level, the class imbalance correction procedures for oversampling the minority class (e.g. SMOTE) and under-sampling the majority class (e.g. RUS) are applied to the training data. For SMOTE, the number of nearest neighbors from which to create synthetic minority class samples was set to five as suggested by Chawla et al. (2002). The under-sampling rate, i.e. the percentage of samples to keep in the training dataset, was selected through sensitivity testing. The under-sampling rate was dependent on the body class distribution.

At the feature level, a set of salient features are selected from the inductive signature and/or WIM data. For the signature only model, only signature features are chosen and the same set of signature features is input for each base classifier at the classifier level. For the WIM-signature combined model, the set of WIM and signature features vary by vehicle configuration class. For example, for semi-tractor trailer combination trucks, the feature set includes inductive signature features from only the portion of the signature partitioned by the WIM axle spacing measurements to represent the trailer. Whereas for single unit trucks, the feature set includes features extracted from the entire signature as well as length and axle spacing measurements.

At the classifier level, each of the base classifiers selected for implementation (e.g. NB, DT, SVM, MLFF, and PNN) is trained using a *S*-fold cross validation approach (Bishop, 2006) to configure the model parameters shown in Table 4.2. In the *S*-fold cross validation approach, *S* partitions of the training data are made. Then *S-1* groups are used for training the model and the remaining group is used for model validation. The procedure is repeated for all *S* groups. This allows as much data as possible to be used for classifier training which is important given the sometimes limited number of samples available for minority classes.

Table 4.2 Configuration Parameters for Base Classifiers

Base classifier	Configuration Parameters
NB	None
DT	Pruning criteria
SVM	Class overlap penalty, Kernel function
MLFF	Number of hidden layers and nodes
CPNN	None

The combination level compares two procedures for combining the predictions of the base classifiers. The MV procedure combines the predictions of the base classifiers by simple majority. The NBC method requires a reference confusion matrix to be stored for each base classifier. A validation dataset was held out from model training for this purpose. After training each base classifier, the trained classifiers are applied to the validation data to produce a confusion matrix.

At all stages of model development the main criteria used to assess the performance of the model is the Correct Classification Rate (CCR). CCR is the proportion of correctly classified vehicles in the dataset. A CCR of 100% indicates a perfect classification model whereas 0% indicates a model in which no samples were correctly classified. The 'overall CCR' (CCR) refers to the total number of correctly classified vehicles over the entire set of body classes. The 'class specific CCR' (CCR_b) refers to the total number of correctly classified vehicles in a specific body class (b) over the total number of vehicles in that body class. For some models, the minority class CCR, the total number of the correctly classified vehicles in the set of minority classes divided by the total number of vehicles in the set of minority classes, was also used to assess model performance.

4.3.2 Model Application Framework

The model application framework is shown in Figure 4.6. To apply the model described in the previous section, first an unknown sample is pre-processed and features are extracted. Then the features needed for the classifiers are selected from the feature set. Next, the MCS model is applied. Each of the five trained classifiers is applied to the unknown sample feature set and five independent predictions are produced. The five predictions can then be combined by MV or NBC. To apply NBC, the class support values are computed by referencing the stored confusion matrices that resulted from applying the trained classifiers to the validation data during model development. The final result regardless of the combination strategy is a single prediction of the body class for the unknown sample.

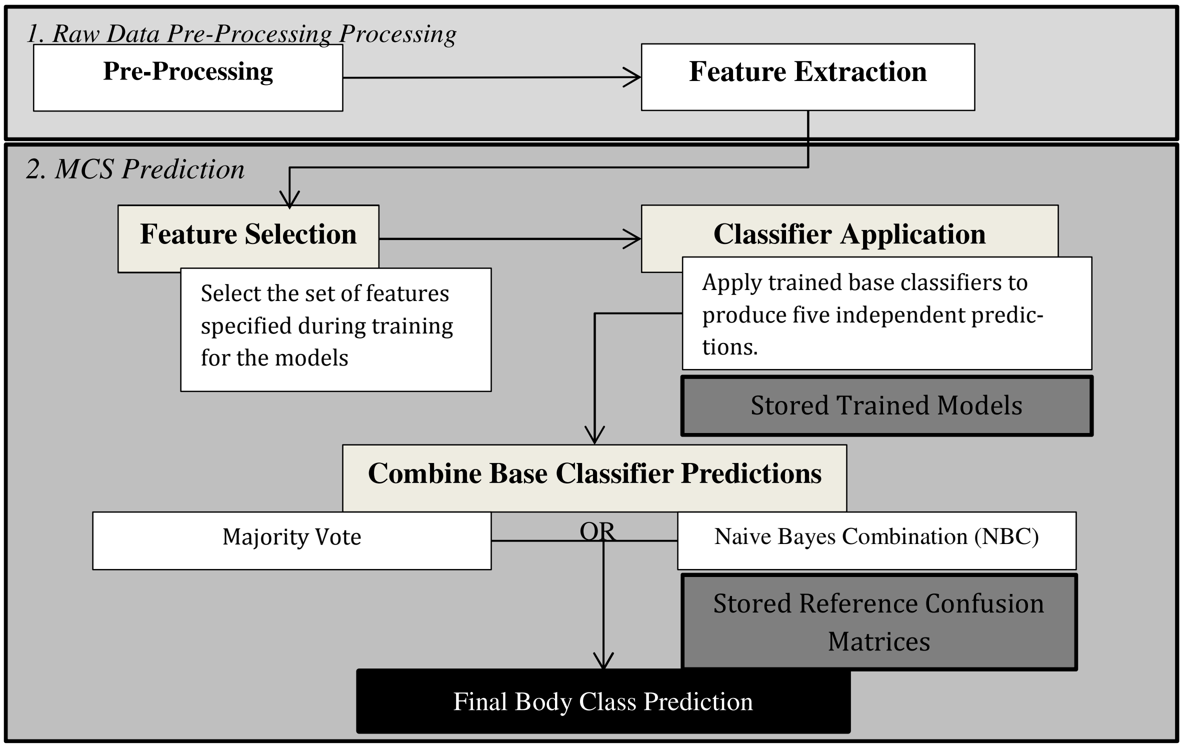


Figure 4.6 Model Application Framework

Improving over existing models, MCS are the chosen implementation approach rather than simply, and possibly naively, selecting a single, sub-par classifier. Furthermore, unlike previous vehicle classification models, especially those using inductive signatures, the methods used in this dissertation fully address the class imbalance problem inherent in vehicle classification data. While the MCS introduces a diverse model set that can increase generalizability, each base classifier in the multiple classifier system might not produce accurate results when trained on imbalanced data. So the method created in this dissertation combines the benefits of multiple classifier systems and class imbalance correction methods.

5 Models and Results

In this Chapter models for obtaining truck body class from WIM data, inductive signature data, and integrated WIM and signature data are presented. The three models are presented in increasing order of input and output resolution to better show the added value in combining WIM and inductive signature data. The first model (Section 5.1) uses only WIM system measurements such as axle spacing and length and produces body class volume estimates as opposed to individual vehicle predictions. The WIM-only model is valid only for five axle combination tractor trailers corresponding to FHWA class 9. The second model (Section 5.2) uses only inductive signature data and produces individual vehicle classifications aligning with the body classification scheme presented in Chapter 3. Unlike the WIM based body class volume model, the inductive signature model classifies all vehicle types including passenger cars, single unit trucks, and combination trucks using a three tiered approach. After determining if the vehicle is a single or multi-unit vehicle, the second tier determines the vehicle configuration (e.g. passenger vehicle, single unit, multi-unit, etc.) and the third tier subsequently determines the body class within the vehicle configuration class. The model applies the multiple classifier systems approach (MCS) with class imbalance correction previously described in Chapter 4. The third and most capable model (Section 5.3) integrates WIM and inductive signature data to produce the highest resolution classifications in line with the body class schemes presented in Chapter 3 and stratified by axle configuration group (e.g. the FHWA axle configuration classification scheme). Like the inductive signature only model, the integrated model employs the MCS approach with class imbalance correction. Because the integrated model pulls data from the WIM system it contains weight and axle configuration in addition to body class, thus improving upon the inductive signature only model.

5.1 WIM-based Truck Body Classification

In a joint effort of the research team assigned to the project from which this dissertation was established, a 'WIM-only' model was developed to estimate site and time specific truck body configuration volumes using existing WIM site data. The motivation for this method was to find a way to get more truck body class information out of historical WIM data for the purposes of validating the California Freight Forecasting Model (CSFFM) to prior validation years. Two models were developed: (1) a tractor body class model and (2) a trailer body class model. Rather than estimating individual vehicle classifications as the models in Section 5.2 and 5.3 produce, the WIM-only model produces aggregate trailer body configuration volumes. This method allows more information to be extracted from axle-based measurement data without requiring modifications to existing infrastructure such as installing inductive signature capable detector cards, thus better leveraging already heavy investments in WIM systems.

The WIM-only model was developed for five axle semi-tractor trailers that have been classified according to their axle spacing and weight measurements to be FHWA class 9 trucks. Five axle semi-tractor trailer combination trucks have distinct axle configuration characteristics, prevalence in the traffic stream relative to other truck types, and unique implications for freight and emissions analysis. Thus, identifying the body classes of five axle semi-tractor trailer combination trucks is of interest.

5.1.1 Data

Data from the four data collection sites described in Chapter 3 were used to develop and test the WIM-only body class models. Data were split by day as shown in Table 1 to create separate training and testing datasets. The Irvine was held out from model training and used as an independent test dataset. The data was partitioned randomly into training and testing datasets with 60% for training and 40% for testing.

The tractor body classification scheme is a two class scheme: (1) cabs with sleepers and (2) cabs without sleepers. This is a condensed version of the scheme presented in Chapter 3 which had five tractor units. The semi-trailer body classification scheme presented in Chapter 3 would be far too detailed to model using only WIM measurements. Therefore, the scheme was collapsed into five representative classes: enclosed vans (vans), platforms, tanks, 40ft containers (containers), and other. Each group shares similar physical attributes and commodity types.

Table 5.1 Data Summary for WIM Only Model Development

Site	Training Data Date	Test Data Date	Number of Five Axle Semi-Trucks (% of total)
Fresno	Nov. 8, 2012	Nov. 7, 2012	4,101 (61%)
Redding	Dec. 11, 2012	Dec. 10, 2012	1,694 (73%)
Willows	Dec. 10-11, 2012	Dec. 12, 2012	3,507 (78%)
Irvine	-	March 20 & 25, 2013	1,632 (35%)

The WIM system measures the number of axles, spacing between each axle, weight of each axle, and overall vehicle length. In addition, overhang was derived. Overhang represents the front and rear portions of the vehicle outside the axles and was obtained as the arithmetic difference between the overall length and the sum of all axle spacing measurements.

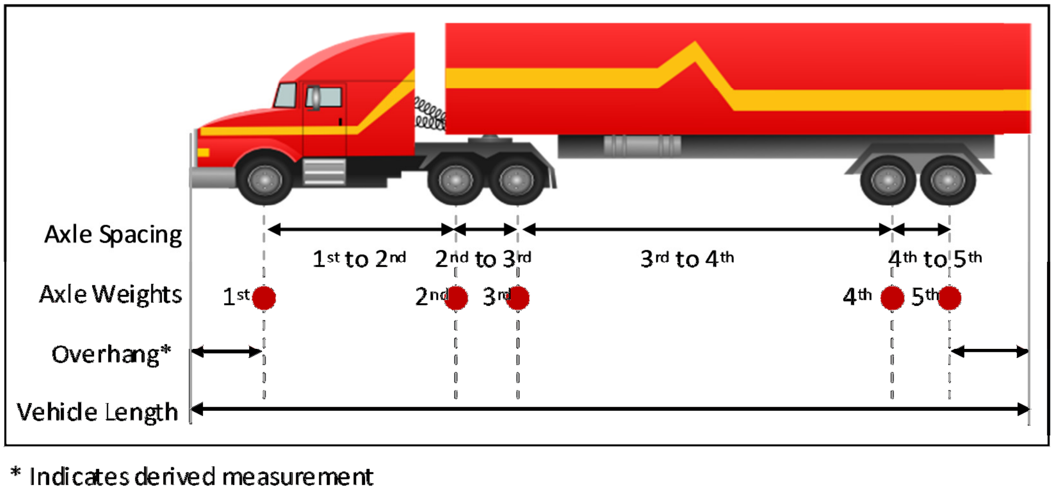


Figure 5.1 WIM system measurement and derived features for five axle semi tractor-trailer trucks

Figure 5.2 shows the distribution of the axle spacing data for the two tractor body classes: cabs without sleepers and sleeper cabs. Approximately 24% of the data are cabs without sleepers and 76% are cabs with sleepers. For the tractor model, the spacing between the 1st and 2nd axles, vehicle length, and an interaction term constructed by multiplying the vehicle length and spacing between the 1st and 2nd axles were used as inputs to the classification model. The spacing between the 2nd and 3rd axle did not vary significantly by tractor body type and was not included in the model.

Cabs without sleepers have shorter spacing between the 1st and 2nd axles than cabs with sleepers. The median spacing between the 1st and 2nd axles were 13.3ft and 17.3ft for cabs without sleepers and cabs with sleepers, respectively. The median vehicle length for cabs without sleepers was 66.4ft and 74.0ft for sleeper cabs.

The interaction term was included to further delineate between the two tractor body types across sites. It was observed that the tractor axle spacing (e.g. spacing between axles 1 and 2) for cabs without sleepers at Redding was significantly larger than that at the other three sites, as shown in Figure 5.4. However, the overall vehicle lengths of cabs without sleepers observed at the Redding site were shorter than at the other three sites. Interacting the terms allowed for better delineation between sleeper and non-sleeper cabs that was consistent across all observed sites.

For the trailer model, the spacing between the 3rd and 4th axles (referred to simply as 'spacing'), vehicle length, and overhang were used as input to the trailer body classification model. Figure 5.5 summarizes the distribution of each of the selected measurements for each body class as box plots. Vans have the longest median length and overhang. Vans have more outliers (red dots extending past the whiskers) due to the intra-class diversity in each of the three measures. Platforms have the second longest length and possess a larger variability than vans across all three measurements as indicated in the box plot by the height of the box which represents the lower and upper quartiles of the data. Tanks have the shortest median length and overhang measurements. Containers, which are solely 40ft containers, display the lowest variance in length, spacing, and overhang. The 'Other' group has the largest variability due to the intra-class diversity of body types. A Kolmogorov-Smirnov (KS) hypothesis test confirmed that the five body groups are indeed differentiable by length, axle spacing, and overhang.

To reduce the effects measurement noise in the WIM measurements due to sensor calibration issues that may exist across sites, a normalization procedure was developed and applied to the WIM data use in the WIM-only model. Sensor calibration issues will result in either systematic over or under estimations in the data at a particular site or for a particular span of time. The spacing between the 2nd and 3rd axles of the tractor unit are fairly static across all trailer body types and geographical location, although as shown previously, they vary by tractor body type. To normalize the length, spacing, and overhang measurements, each variable was divided by the spacing between the 2nd and 3rd axle spacing. Thus, if a WIM station was consistently overestimating length and spacing measurements, after normalizing the data by the 2nd and 3rd axle spacing would effectively cancel out the overestimation.

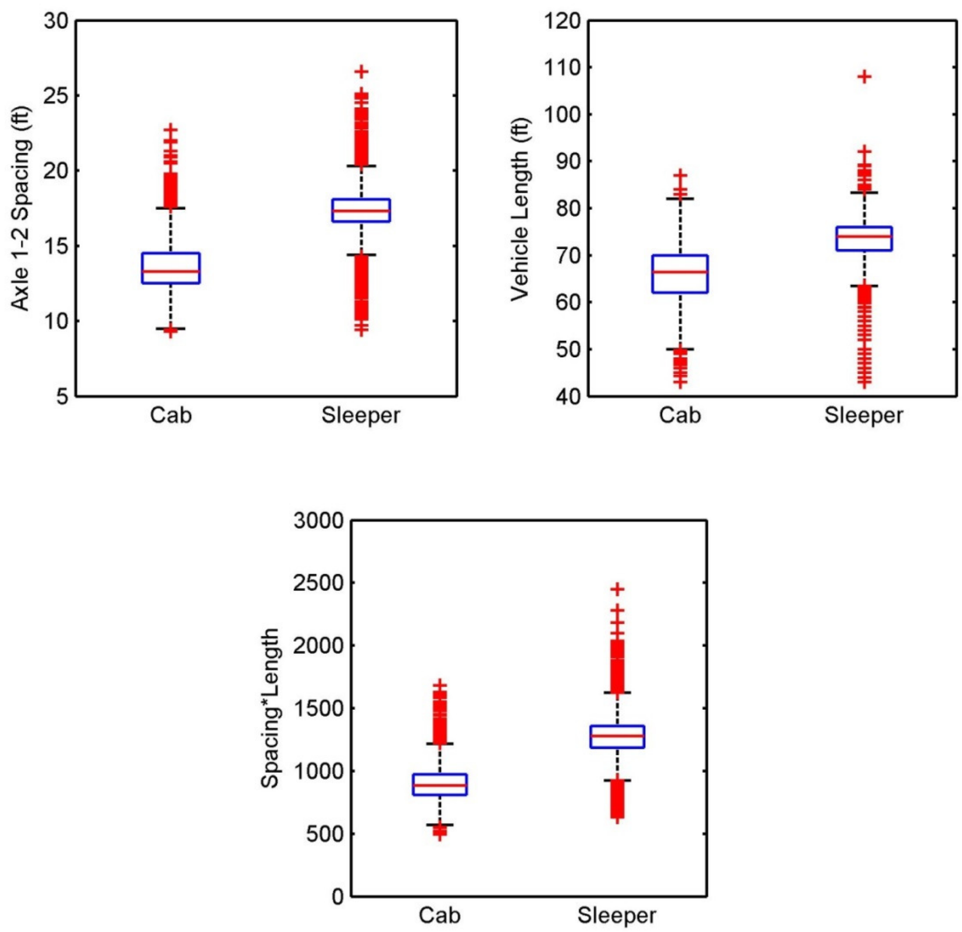


Figure 5.2 Box plots of spacing between the 1st and 2nd axles, vehicle length, and vehicle length interacted with axle spacing by tractor body class

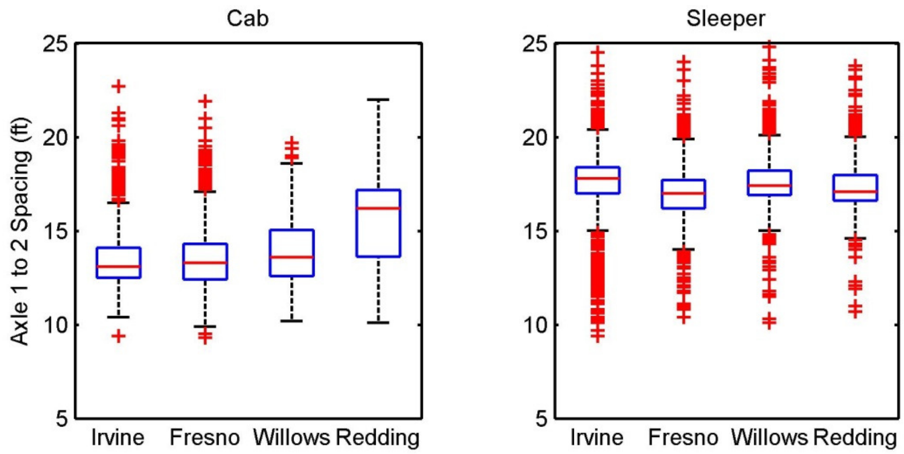


Figure 5.3 Box plots of spacing between the 1st and 2nd axles

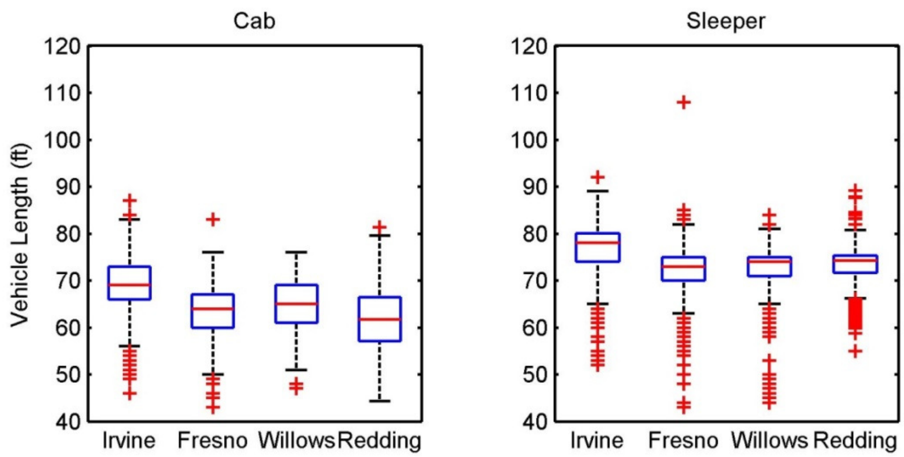


Figure 5.4 Box plots of vehicle length by tractor body class and data collection site

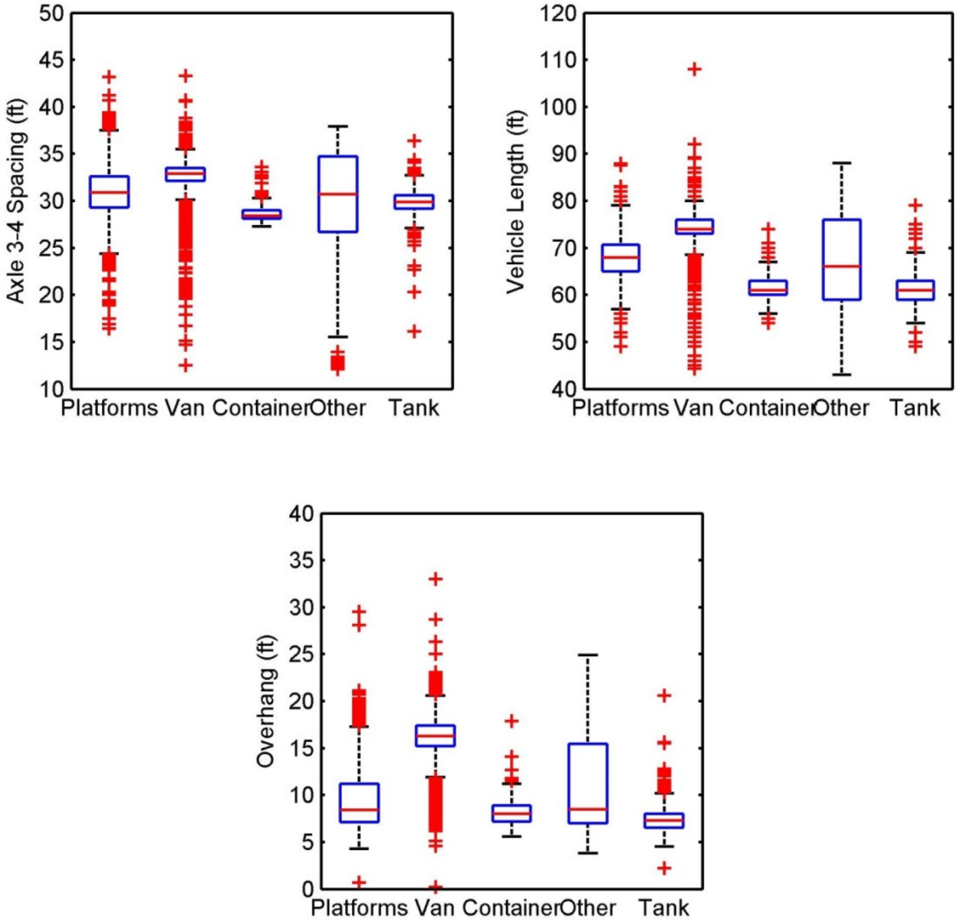


Figure 5.5 Box plots of length, axle spacing, and overhang for five trailer body classes

5.1.2 Modeling Approach

The tractor body class was modeled using a Naïve Bayes model and the trailer body class was modeled using an adapted decision tree approach. For the tractor model, several other models were tried including a support vector machine, multilayer feed forward neural network, and decision tree. All models had similar results.

The description in this section follows from (Hyun et al., 2015). The WIM-only model employs an adapted decision tree (ADT) approach to estimate trailer body class volumes. Whereas a standard decision tree (DT) assigns singular predictions to each sample collected at a terminal node of the tree, our ADT approach instead applies predetermined probabilities of each body configuration to the collection of samples that accumulate at each terminal node. To produce volume estimates at an aggregate level rather than individual vehicle classification, the probabilities of body configurations estimated at each terminal node were used to produce body configuration volume rather than assign a single prediction to all samples collected at a terminal node. Predetermined probabilities resulting from training the tree on observed field data are applied to distribute the samples by body configurations at each terminal node. Then, the estimated volumes of each body configuration from each terminal node are aggregated across all terminal nodes to produce the body configuration volume estimates as follows:

$$V_{body\ configuration\ i} = \sum_{n} V_i^n = \sum_{n} Pr_i^n \times v^n$$

Where V_i = total volume of body configuration i

V_i^n= volume of body configuration i at terminal node n

Pr_i^n = probability of body configuration i at a terminal node n

v^n= total volume collected at a terminal node n

The input variables of the ADT represent each body configuration's length, spacing, and overhang which were statistically invariant by site or time, thus the terminal node's body configuration proportions from the observed field data (i.e. training data) can be used to predict the body configuration volumes when the same input variables are used to bin new, unseen data via the ADT.

The final trained ADT is provided in Appendix 1 with the probabilities of body configurations displayed at each terminal node along with the branching criteria. The ADT has 12 decision branches and 13 terminal nodes. The branching criteria values shown in the figure are the normalized values of the input variables. Several of the terminal nodes are dominated by a particular body class. For instance, the proportion of platforms at Node 10 is 83.5%. This means that platforms share a unique combination of overhang (Node 1 and 5 branches) and length (Node 2 branch). Other terminal nodes contain more uniform proportions of each body class, although each node is dominated to some degree by one body class. For instance, Node 18 has 1.4% vans, 24.7% platforms, 39.7% tanks, 17.8% containers, and 16.4% other.

To apply the tree to new data, normalized vehicle records would be fed into the tree. Then based on the branching criteria, the new data would be binned into each of the terminal nodes. Finally, the terminal node body class proportions would be applied at each terminal node and body class volumes would be estimated by summing across all nodes. For example, if 1000 vehicle records terminate at Node 8, 58 would be counted as vans, 194 as platforms, 38 as tanks, 0 as containers, and 79 as other.

5.1.3 Results

5.1.3.1 *Tractor Model*

Model performance was measured by the correct classification rate (CCR). As summarized in Table 5.2, the total CCR was 91.9% for the 4,999 test samples. Cabs without sleepers had a CCR of 83.4% while sleeper cabs had a CCR of 94.6%.   The overall CCR were 90.1%, 96.2%, and 94.0% for Fresno, Willows, and Redding, respectively.

Both the training and test data from Redding had lower than average accuracy for cabs without sleepers. As previously mentioned, the spacing of the 1st and 2nd axles of cabs without sleepers observed at Redding was larger than the average across the other four sites. This configuration was found at each of the four sites but dominated the Redding site data.   Tractors without sleeper cabs that have longer tractor chassis might be considered as an additional unique body type, however, there is no clear visual features by which the body could be identified to provide groundtruthed model data.

Table 5.2 Results of the WIM-Only Tractor Classification Model

	Cabs without sleepers	Sleeper Cabs	Count	CCR
Fresno	86.4%	91.8%	1,692	**90.1%**
Willows	79.8%	97.4%	1,474	**96.2%**
Redding	60.3%	97.2%	670	**94.0%**
Overall	**83.4%**	**94.6%**	**4,999**	**91.9%**

Spatial Transferability

The Irvine data was held out during model training so that it could be used independently for spatial transferability testing. Table 5.3 summarizes the spatial transferability results. The overall CCR was 88.0%. The CCR for cabs without sleeper was 83.6% and for sleeper cabs the CCR was 91.2%. The results support the conclusion that the model is reasonably transferable to locations that were not included in model training.

Table 5.3 Spatial Transferability Results of the WIM-Only Tractor Classification Model

	Cabs without sleepers	Sleeper Cabs	Count	CCR
Irvine	83.6%	91.2%	1,163	**88.0%**

5.1.3.2 *Trailer Model*

To evaluate model performance, the absolute percentage error (APE) in volume was used. APE measures the deviation of estimated from actual truck volumes by body configuration. The overall APE representing all sites by body configuration can be obtained from the volume weighted average of each body configuration's APE at each site as follows:

$$APE_{body\ configuration\ i}^{site\ t} = \frac{|Actual_i^t - Estimated_i^t|}{Actual_i^t} \times 100\ (\%)$$

$$\text{APE}_{body\ configuration\ i}^{all\ sites} = \frac{\sum_t (APE_i^t \times Actual_i^t)}{\sum_t Actual_i^t} \times 100(\%)$$

The overall APE across all sites weighted by body class volume was 5.3%. Redding possessed the lowest overall APE of 4.7% across all body classes while Willows had the highest APE at 5.9%. Across all sites, vans had the lowest APE between 0.4 and 1.9% while 40ft Containers had the highest between 23 and 44%. Minority body class groups such as 40ft containers and tanks have very low volumes, and have higher errors than the majority classes of vans and platforms. The detailed results are given in Appendix 1.

To get a better sense of the accuracy of the proposed ADT approach, two baseline approaches were developed for comparison. The baseline approaches represent what practitioners could do to estimate body classes at a particular WIM site without developing a model like the ADT model.

The first is based on body configuration proportions calculated from observed, site specific data. The proportions are determined from the training data at each site. The static proportions of body types do not vary by time of day, but only by location. To apply such a method in practice, manual field data collection and classification would need to be performed at each site where body class volumes are needed. This is not a practical approach since physical data collection would need to be performed at each WIM site and have significant labor costs.

The second is based on national level body configuration proportions collected in VIUS which have been adjusted by Average Annual Truck Miles by body configuration. VIUS does not include intermodal container trucks so this body configuration cannot be estimated under this baseline approach. Also, VIUS is a national level estimate and might deviate significantly from a State's body class distribution. For example, Southern California is the home to two major Port complexes and would thus have a significant amount of container traffic.

The static proportions derived from site observations and VIUS were applied to the same test data used for the ADT model to estimate body class volumes. Resulting APE values for each of the baseline approaches are provided in Appendix 1. Overall APE comparisons are shown in Figure 5.6. The ADT approach produces the lowest APE overall and across all sites whereas the baseline approach using site specific static proportions is slightly higher than the ADT approach and the baseline approach using VIUS proportions is significantly higher. In fact, the VIUS based approach produces over 50% error for all sites. A major fault in the baseline approaches it that, unlike the ADT method, they do not consider the trucks physical characteristics as measured by the WIM controller in determining vehicle body class volumes. Rather, the baseline approaches only apply observed or reported proportions.

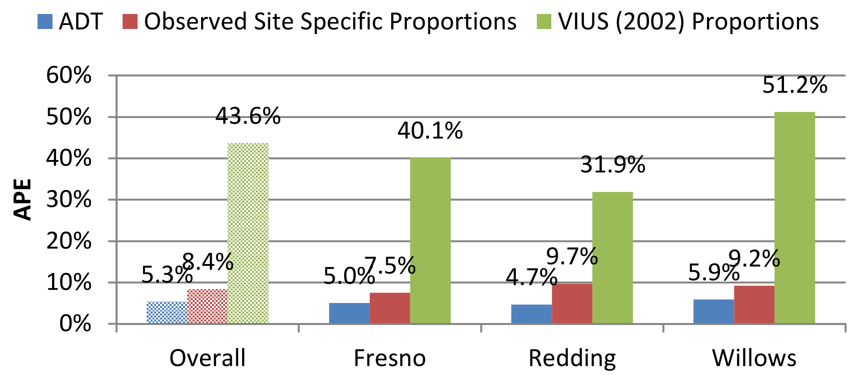


Figure 5.6 Overall APE comparisons of baseline and ADT approaches by site

Spatial and Temporal Transferability

The Irvine data from March 20th and 25th was held out from model training so that it could be used to test the spatial transferability of the ADT model. Table 5.4 summarizes the results for the Irvine data and provides a comparison to the ADT performance on the Fresno, Willows, and Redding ('Overall') data as well as the VIUS baseline approach. The Irvine site preforms reasonably well with overall APE of 7.6% compared to 5.3% APE observed across the other three sites. The largest APE is seen for 40ft containers, although it is lower than the overall APE from the other three sites. The slightly higher APE might be explained by the different body class distribution seen at the Irvine site due to its more urban location compared to the other three sites which were more rural. The ADT model preforms much better than the VIUS baseline approach which had APE of 51.7% overall.

Table 5.4 Results of the WIM-Only Trailer Body Classification Model for Irvine compared to Overall

Site		Van	Platform	Tank	40ft Container	Other	Overall APE (%)
Irvine	Actual Volume	1159	162	51	28	69	1469
	Estimated Volume	1215	135	42	20	58	
	Absolute Difference	56	-27	-9	-8	-11	111
	APE (%)	**4.8%**	**16.7%**	**17.6%**	**28.6%**	**15.9%**	**7.6%**
Overall*	APE (%)	**1.7%**	**5.4%**	**21.2%**	**31.5%**	**22.3%**	**5.3%**
VIUS	APE (%)	**30.3%**	**117.9%**	**15.7%**	**100.0%**	**262.3%**	**51.7%**

* From the test sites at Fresno, Redding, and Willows

5.1.4 Discussion

The purpose of the WIM-only model was to demonstrate what could be done to better understand truck body class using only the measurements available from WIM controllers. Two body classification models were developed for five axle semi tractor-trailer combination trucks: a tractor model and a trailer model.

The tractor model distinguished between sleeper and non-sleeper cabs with an overall accuracy of 92.7% for the test data from Fresno, Willows, and Redding. The model used the spacing between the 1st and 2nd axles, vehicle length, and a term interacting vehicle length with spacing between the 1st and 2nd axles as input and employed a Naive Bayes model for classification. The tractor model was tested for spatial transferability by applying the trained model to the Irvine dataset which had been held out from training. The overall classification accuracy for the Irvine data was 88.0%. The model performs reasonably well given the limited set of features available for modeling from WIM data alone and the significant overlap in those features across tractor body types.

The trailer model estimated body class volumes for five body classes: vans, tanks, platforms, 40ft containers, and others. The WIM-only trailer body classification model was shown to be spatially and temporarily transferable. The WIM-only model was also compared to two baseline approaches which referenced static proportions of body class from site observed data and VIUS national estimates. The WIM-only model produced slightly better volume estimates than the observed site specific baseline approach and significantly better than the VIUS baseline approach.

Even though the WIM-only model was an improvement compared to simple static proportion approaches, there is still much to be desired in terms of the resolution of the model output. First, the WIM-only model was only applied to five axle semi tractor-trailers although the same method could potentially be applied to two axle single unit trucks. However, for classes with little diversity in axle spacing, length, or overhang by body type, it is to be expected that using WIM data alone will not be enough to sufficiently distinguish detailed body types. Second, the WIM-only trailer body class model produces body class volume estimates, not individual predictions of body class for each vehicle. The low resolution of the model output might not be sufficient for detailed freight studies such as calculation of average payloads because individual vehicle body types are not predicted. Additionally, only five body class groups are included in the model and these groups contain a diverse range of body classes. For example, many commodity specific body types like logging and livestock trailers are grouped into the 'other' category. In order to produce higher resolution classifications, higher resolution data is needed. In the next section, body class models using inductive signatures are presented.

5.2 *Inductive Signature-based Truck Body Classification*

WIM data alone cannot adequately provide body class information as demonstrated in the previous section. The 'Inductive Signature-based Body Classification' model does not rely on WIM data. While the WIM-only model is applicable at any WIM site, the inductive signature only model in this section is applicable at any loop detector site that has been equipped with advanced loop detector cards.

5.2.1 Data

Data described in Chapter 3 was split by day and site to create datasets for model training and testing. The data was split as shown in Table 5.5 in order to have a balanced and representative sample of each body class in the training and testing datasets. In total, 9,697 samples were used for model training and 14,634 samples for model testing.

Table 5.5 Data Summary for Inductive Signature-based Model Development

Site	Training Data Date	Training Samples	Test Data Date	Testing Samples
Irvine	Oct. 2 & 3, 2012	2,039	March 20 & 25, 2013	9,809
Fresno	Nov. 8, 2012	4,312	Nov. 7, 2012	3,248
Willows	Dec. 10, 2012	1,492	Dec. 11 & 12, 2012	4,323
Redding	Dec. 11 & 12, 2012	1,854	Dec. 10, 2012	499
All		**9,697**		**17,879**

Inductive signatures require pre-processing to convert raw inductive signatures to feature sets. The complementary preprocessing procedures developed by Jeng (2007) and Tok (2008) were used to process the signatures. The preprocessing procedure includes (1) noise filtering, (2) magnitude (vertical axis) and time (horizontal axis) normalization, and (3) feature extraction. The pre-processing procedure is shown in Figure 5.7.

First, the raw inductive vehicle signature is cleaned by applying a magnitude cutoff criterion to reduce measurement noise at the signature tails (Figure 5.7 (a)). Second, the signature is normalized by its peak magnitude along the vertical axis and total duration along the horizontal axis (Figure 5.7 (b)). Magnitude normalization helps to remove loop detector sensitivity differences across sites. Third, inductive signatures can possess anywhere from 200 to 1200 or more data points depending on vehicle length and traffic conditions. The variable number of data points needs to be reduced to a common number of points for modeling. The cubic spline method Jeng (2007) was applied to reduce the variable number of samples into a defined set of equally spaced magnitudes (Figure 5.7 (c)). Finally, a second feature set is computed as the difference between consecutive interpolated magnitude points (Figure 5.7 (d)) (Tok, 2008).

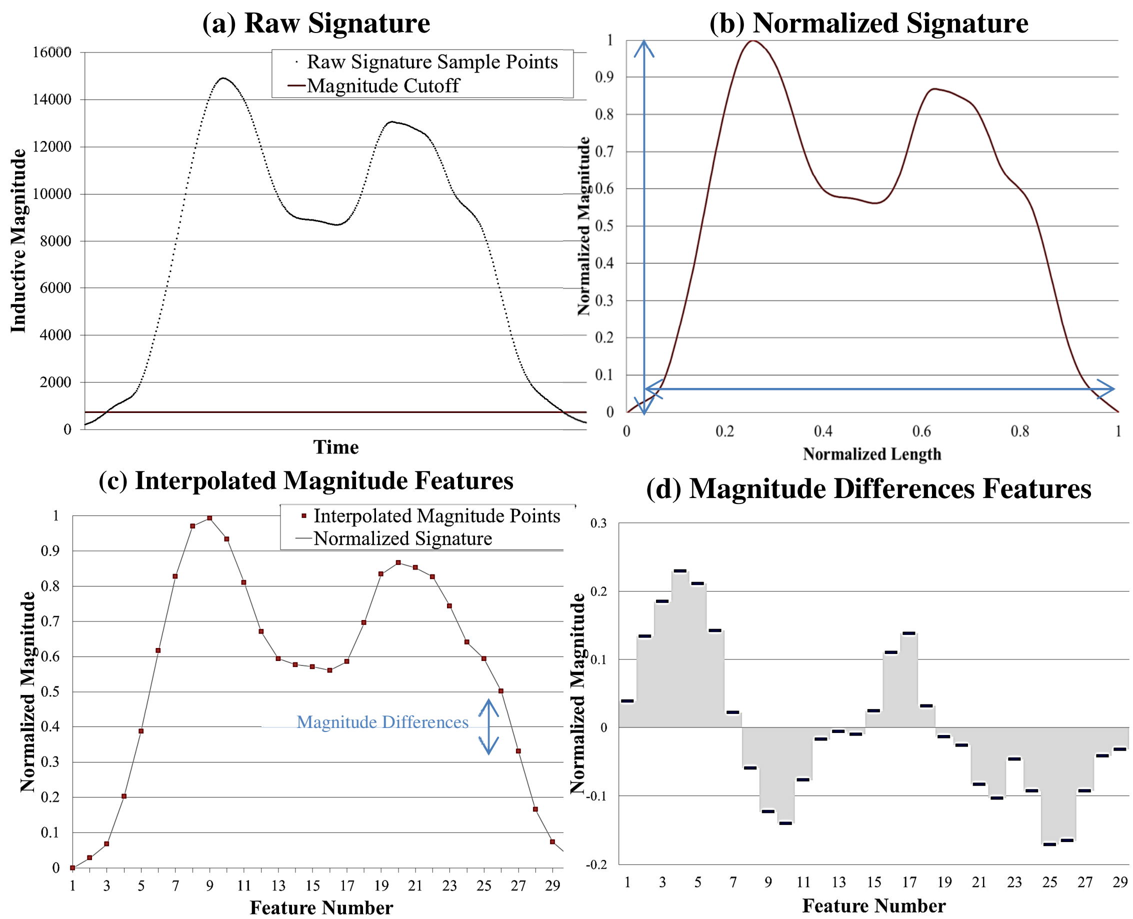


Figure 5.7 Inductive signature feature extraction procedure.

5.2.1.1 ***Sensor type (VDS to WIM-loop) transferability***

The data collected for much of the modeling in this dissertation came from WIM site loop detectors which differ in geometric configuration from loop detectors at vehicle detector sites (VDS). However, it is desirable to apply the classification model developed from WIM signatures to VDS sites. The main issue in doing this is that loop detectors at WIM and VDS sites have different geometries: WIM loop detectors are square whereas VDS detectors are round. Prior work by Jeng (2007) found that round and square loops could be used interchangeable for vehicle re-identification using inductive signatures. Although both loop detectors were equipped with the same advanced detector card technology, due to loop geometry differences in the signatures may arise that could produce modeling error when applying the models developed with WIM signature data to VDS signature data.

Concurrent VDS and WIM loop detector data was collected at the Irvine site. The VDS and WIM signatures were manually matched. Examples of WIM and VDS signatures are shown in Figure 5.8 for several vehicle types. Differences in the inductive signature magnitudes are the result of vehicle dynamics over the sensors since the sensors are around 210ft apart or due to the different loop geometries.

A statistical comparison between the VDS and WIM signatures was performed to determine the compatibility of the data. The VDS and WIM signatures were compared by examining the differences between paired signature features. The aggregate sum of the paired differences, referred to as agg_diff was computed as:

$$\mathrm{agg\_diff} = \sum_{i=1}^{30} f_i^{VDS} - f_i^{WIM}$$

where

f_i^{VDS} = feature I of VDS signature

f_i^{WIM} = feature i of WIM signature

Figure 5.9 shows the histogram of the aggregate differences (agg_diff) for the 14,970 pairs of VDS and WIM signatures. The mean difference is 0.356 with a standard deviation of 0.718. The normality of the errors was assessed by applying an Anderson-Darling test under the null hypothesis that the errors are normally distributed. It was found that the aggregate paired errors are not normally distributed ($p < 0.001$), so non-parametric tests were used to further test the statistical evidence on a pair by pair basis that WIM and VDS signatures are comparable. A two-sample Kolmogorov-Smirnov (KS) test at the 95% confidence level was used to assess each pair of signature samples under the null hypothesis that both signatures arise from the same distribution. Of the 14,970 pairs of VDS and WIM signature samples, the null hypothesis failed to be rejected for 14,850 samples, or 99.2%. Only 120 (0.8%) of the samples rejected the null hypothesis, i.e. the signatures were not statistically similar. Because the VDS and WIM sites were located approximately 200ft apart, significant differences arising in the 120 signature pairs found to be statistically dissimilar can be attributed to vehicle dynamics over the loop detectors such as off-center traversal or stop-and-go conditions. Based on the statistical evidence and previous studies comparing differing loop configurations (Jeng, 2007), it can be concluded that the inductive signature only model can effectively be developed using WIM loop detector data.

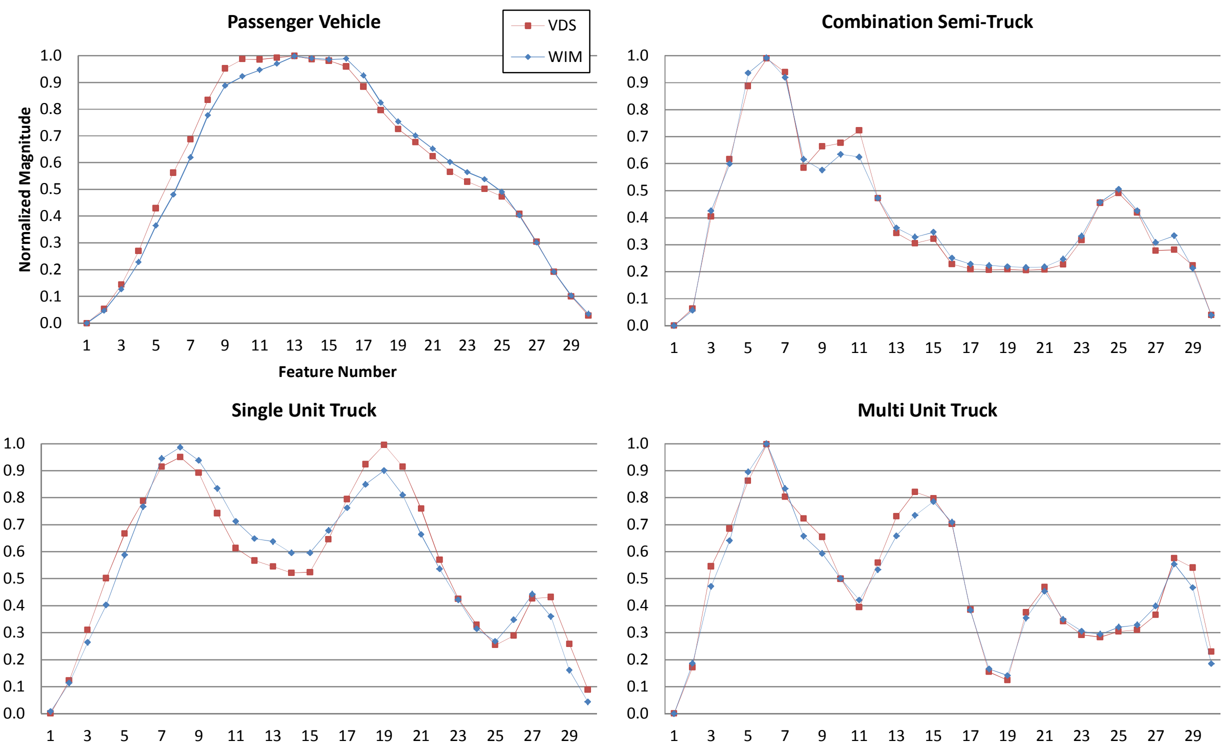


Figure 5.8 Comparison between VDS and WIM inductive signature for passenger vehicle, single unit truck, combination semi-truck and multi-unit truck

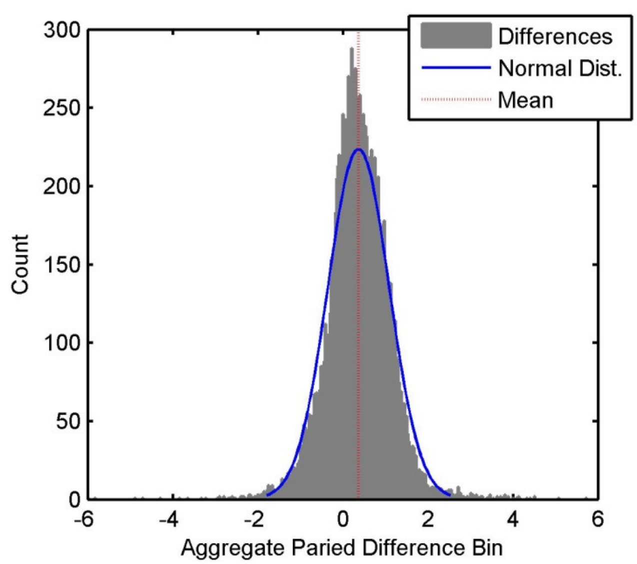


Figure 5.9 Histogram of Aggregated Paired Differences for WIM and VDS signatures

5.2.2 Modeling Approach

The inductive signature only model implements a three tiered approach as shown in Figure 5.10. The first tier separated vehicles into two general vehicle configuration groups: single unit and multi-units. The second tier further divides the two groups into more specific body configuration groups. For single units, vehicles are classified as passenger vehicles or single unit trucks. For multi-units, vehicles are classified as single units with trailers, semi-tractor single semi-trailer configurations, or semi-tractor multiple semi-trailer configurations. The final and third tier consists of the body classification models for each body configuration group.

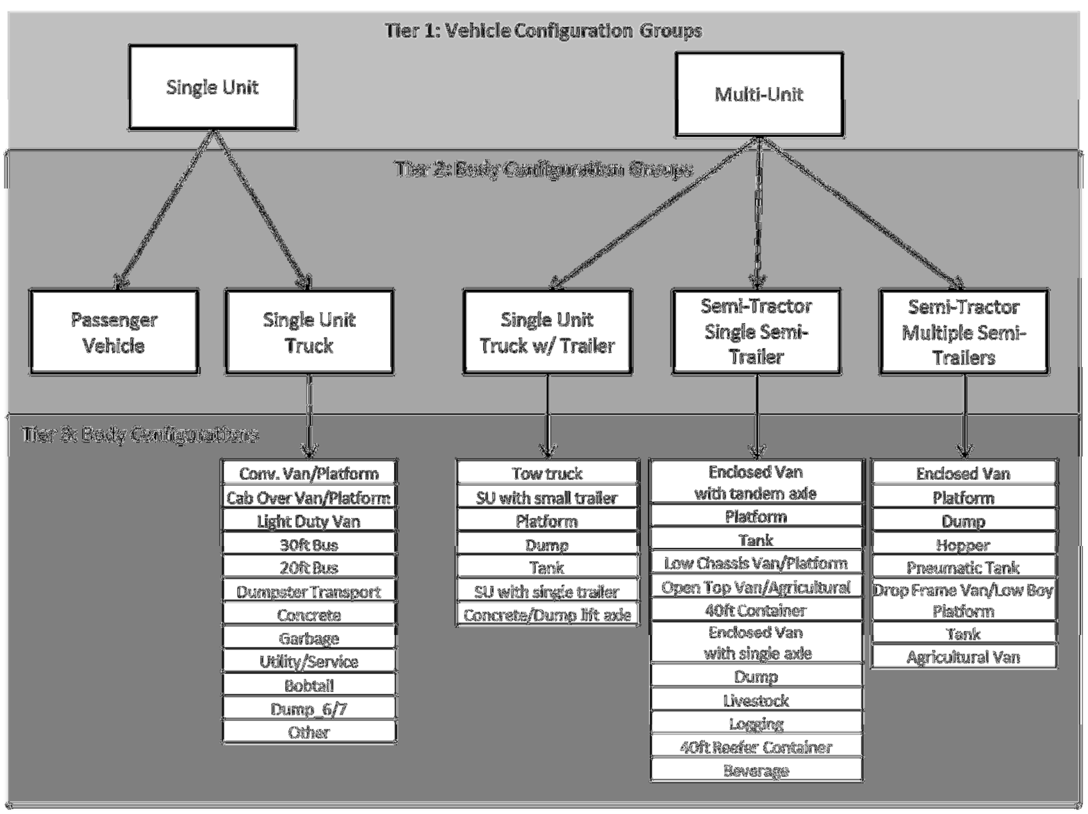


Figure 5.10 Inductive Signature Based Model Framework

All three tiers of the model use 30 interpolated magnitude features and 29 magnitude differences for a total of 59 input features. The first tier was implemented as a decision tree. The second tier was implemented as a feed forward neural network with two hidden layers of 15 neurons. The third tier was implemented as a multiple classifier system with correction for class imbalance via SMOTE.

5.2.3 Results

The results are presented for the first and second tiers of the model followed by the results of the third tier body classification models for each of the body configuration categories. Results are presented in terms of the cross classification table, the volume error, and the error reduction occurring from the SMOTE method. The terms used to assess the models include accuracy, class specific Correct Classification Rate (CCR), precision, Absolute Percent Error (APE), and Mean Absolute Percent Error (MAPE). These are defined as follows:

$$\text{Accuracy} = \frac{\sum_b {N_b}^{Correct}}{N} \times 100\ (\%)$$

$$CCR_b = \frac{{N_b}^{Correct}}{N_b^{Observed}} \times 100\ (\%)$$

$$Precision_b = \frac{\sum_b {N_b}^{Correct}}{N_b^{Predicted}} \times 100\ (\%)$$

$$APE_b = \frac{|N_b^{Observed} - N_b^{Predicted}\,|}{N_b^{Observed}} \times 100\ (\%)$$

$$\text{MAPE} = \frac{\sum_b (APE_b \times N_b^{Observed})}{N} \times 100\ (\%)$$

where

b = body class

${N_b}^{Correct}$ = number of vehicles correctly classified in body class b

$N_b^{Observed}$ = number of vehicle observed in body class b (e.g. the true vehicle count)

$N_b^{Predicted}$ = number of vehicles predicted in body class b

N = total number of vehicles in test dataset

The cross classification table contains the predicted classes along the columns and the observed (or true) classes along the rows. Each element (i,j) of the table represents the number of samples that were observed as class i but predicted as class j. The sum across each row is the total number of observed vehicles for that body class (i) while the sum of the columns is the total number of predicted vehicle for that body class (j). The diagonal elements (i=j) are the correctly classified samples and the off diagonal elements (i ≠j) are incorrectly classified samples.

Accuracy is the overall correctness of the model in terms of total number of correctly classified vehicles divided by the total number of samples being tested. CCR and precision are both included as measures of individual body class classification accuracy. CCR (or recall, as it is more commonly referred to in the machine learning literature) captures the ability of the model to select instances of a certain class from the data. CCR ranges between 0 to 100%. High CCR can be achieved by simply assigning all vehicles to one class. Therefore, precision can be used to assess the model accuracy in addition to CCR. In the case where all vehicles are assigned to a single class, the precision for that class would be 0%. There is a tradeoff between CCR and precision so an ideal model will balance the two.

APE and MAPE assess the volume accuracy of the classification models. A drawback of APE is that it is irrelevant when there are zero observed counts within a class. Also, when the class has low volume, small volume prediction errors can result in high APE.

5.2.3.1 *Tier 1 and 2 Results*

The first tier of the model which separated single units from multi-unit vehicles had an overall CCR of 98.4%. The CCR for single units was 98.3% and 98.4% for multi-unit configured vehicles. Vehicles classified as single unit vehicles by the first tier were then classified as either passenger cars (PC) with CCR of 95.3% or single unit trucks without trailers (SU) with CCR of 89.6%, for an overall CCR of 93.4%. Vehicle classified as multi-unit vehicles by the first tier were then classified as single units with trailers, single semi-trailers, or multiple semi-trailers, with CCR of 82.7%, 98.6%, and 96.1% respectively. The overall CCR for multi-unit vehicles was 96.3%. The combined result of the first and second tiers is shown in the confusion matrix in Table 5.6. Common misclassifications occur for single units with trailers. A possible reason for the low performance of the single unit with trailers class is that signatures for these vehicles closely mimic those of smaller three or four axle semi-tractor trailers. Secondly, smaller trailers towed by single unit trucks do not result in signatures that are distinctly different from those of larger single unit trucks without trailers. In all, the first and second tiers of the model produce reasonably accurate classifications. MAPE in volume of the combined first and second tiers is 1.3%. APE in volume ranges between 0.5% and 7.6%. Single units with trailers have the highest APE, but overall the model produces accurate volume estimates of each of the five vehicle-body configuration groups.

Table 5.6 Inductive Signature Only Model Tier 1 and 2 Cross Classification Table and Volume Accuracy

Vehicle-Body Configuration Groups	Single Unit		Multi-Unit			Total	CCR (%)
	PC	SU	SU w/ Trailer	Single Semi	Multi Semi		
Passenger Car	5,389	263	3			5,655	**95.3**
Single Unit (SU)	298	2,417	121	20		2,856	**84.6**
SU w/Trailer		104	925	186	23	1,238	**74.7**
Single Semi		47	89	7,415	9	7,560	**98.1**
Multi Semi			6	16	548	570	**96.1**
Total	5,687	2,831	1144	7,637	580	17,879	**93.4**
Volume APE (%)	0.5	0.9	7.6	1.0	1.8		

5.2.3.2 *Tier 3 Results*

Detailed results including the cross classification table, MCS summary, volume accuracy, and effects of the SMOTE training algorithm are shown for single unit trucks without trailers and single semi-trucks as these are the more common classes observed on the highways. Results for single unit trucks with trailers and multi semi-trailers are discussed briefly with detailed tables given in Appendix 2.

Single Unit Truck without Trailers

The model consists of 13 body classes. Table 5.7 summarizes the CCR results for each of the base classifier models and the two model combining strategies, Majority Vote (MV) and Naïve Bayes Combination (NBC). NBC achieved superior performance over the best performing base classifier with CCR of 72.4%. For all but four body classes, the NBC approach performed better than the best base classifier. Nine of the 13 body classes have CCR above 70%, of which five achieve CCR of at least 80%, and finally, two models have CCR above 90.0%. Still several body classes have low classification accuracy. Single units without trailers have a wide variety of body types and due to their shorter length, have less distinguishing inductive signature features. This leads to low classification performance in this class.

Table 5.8 shows the cross classification matrix for the results of the MCS with NBC approach. The most common errors resulted from vehicles being misclassified into the majority classes of conventional or cab-over van/platforms as well as utility/service trucks. This is most likely due to the variability in the signature features of these classes. The last column of the cross classification table represents the difference between the CCR values with and without the SMOTE method to alleviate the class imbalance problem. A positive difference indicates improved performance due to SMOTE while a negative value indicates a decrease in performance. Overall, the SMOTE method reduced CCR by 0.7% (i.e. from 71.0 with SMOTE to 71.7% without SMOTE) while a 1.1% improvement was achieved for minority body classes (i.e. all classes except conventional vans/platforms, utility/service, and cab over vans/platforms). The largest improvements were observed for multi-stop vans and RVs, street sweepers, and dump trucks with triple rear axles.

The MAPE in volume is 15.4% for the MCS modeling approach. Class specific volume APE ranges from 0.0 to 287.0% for the MCS approach. The largest discrepancies in volume arise from several low volume classes (< 30 samples) such as concrete mixers, dump trucks with triple tandem axles, and street sweepers. In these cases, the APE measurement somewhat exaggerated the small absolute differences in volume.

Table 5.7 Single Unit Truck without Trailer MCS Summary

Body Class	Vol.	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Conv. Van/Platform	*333*	72.4	69.7	56.5	67.3	67.6	**74.2**	**74.5**
Utility/Service	*312*	74.4	68.3	59.3	64.4	58.7	**76.0**	**68.9**
Cab Over Van/Platform	*209*	30.6	56.0	23.4	35.9	45.5	**47.4**	**68.4**
30ft Bus	*114*	86.8	89.5	89.5	76.3	85.1	**90.4**	**89.5**
Bobtail	*107*	88.8	86.9	74.8	69.2	82.2	**87.9**	**89.7**
Garbage	*93*	77.4	91.4	90.3	74.2	66.7	**86.0**	**88.2**
Multi Stop Van/RV	*77*	39.0	35.1	29.9	44.2	15.6	**48.1**	**51.9**
20ft Bus	*74*	44.6	70.3	63.5	67.6	17.6	**66.2**	**78.4**
Dump/Tank	*66*	27.3	39.4	28.8	39.4	36.4	**39.4**	**36.4**
Dumpster Transport	*59*	49.2	61.0	50.8	35.6	52.5	**55.9**	**54.2**
Concrete	*21*	81.0	100.0	100.0	85.7	61.9	**100.0**	**95.2**
Dump w/ Triple Rear	*8*	62.5	75.0	62.5	12.5	62.5	**75.0**	**75.0**
Street Sweeper	*3*	66.7	100.0	100.0	33.3	0.0	**66.7**	**66.7**
OVERALL	***1,476***	***63.5***	***68.6***	***56.6***	***59.7***	***57.5***	***70.1***	***72.4***
Minority Classes	***622***	***64.3***	***72.5***	***66.6***	***61.3***	***55.5***	***72.5***	***74.3***

Table 5.8 Single Unit Truck without Trailer Cross Classification Table

	Conv. Van/Platform	Cab Over Van/Platform	30ft Bus	20ft Bus	Multi Stop Van/RV	Utility/Service	Concrete	Dumpster Transport	Garbage	Bobtail	Dump Triple Rear	Street Sweeper	Dump/Tank	**Total**	**Correct**	**CCR (%)**	**SMOTE Difference in CCR) (%)**
Conv. Van/Platform	251	20	1		7	22	5	9	2	2	5	1	8	333	251	75.4	-3.0
Cab Over Van/Platform	12	132	1	3	8	33	1	6	6	1	1		5	209	132	63.2	0.6
30ft Bus		3	101		5				2	2			1	114	101	88.6	-4.7
20ft Bus		4		54	6	10								74	54	73.0	-0.9
Multi Stop Van/RV	5	8	3	2	37	10		2		3	5		2	77	37	48.1	-2.8
Utility/Service	13	30	1	5	12	220	3	9	2	3	3	3	8	312	220	70.5	0.0
Concrete		1					20							21	20	95.2	23.4
Dumpster Transport	7	13			1	3		29	3	1		1	1	59	29	49.2	-8.1
Garbage	1	3						4	82		2	1		93	82	88.2	1.6
Bobtail		3	1		2	6				89			6	107	89	83.2	-10.1
Dump Triple Rear										1	6		1	8	6	75.0	0.0
Street Sweeper												3		3	3	100.0	25.0
Dump/Tank	1	12	1		4	7	2	4		2	9		24	66	24	36.4	66.7
Total	290	229	109	64	82	311	31	63	97	104	31	9	56	**1,476**	**1,048**	**71.0**	**-0.7**
Correct	251	132	101	54	37	220	20	29	82	89	6	3	24				
Precision (%)	86.6	57.6	92.7	84.4	45.1	70.7	64.5	46.0	84.5	85.6	19.4	33.3	42.9				
Volume APE (%)	12.9	9.6	4.4	13.5	6.5	0.3	47.6	6.8	4.3	2.8	287.5	200.0	15.2				

Single Unit Trucks with Trailers

The body classification model for Single Unit Trucks with Trailers covers nine truck-trailer combinations. A tractable set of unique truck-trailer combinations were observed in the data so separate models to predict trucks and trailers was not necessary. The body classes are presented as truck –trailer combinations, e.g. Dump- Dump is a dump truck pulling a dump trailer. Table 5.9 summarizes the CCR for each of the base classifiers and the two model combining strategies. Using the NBC method, the overall CCR is 94.2% while the MV is 93.4%. The best base classifier varied for each body class. For example, NB was best for single units with small trailers (SU small trailer) while SVM was best for RV w/ towed vehicles. Although the overall CCR of the MV and NBC methods is slightly less than the overall CCR for the best base classifier, the MV and NBC methods achieve superior performance for each of the eight body types than any of the base classifiers.

Single units with small trailers and RVs with towed vehicles are commonly cross classified due to the similarities in the signature shapes of these two classes. Concrete trucks with lift axles extended achieve superior performance in terms of CCR and precision. The MAPE in volume was 8.2% across all classes with four classes achieving APE below 10%. Tow trucks, tanks with tank trailers (Tank-Tank), and dump trucks with lift axles extended which had poor classification accuracy, likewise have low volume accuracy. Lastly, the SMOTE method significantly improved the classification accuracy of tow trucks towing vehicles and platforms with platform trailers. However, the classification accuracy was diminished for RVs with towed vehicles and tanks with tank trailers.

Table 5.9 Inductive Signature Only Model Tier 3 Single Unit Truck with Trailer MCS Results

Body Class	Vol.	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
SU small trailer	515	95.0	93.0	85.6	94.8	97.9	**94.6**	**96.3**
Dump-Dump	87	92.0	100.0	100.0	93.1	100.0	**100.0**	**100.0**
RV w/ Towed Vehicle	49	67.3	93.9	81.6	59.2	91.8	**87.8**	**85.7**
Concrete w/Lift Axle	34	100.0	100.0	88.2	91.2	79.4	**100.0**	**100.0**
Tank-Tank	30	83.3	100.0	93.3	66.7	70.0	**90.0**	**76.7**
Platform-Platform	20	35.0	25.0	50.0	30.0	70.0	**55.0**	**65.0**
Tow Truck w/ vehicle	8	87.5	50.0	75.0	87.5	62.5	**75.0**	**75.0**
Dump w/ Lift Axle	3	100.0	66.7	66.7	100.0	66.7	**66.7**	**66.7**
OVERALL	***746***	***90.9***	***92.1***	***86.3***	***89.1***	***94.5***	***93.4***	***94.2***

Semi-Tractor Trailer Combinations with Single Semi Trailers

There are 19 trailer body classes included in the model for single semi-trailers. This class consists of semi-trailers with several difference axle configurations including those with single axle trailers resembling FHWA class 8, those with tandem axle trailers resembling FHWA class 9, as well as triple or more axle trailers. Enclosed vans were separated into two groups which approximate FHWA class 9 (five axle) and 8 (three or four axle) semi-trailers. Each of the remaining 17 body classes contains both single and tandem rear axle configurations within its class. The classification performance of the MCS method is summarized in Table 5.10 along with the CCRs for each of the base classifiers. The overall CCR of the MCS is 74.3% and 73.8% when considering only minority classes. In this model, minority classes refer to all body classes except enclosed vans and enclosed van reefers in FHWA 8 and 9. Seven of the 19 body classes have CCR between 70% and 80%, five have CCR between 80% and 90%, and two have CCR above 90%. Low performance in terms of CCR is observed for enclosed van reefers in FHWA class 8, 53ft containers, and agricultural vans. Several unique body classes including logging, livestock, and beverage trailers have CCR above 80% and precision above 75%.

The cross classification matrix is shown in Table 5.11. Enclosed Van body types including FHWA class 8 and 9 reefer and non-reefer configurations and 53ft containers were commonly cross classified. Essentially, the subtle difference in the signatures caused by the configuration of the chassis for these set of body types is not able to be picked up by the models. Also, vehicles are commonly misclassified as platform trailers. This is likely due to the diverse set of body types and axle configurations within the platform body class. For example, platform trailers can have split tandem axle configurations causing differing inductive signature shapes.

The last row of the cross classification table shows the volume APE. The MAPE in volume was 11.3% for all classes and 17.5% for minority classes. Class specific APE ranged from 3.7% (Enclosed vans Reefer FHWA 9) to 149% (Drop Frame Vans). APE errors above 20% were observed for enclosed reefer vans in FHWA class 8, 40ft reefer container 20ft containers, low chassis trailers including low boy platform and drop frame vans, dump trucks, agricultural vans, and beverage trailers. The low CCR and APE in volume can be improved by further collapsing commonly cross classified classes. For example, if collapsed to nine classes, the total CCR rises to 90.5% and MAPE in volume becomes 9.6% with class specific CCR between 59 and 95% and APE between 7 and 100%.

The overall effect of applying SMOTE was a decrease in overall CCR. As expected, by increasing the number of training samples for minority classes through the SMOTE method, increased performance for several minority classes was achieved including enclosed van reefers (FHWA class 8), 53ft container, 40ft reefer containers, 20ft containers, drop frame vans, and agricultural trailers. In total, SMOTE improved the CCR of nine classes, which several increases in performance above 15%. The vans and platforms which represent the majority saw decreased performance of 4.4% and 1.6%, respectively, since the models could not simply rely on class priors for class prediction.

Table 5.10 Semi Tractor Trailers MCS Summary

Body Class	Vol.	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Enclosed Van (FHWA 9)	*2343*	31.2	33.1	87.5	63.8	46.4	**59.2**	**74.6**
Enc. Van Reefer (FHWA 9)	*1624*	54.4	71.9	22.9	71.2	44.3	**69.3**	**74.3**
Enclosed Van (FHWA8)	*89*	66.3	69.7	86.5	77.5	71.9	**83.1**	**83.1**
Enc. Van Reefer (FHWA 8)	*13*	76.9	46.2	0.0	30.8	38.5	**53.8**	**46.2**
53ft Container	*124*	71.0	74.2	21.8	64.5	37.9	**68.5**	**57.3**
40ft Container	*136*	68.4	51.5	19.1	81.6	19.9	**68.4**	**75.0**
40ft Container Reefer	*17*	88.2	88.2	82.4	70.6	82.4	**100.0**	**94.1**
20ft Container	*14*	71.4	85.7	0.0	57.1	71.4	**78.6**	**85.7**
Platform	*796*	57.4	60.2	70.4	64.2	83.8	**72.4**	**77.5**
Tank	*283*	58.3	65.0	78.1	71.7	64.3	**73.1**	**70.7**
Open Top Van	*185*	42.2	54.1	51.4	67.6	28.1	**57.3**	**60.5**
Auto	*86*	61.6	61.6	66.3	52.3	88.4	**77.9**	**77.9**
Low Boy Platform	*184*	58.7	75.5	97.3	63.6	71.2	**86.4**	**82.1**
Drop Frame Van	*51*	54.9	49.0	3.9	62.7	70.6	**60.8**	**60.8**
Dump	*54*	59.3	66.7	44.4	48.1	59.3	**68.5**	**70.4**
Logging	*15*	86.7	80.0	80.0	73.3	73.3	**80.0**	**80.0**
Livestock	*56*	78.6	83.9	67.9	78.6	28.6	**80.4**	**80.4**
Agriculture	*29*	44.8	79.3	13.8	51.7	13.8	**55.2**	**58.6**
Beverage	*14*	92.9	92.9	0.0	50.0	7.1	**85.7**	**92.9**
Overall	***6113***	**47.4**	**54.2**	**61.5**	**66.6**	**52.0**	**66.5**	**74.3**
Minority Classes	***2044***	**59.6**	**63.7**	**62.3**	**66.2**	**64.1**	**72.5**	**73.8**

Table 5.11 Semi Tractor Trailers Cross Classification Table

	Enclosed Van 9	Reefer 9	Enclosed Van 8	Reefer 8	53ft Container	40ft Container	40ft Reefer	20ft Container	Platform	Tank	Open Top Van	Auto	Low Boy Platform	Drop Frame Van	Dump	Logging	Livestock	Agriculture	Beverage	**Total**	**CCR (%)**	**SMOTE Difference (%)**
Enc. Van 9	1749	345	1	1	61	6	2	1	76	4	31		20	41	2			2	1	2343	74.6	-4.4
Reefer 9	249	1207	11	2	6	4	1	5	85	4	27		4	12	1			6		1624	74.3	0.1
Enc. Van 8	1		74	6				4	1		2			1						89	83.1	-5.6
Reefer 8			4	6					2				1							13	46.2	15.4
53ft Container	53				71															124	57.3	8.9
40ft Container		1				102		1	10	2	8				9			3		136	75.0	-1.5
40ft Reefer							16		1											17	94.1	11.8
20ft Container			1					12	1											14	85.7	42.9
Platform	30	6	6	2	2	9	16	5	617	29	33	5	17	9	5	1		4		796	77.5	-1.6
Tank		2	1			1	3		41	200	6	1	2	3	16			7		283	70.7	-2.5
Open Top Van	7	3				5			39	11	112		1	1	3			3		185	60.5	-13
Auto									1			67	10	7				1		86	77.9	-1.2
Low Boy Plat.									5			5	151	18			4		1	184	82.1	-4.3
Drop Frm. Van												3	14	31			2		1	51	60.8	11.8
Dump						5				11					38					54	70.4	1.9
Logging									3							12				15	80.0	0.0
Livestock													8	2			45		1	56	80.4	1.8
Agriculture						1			3	5	1			2				17		29	58.6	27.6
Beverage												1							13	14	92.9	0.0
Total	2089	1564	98	17	140	133	38	28	885	266	220	82	228	127	74	13	51	43	17	6113	74.3	-2.0
Correct	1749	1207	74	6	71	102	16	12	617	200	112	67	151	31	38	12	45	17	13			
Precision (%)	83.7	77.2	75.5	35.3	50.7	76.7	42.1	42.9	69.7	75.2	50.9	81.7	66.2	24.4	51.4	92.3	88.2	39.5	76.5			
APE (%)	10.8	3.7	10.1	30.8	12.9	2.2	123.5	100	11.2	6.0	18.9	4.6	23.9	149	37.0	13.3	8.9	48.3	21.4			

Semi-Tractor Trailer Combinations with Multiple Semi Trailers

There are seven trailer body classes included in the model semi-tractor trailers combination trucks with multiple semi-trailers. Each trailer in the multi trailer configuration was of the same body class for all of the observed data. For example, two enclosed van trailers, or two tank trailers, but not one enclosed van and one tank trailer. The body classes listed in the follow tables represent the body class of both trailers in the multi-semi trailer configuration. The class labeled 'platforms/tanks' contains tank-tank and platform-platform trailers, not to be confused with tank-platform trailers. The model was trained with separate distinctions for platforms and tanks, but later the classes were merged due to the inability of the models to effectively distinguish between these two classes. Likewise, the low chassis van/platform class represents a merged class, rather than a mixed trailer configuration.

Table 5.12 summarizes CCR for each of the base classifiers and the two model combining strategies. The NBC and MV methods had about equal performance across all body types although the MCS approach outperformed the MV approach for dump trailers. As with the previous models, the MCS approach achieves overall higher CCR compared to the best performing base classifier and is more consistent across body classes than any of the of the base classifiers. Using MCS, all seven body classes achieve above 70% CCR with five of these having CCR above 90%. In examining the cross classification matrix for the MCS approach it can be seen that common misclassifications occur between enclosed vans and platforms/tanks. The MAPE for the multi-trailer model was 7.0%. Enclosed vans, platform/tanks, and dump multi-trailers all have APEs lower than 7%. The APEs of the remaining classes ranges from 22 to 50%. Lastly, applying the SMOTE method to the training data increases the overall and minority class CCRs by 3.0% and 3.7%, respectively. The only class that saw a decrease in performance due to SMOTE were the low chassis vans/platforms however this represents only one vehicle being misclassified after SMOTE.

Table 5.12 Multiple Semi Tractor Trailer Combination Trucks MCS Summary

Body Class	Vol.	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Enclosed Van	*253*	92.1	93.3	77.6	87.4	77.6	**92.5**	**92.9**
Platform/Tank	*121*	91.7	86.8	25.6	71.1	95.0	**91.7**	**90.1**
Dump	*126*	84.1	88.9	90.5	84.9	80.2	**86.5**	**90.5**
Pneumatic Tank	*36*	72.2	75.0	80.6	72.2	66.7	**77.8**	**75.0**
Hopper	*46*	84.8	37.0	54.3	95.7	93.5	**91.3**	**91.3**
Agricultural Van	*2*	100.0	0.0	100.0	50.0	0.0	**100.0**	**100.0**
Low Chassis Van/Pltfr.	*20*	95.0	80.0	100.0	75.0	100.0	**95.0**	**85.0**
OVERALL	***604***	***88.8***	***84.9***	***69.1***	***82.8***	***82.7***	***90.2***	***90.4***
Minority Classes	***351***	***86.3***	***78.9***	***63.0***	***79.5***	***86.3***	***88.6***	***88.6***

5.2.4 Discussion and Conclusions

The inductive signature only model used inductive signature data as the sole input. The model was structured into three tiers. The first tier distinguished between single units and multi units. The second tier separated vehicles in each of the first tier bins into axle configuration classes. For single units, these are passenger cars and single unit trucks without trailers. For multi units, these are single units with trailers, semi-tractor trailer combination trucks with single semi-trailers, and semi-tractor trailer combination trucks with multiple semi-trailers. Combined together, Tiers 1 and 2 achieved CCR of 93.4% and volume error of only 1.3%. The four body classification models on Tier 3 are summarized by their training and testing dataset sample sizes, number of body classes, CCR, and APE in Table 5.13.

The major contribution of the Inductive Signature only model is that it greatly increases the level of information available from an inductive loop sensor. Current methods found in the vehicle classification literature can at best distinguish vehicles into a few length based bins using conventional inductive loop detectors, and methods using inductive signatures are capable of classifying vehicles into a handful of body groups. The method presented in this section distinguished amount 47 body classes representing a vast expansion over existing methods.

Notable body class distinctions for single unit trucks include 30 and 20ft buses, concrete mixers, garbage trucks, bobtails, and street sweepers. Knowledge of these body classes can assist in separate freight from service trucks for freight modelling as well as for emissions estimation. Other notable body class distinctions for single semi unit trucks include distinction between five and three or four axle semi trucks, container transport trailers including 40ft, 40ft reefer, and 20ft containers, and specialty trailers like dump, beverage, livestock, and logging trailers. Commodity specific body types can be especially useful for commodity based freight modeling.

Histograms and cumulative distributions of classification error (100% - CCR%), precision error (100%-Precision(%)), and volume APE for each of the 47 body classes are shown in Figure 5.11. 34 of body class models have CCR above 70% and 19 have APE in volume lower than 10%. Single unit and single semi-trailer models have the largest variety of body types and therefore also possess higher volume error and lower classification accuracy. Low performance in these classes is due to the varied axle configurations in the class. For example, single units can be two to four axle trucks and semi-trailers can be three to five axle trucks. Inductive signatures are not apt at distinguishing axle configuration thus this diversity maybe partly to blame for lower performance in these classes.

The models developed in this section can be improved in several ways. The first avenue for improvement is through model selection. The MCS approach is very promising and could be enhanced by expanded the diversity of the base classifiers, or by training base classifiers on different feature sets or different sample sets, for example. Furthermore, in addition to the NBC and MV strategies, alternate combining architectures could be considered. Second, alternate signature preprocessing and feature extraction algorithms can be employed. For instance, Oh et al. (2007) suggested using extracting skewness, kurtosis, degree of symmetry, area, and standard deviation values from the inductive signature to use as features. Additionally, the feature set can be expanded by incorporating axle and weight information. Using Blade sensor technology which produces inductive signatures that capture axle information, Tok (2009) and Oh (2007) derived highly detailed body class information. In the next section (Section 5.3), the inductive signature based body classification model is integrated with WIM system data including axle spacing, axle weight, and vehicle length.

Table 5.13 Inductive Signature Only Model Tier 3 Results Summary

Model	Training Samples	Testing Samples	Body Classes	CCR (%)	Volume MAPE (%)
Single Units	1,553	1,476	13	72.3	15.4
Single Units with Trailers	714	746	8	94.2	8.2
Single Semi Trailers	3,720	6,113	19	74.2	11.3
Multiple Semi Trailers	375	605	7	90.4	7.0
Overall	**6,362**	**8,940**	**47**	**34 models CCR > 70%**	**27 models APE < 10%**

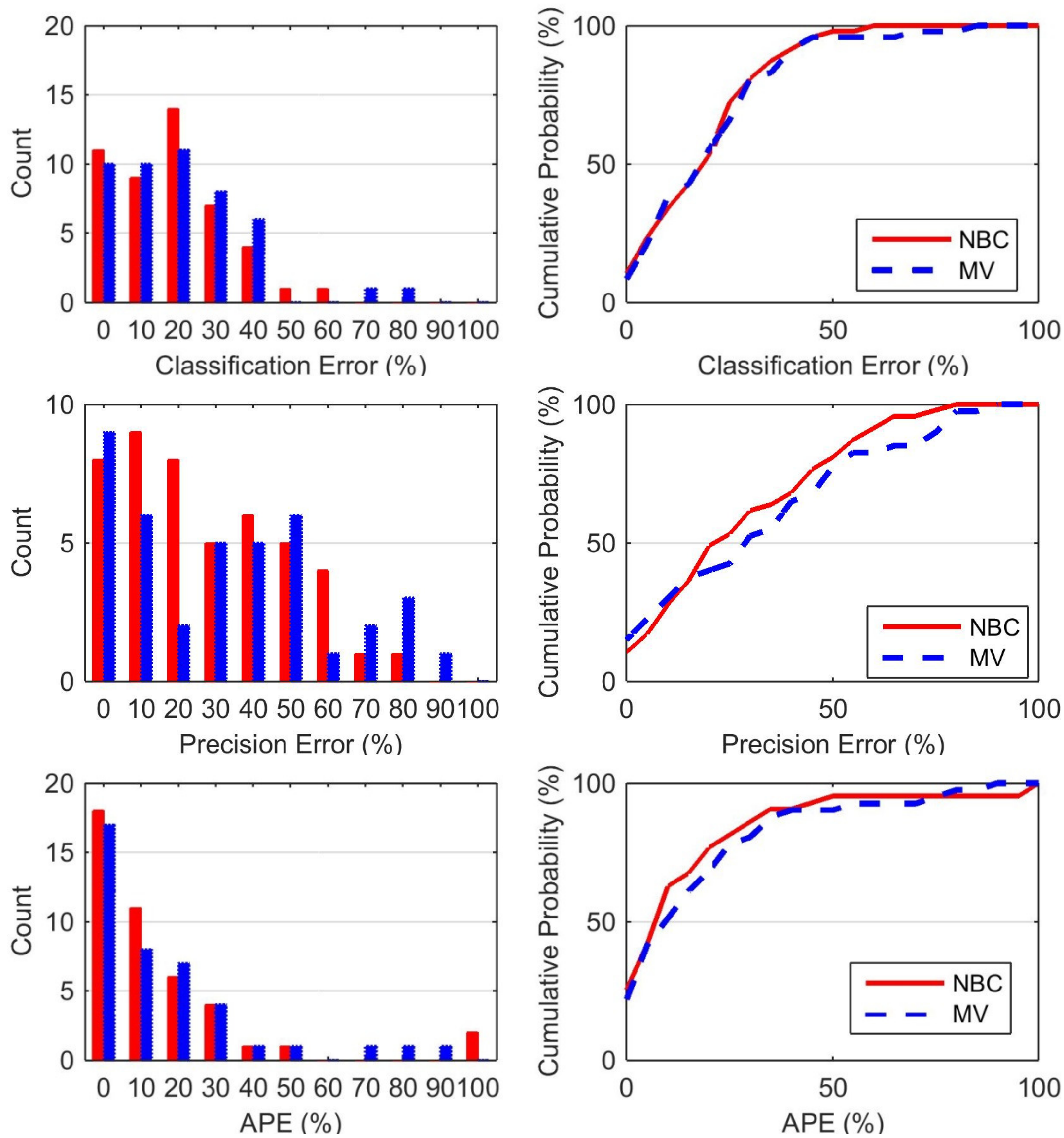


Figure 5.11 Summary of Model Accuracy for Naïve Bayes Combination and Majority Vote MCS Methods for Inductive Signature Only Tier 3 Models

5.3 Integrated WIM and Inductive Signatures Truck Body Classification

Using WIM data alone, the WIM-only model (Section 5.1) was capable of predicting body class volumes for five axle semi-tractor trailer combination trucks across five body class groups. Using signature data alone, the Inductive Signature only model was capable of predicting the body class of each vehicle across two vehicle configuration groups, five body configuration groups, and 43 body classes. In this section, the integrated model which combines WIM data and inductive signatures is presented. The integrated model represents the highest resolution at which body class can be obtained from the two data sources.

5.3.1 Data

The data used for model training and testing follows the same division by day and site as the data used in the Inductive Signature only model. Inductive signatures were pre-processed using the same basic approach presented in Section 5.2.1 for the Inductive Signature Only Model (Figure 5.7). For five axle semi-tractor trailer units, axle spacing measurements were used to parse inductive signatures into tractor and trailer portions, as shown in Figure 5.12. The raw inductive signature (Figure 5.12a) is first normalized by length using the measured vehicle length determined from the WIM system (Figure 5.12b). Next, the spacing of the drive (axle 1) and steering axles (axle 2) are used to parse the signature into the tractor and trailer segments (Figure 5.12c). An assumption of the frontal overhang, i.e. the distance from the beginning of the inductive signature to the location of the first axle, is required to determine the location of the steering axle. An assumed value of 4ft of frontal overhang was used. Next, rather than normalizing the magnitude by the maximum magnitude of the entire signature, the trailer portion of the signature is normalized by the maximum magnitude of the trailer portion of the signature (Figure 5.12d). Finally, the parsed section of the signature representing the trailer was processed according to the same feature extraction procedure used for the Inductive Signature Only Model. The signature parsing approach can help improve classification accuracy since the model will not be influenced by features from the tractor in predicting the body class of the trailer.

The parsing procedure is only applied to FHWA class 9 five axle semi-tractor trailers.

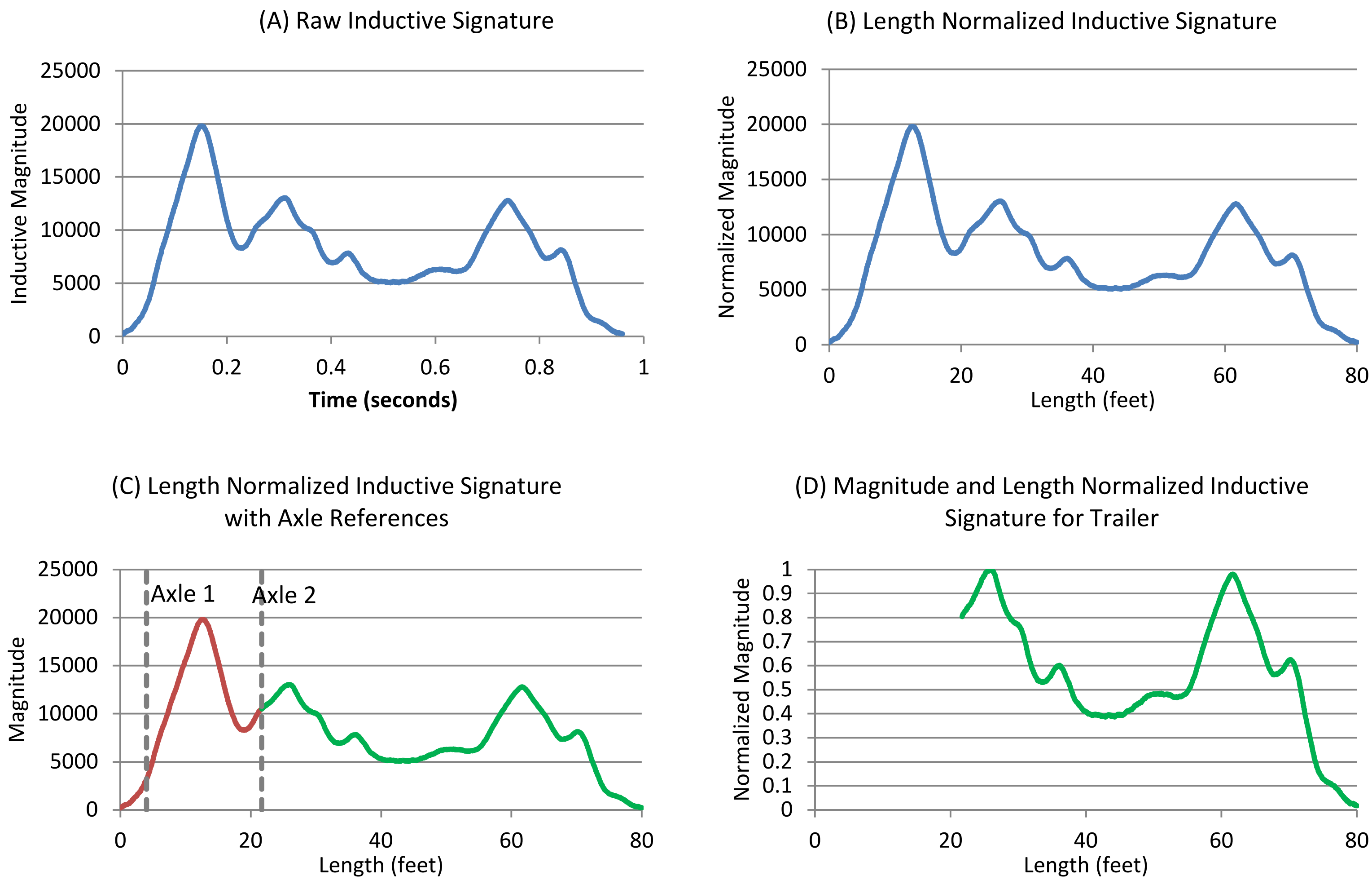


Figure 5.12 Inductive Signature Parsing using WIM axle spacing measurements

5.3.2 Modeling Approach

Like the Inductive Signature only model, the WIM-Signature integrated model also follows a tiered approach. The first tier uses the FHWA axle configuration classification sieve to determine the axle configuration group to which the vehicle belongs. The sieve uses axle count, spacing measurements between all axle pairs, vehicle length, and gross vehicle weight to determine which of the 14 axle class groups the vehicle should be assigned to. Then, for each of the 14 axle groups, body class is subsequently determined using inductive signature data and additional WIM system measurements. For single unit trucks, the body class of the drive unit was modeled. For semi-tractor trailers, the body class of the trailer unit was modeled. For single unit trucks with single trailers, the modeled body class corresponds to the combination of the drive unit and trailer unit. A separate model was estimated for each truck axle configuration group corresponding to the FHWA scheme, yielding a total of nine body classification models.

Furthermore, trucks designated as FHWA class 5 were separated into more refined axle configuration classes prior to body class modeling. FHWA class 5 contains single unit trucks with and without small trailers. The axle count from the WIM system can be used to easily separate single unit trucks with trailers (e.g. axle count greater than two) from those without trailers (e.g. axle count of two) excepted in the case of missing axle detections. Due to the low weight of small trailers, sometimes the WIM controller fails to detect the presence of the trailer. In this case, a two axle single unit truck with a small two axle trailer might be reported as having only two total axles by the WIM controller when it actually has four total axles. This type of error occurred in approximately 2.0% (74 samples) of the records classified by the WIM controller as FHWA class 5 single unit trucks. Luckily, the inductive signature detects the presence of the small trailer regardless of the WIM missed axle detection. Therefore, an additional tier (Tier 2) was added prior to body classification (Tiers 3a and 3b) to separate trucks with trailers from those without. The model is implemented as MLFF based on inductive signature features. The third tier subsequently classified non-trailer trucks by body type following the MCS method. Due to low sample size for FHWA class 5 trucks with trailers a stable model could not be estimated for these vehicles and is therefore not included in this dissertation. The model framework for FHWA Class 5 Single Unit Trucks is shown in Figure 5.13.

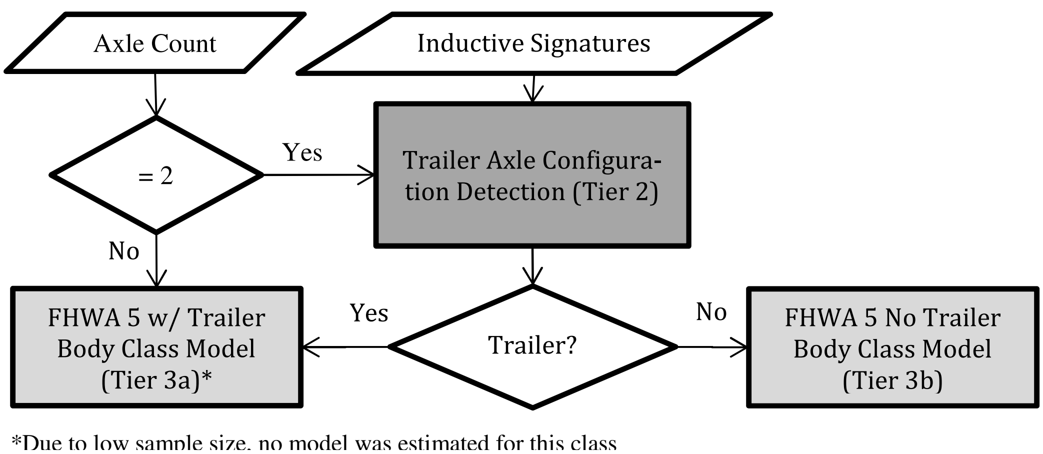


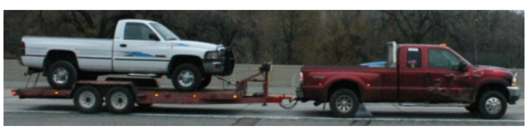
Figure 5.13 FHWA Class 5 Model Framework

Even though based on axle spacing, length, and gross vehicle weight each vehicle types shown in Figure 5.14 fall into the FHWA class 8 category, each has a very different body configuration and inductive signature pattern. Therefore, vehicles classified into FHWA class 8 by the axle based classification sieve were first separated into four further refined axle based categories: three or four axle semi-tractor trailers (Figure 5.14 a), two axle single unit trucks with trailers (Figure 5.14 b), two axle small trucks with trailers

(Figure 5.14 c), and three axle trucks with lift axles (Figure 5.14 d). A MLFF neural network was used to classify vehicles designated as FHWA class 8 into the four refined axle categories. Only those predicted to be three or four axle semi-tractor trailers, approximately 71% of the FHWA class 8 records, were subsequently classified by body type. Vehicles predicted to be two axle single unit trucks with trailers became part of the FHWA class 5 with trailer model. Vehicles predicted to be three axle trucks with lift axles became part of the FHWA class 7 model. Lastly, vehicles predicted to be two axle small trucks with trailers were removed from modeling efforts since these are not trucks.

(a)Three or Four Axle Semi-Tractor Trailers

(b) Two Axle Single Unit Truck with Trailers



(c)Two Axle Small Trucks with Trailers

(d) Three Axle Trucks with Lift Axles

Figure 5.14 Examples of Axle Groups with FHWA Class 8

Multi-trailer units (FHWA 11 and 12) differ in the axle count and configuration but share the same set of trailer body types, so the two classes were merged into one model. Multi-trailer configurations consisted of two trailers of the same body type, so the body class model outputs a single prediction representing all trailers of a truck. Seven or more axle multi-unit trucks (FHWA 13) tend to be specialized equipment movers or other unique body types and had only three samples in the observed data, so no model was developed for this class.

The framework for the WIM-Signature Integrated Body Classification Model is shown in Figure 5.15. Each model uses a slightly varied set of inputs but are invariably comprised a combination of WIM measurements and inductive signature features as shown in Table 5.14. WIM input features include axle spacing (feet) and weights (kips), vehicle length (feet), and several derived features such as overhang (feet) and ratios between axle weights. Overhang represents the front and rear portions of the vehicle extending beyond the axles, and is obtained as the arithmetic difference between the overall length and the sum of all axle spacing measurements. Weight ratios are calculated as the ratios between the steering, drive, or trailer axles. For all FHWA classes except FHWA class 9, WIM measurements are raw measurements that have not been normalized. For FHWA class 9, the WIM measurements used in the model have been normalized by the spacing between the 2nd and 3rd axles for the reasons described in Section 5.1.1.

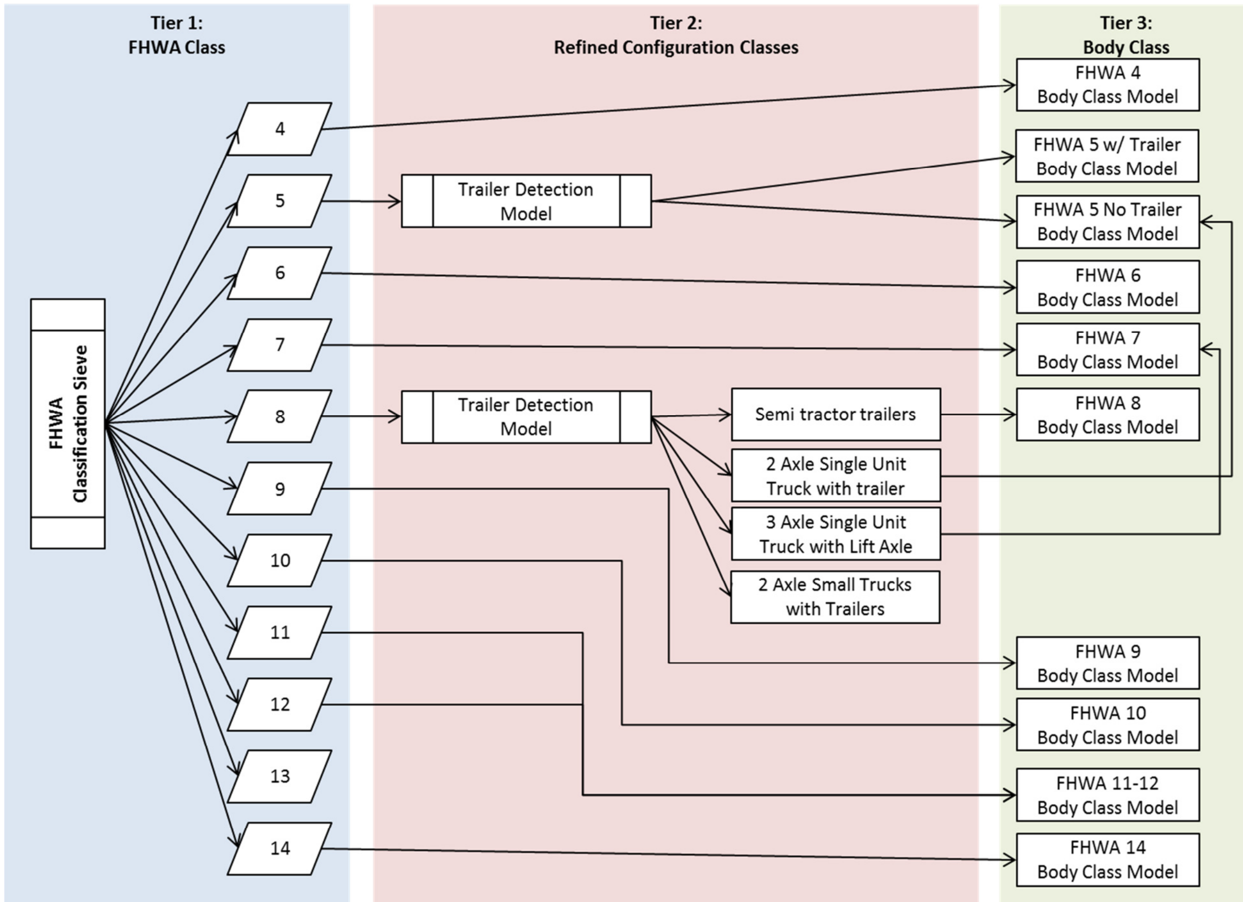


Figure 5.15 WIM-Signature Integrated Model Framework

Table 5.14 Summary of Input Feature Sets for WIM-Signature Model

FHWA Class	WIM Feature Set [# features]	Inductive Signature Feature Set [# features]	Total Number of Features
Single Unit Trucks			
FHWA 4	Overhang and Length [2]	30 normalized interpolated magnitudes and 29 magnitude differences [59]	61
FHWA 5 (Tier 3)	Spacing between 1st and 2nd axles, Ratio of 1st to 2nd axle weight, Length [3]		62
FHWA 6	Overhang and Length [2]		61
FHWA 7	Overhang and Length [2]		61
Semi-Tractor with Single Semi-Trailers			
FHWA 8 (Tier 3)	Spacing between 2nd and 3rd axles, Ratio of 2nd axle weight to GVW, Overhang, and Length [4]	30 normalized interpolated magnitudes and 29 magnitude differences [59]	63
FHWA 9	Spacing between 3rd and 4th axles, Overhang, Length [1] [3]	30 normalized interpolated magnitudes and 29 magnitude differences + 30 normalized magnitudes of the trailer portion of the signature [89]	91
FHWA 10	Overhang and length [2]	30 normalized interpolated magnitudes and 29 magnitude differences [59]	61
Semi-Tractor with Multiple Semi-Trailers			
FHWA 11-12	Overhang [1]	30 normalized interpolated magnitudes and 29 magnitude differences [59]	60
Single Unit Trucks with Single Trailers			
FHWA 14	Spacing between 2nd and 3rd axles , Spacing between 3rd and 4th axles [2]	30 normalized interpolated magnitudes and 29 magnitude differences [59]	61

1 Normalized by the spacing between the 2nd and 3rd axles

5.3.3 Results

In this section, a summary of the training data and modeling results are presented in term of the cross classification table for the MCS with NBC model combination, CCR, Precision, volume APE and MAPE, and summary of MCS base classifier performance. Full results are shown in this section for FHWA class 5 without trailers and FHWA class 9 semi-trailers. Results for all other axle groups are provided in Appendix 3. In the summary table of the MCS base classifier performance, models with less than ideal performance, deemed to be less than 60% CCR, have been highlighted in red to emphasize the cases where an individual base classifier would not perform well.

5.3.3.1 ***FHWA Class 4 Body Classification Model***

Vehicles classified into FHWA class 4 are meant to be of two or three axle buses, the classification sieve captured several non-bus body classes including vans and platforms, as well as recreational vehicles (RVs). The model was trained with 63 samples and tested on 62 samples. A summary of the MCS base classifier performance is provided in Table 5.15. The overall CCR for the MCS approach with NBC voting was 95.2% and for MV the CCR was 98.4%. None of the five base classifier models exceeded the CCR of the NBC or MV approach across all body classes. CCR and precision are near or above 90% across all four body classes. The model underestimates the volume of 30ft buses with single rear axles by 12% but the overall MAPE stands at 9.7%. SMOTE produced a minor positive improvement of 0.2% in CCR with the greatest improvement seen for vans or platforms.

Table 5.15 FHWA Class 4 MCS Summary

Body Class	*Vol.*	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Van or Platform	*26*	92.3	92.3	76.9	88.5	96.2	**96.2**	**92.3**
30ft Bus Tandem	*11*	100.0	100.0	90.9	81.8	45.5	**100.0**	**90.9**
30ft Bus Single	*25*	96.0	0.0	84.0	100.0	100.0	**100.0**	**100.0**
RV	*0*	-	-	-	-	-	-	-
Overall CCR (%)	**62**	**95.2**	**56.5**	**82.3**	**91.9**	**88.7**	**98.4**	**95.2**

5.3.3.2 ***FHWA Class 5 Trailer Axle Detection Model (Tier 2)***

The second tier of the FHWA class 5 model divides vehicles designated as FHWA class 5 two axle trucks by the FHWA classification sieve into those with trailers and those without. A total of 2,078 samples were included in model training and 947 in testing. Approximately 3% of the vehicles have trailers. The overall CCR is 99.3% for the two class model. Single unit trucks without trailers had CCR of 99.7% while those with trailers have CCR of 87.1%. Only 31 of the 947 samples were vehicles with trailers.

5.3.3.3 *FHWA Class 5 without trailers Body Classification Model*

Vehicles detected with only two axles by the WIM system or those identified by the axle detection model shown above as having no trailer are included in the FHWA class 5 without trailer body classification model. A total of 10 groups were created from the 21 body classes observed in the data. Groups were formed based on shared body characteristics, general usage characteristics, and the models ability to distinguish between particular classes. Of note are platforms and vans which were not able to be distinguished effectively by the models and were therefore lumped into a body class group. Also, platform trucks were separated into four types that represent body class characteristics matching other vehicles in the dataset. For example, cab over platforms were grouped with cab over vans since both have similar body characteristics and could not be distinguished by the models. Vehicles grouped into the 'other' category were not able to be distinguished as any of the 18 listed body classes.

The CCR results of the MCS base classifiers and combination strategies are summarized in Table 5.16. The overall CCR of the NBC approach was 75.3%. Of all the base classifier models, the SVM classifier performs best overall with 71.3% CCR, however has CCR below 60% for several classes while the NBC approach achieves CCR above 60% for all but one class ('other' trucks). The cross classification table for the NBC approach is given in Table 32. The majority of body classes have CCR and precision above 70%. Low performing classes include light vans/RVs, 12 passenger vans, and 'other' trucks. Misclassifications tend to occur by assigning vehicles into the van/platform and utility/platform/pickup categories. The MCS with NBC approach yields a MAPE in volume of 6.8% with volume APE for each class between 0.0% and 25.0%. Overall the SMOTE increased CCR by 2.3% with the largest improvement attributed to light van/RV, tow truck/platform, and bobtails.

Table 5.16 FHWA Class 5 without Trailer MCS Summary

Body Class	Vol.	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Cab Over Van/Platform	*215*	41.4	73.5	47.9	54.0	63.3	**65.6**	**71.6**
Conv. Van/Platform	*180*	86.1	89.4	58.9	80.0	86.7	**88.3**	**88.3**
Utility/Platform/Pickup	*174*	66.1	62.1	49.4	62.6	64.4	**70.7**	**73.6**
Light Van/RV	*104*	67.3	51.9	47.1	61.5	54.8	**68.3**	**67.3**
20ft Bus	*71*	83.1	87.3	69.0	71.8	18.3	**85.9**	**83.1**
Tow Truck/Platform	*61*	67.2	47.5	26.2	49.2	60.7	**65.6**	**70.5**
12 Pass Van	*41*	73.2	78.0	58.5	63.4	19.5	**73.2**	**65.9**
30ft Bus	*32*	87.5	96.9	93.8	81.3	84.4	**93.8**	**96.9**
Other	*22*	63.6	18.2	59.1	45.5	22.7	**59.1**	**22.7**
Bobtail	*12*	91.7	91.7	100.0	91.7	83.3	**100.0**	**91.7**
Overall CCR (%)	*912*	67.1	71.3	53.5	64.4	61.5	**74.6**	**75.3**

Table 5.17 FHWA Class 5 without Trailer Cross Classification Table

	Cab Over Van/Platform	Conv. Van/Platform	Utili-ty/Platform/Pick up	Light Van/RV	20ft Bus	Tow Truck/Platform	12 Pass Van	30ft Bus	Other	Bobtail	Total	Correct	CCR (%)	SMOTE Differ-ence (%)
Cab Over Van/Platform	154	6	25	9	4	8	2	1	6		215	154	71.6	0.9
Conv. Van/Platform	8	159	2			9			1	1	180	159	88.3	0.6
Utility/Platform/Pickup	18	5	128	2	4	3	4		9	1	174	128	73.6	4.6
Light Van/RV	12	5	4	70	3	5		3	1	1	104	70	67.3	6.7
20ft Bus	5		4	3	59						71	59	83.1	-1.4
Tow Truck/Platform		4	5	4	1	43			4		61	43	70.5	6.6
12 Pass Van	1		9	3	1		27				41	27	65.9	-2.4
30ft Bus				1				31			32	31	96.9	3.1
Other	4	1	6	1		3	1		5	1	22	5	22.7	-4.5
Bobtail									1	11	12	11	91.7	8.3
Total	202	180	183	93	72	71	34	35	27	15	**912**	**687**	**75.3**	**2.3**
Correct	154	159	128	70	59	43	27	31	5	11				
Precision (%)	**76.2**	**88.3**	**69.9**	**75.3**	**81.9**	**60.6**	**79.4**	**88.6**	**18.5**	**73.3**				
Volume APE (%)	**6.0**	**0.0**	**5.2**	**10.6**	**1.4**	**16.4**	**17.1**	**9.4**	**22.7**	**25.0**				

5.3.3.4 ***FHWA Class 6 Body Classification Model***

There were 215 samples in the training dataset representing 15 distinct body class which collapsed into the eight included in the model. Dump, dumpster transport, and garbage trucks are the most prevalent in this class. The CCR of each base classifier by body class and the MCS combining strategies are shown in Table 5.18. The MCS with NBC combination has an overall CCR of 80.5% with class CCR all above 60%. The MV combination strategy did reasonably well but had significantly poorer performance for trucks with trailers which were commonly misclassified as platform trucks. The model performs exceptionally well in identifying bobtail tractors with 91.5% CCR and 95.6% precision, and trucks with trailer assigned to FHWA class 6 with 92.9% CCR and 100.0% precision. Common cross classification occurred into the 'platform/van/tank/other' class. However this is to be expected given the wide diversity of body types and feature distributions within this class. The MCS approach has a MAPE in volume of 9.4% with class specific APE ranging from 0.0% to 27.6%. Garbage trucks and concrete mixers possess the largest APEs in volume, while bobtails, buses, and dumpster transport truck have APE in volume below 10%. SMOTE has an overall positive effect of increasing the CCR by 1.4% with much of the improvement stemming from the 'platform/van/tank/other' truck class. Unfortunately, the SMOTE method resulted in a decrease in CCR for concrete trucks. This could be due to the synthetic samples being drawn from two small of a population which may have contained noisy signatures.

Table 5.18 FHWA 6 MCS Summary

Body Class	*Vol.*	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Dumpster	95	72.6	74.7	42.1	76.8	67.4	**80.0**	**78.9**
Bobtail	94	92.6	97.9	85.1	89.4	90.4	**96.8**	**91.5**
Platform/Van/Tank/Other	89	59.6	39.3	53.9	65.2	92.1	**61.8**	**73.0**
Dump	88	75.0	76.1	40.9	47.7	60.2	**77.3**	**78.4**
Garbage	29	72.4	89.7	86.2	51.7	37.9	**75.9**	**79.3**
Concrete	16	81.3	93.8	93.8	68.8	18.8	**81.3**	**68.8**
FHWA 6 w/ trailer	14	57.1	92.9	85.7	85.7	35.7	**57.1**	**92.9**
Bus	1	0.0	100.0	100.0	100.0	0.0	**100.0**	**100.0**
Overall CCR (%)	*426*	***74.4***	***75.1***	***60.3***	***69.5***	***71.1***	***78.4***	***80.5***

5.3.3.5 *FHWA Class 7 Body Classification Model*

FHWA Class 7 three axle single unit trucks are divided into four body classes. From the observed data it was found that two axle single unit trucks with extended lift axles were often categorized as three axle trucks by the FHWA classification sieve. Therefore the body classes include two axle dump trucks and concrete mixers with lift axles in addition to three axle dump trucks ('dump triple') and garbage trucks ('garbage triple'). The 72 samples in the training data come from the Irvine and Fresno sites as none were observed at the Willows or Redding sites. This was to be expected since three axle single unit trucks tend to be urban service trucks, e.g. garbage or dump trucks, and would therefore not be found in more rural areas like Redding and Willows.

The test dataset was comprised of a limited set of 19 samples. Table 5.19 summarizes the performance of the base classifiers and MCS combination methods on the test data. The MCS with NBC performs with 100.0% CCR across all body classes, significantly improving upon all of the individual base classifiers and the MV combination method. Since the MCS with NBC had 100.0% CCR and Precision accuracy there were no cross classifications. The MAPE in volume was 0.0%. Lastly, the SMOTE method had no effect on the CCR performance of the MCS method using MV or NBC although minor improvements in CCR were found for each of the base classifiers using SMOTE.

Table 5.19 FHWA 7 MCS Summary

Body Class	Vol.	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Garbage Triple Tandem Axle	9	77.8	0.0	100.0	100.0	66.7	77.8	100.0
Concrete Tandem w/ Lift	7	100.0	100.0	42.9	100.0	42.9	100.0	100.0
Dump Triple Tandem Axle	1	100.0	0.0	100.0	100.0	100.0	100.0	100.0
Dump Tandem w/ Lift	2	100.0	100.0	50.0	100.0	100.0	100.0	100.0
Overall CCR (%)	19	89.5	47.4	73.7	100.0	63.2	89.5	100.0

5.3.3.6 *FHWA Class 8 Trailer Axle Detection Model (Tier 2)*

The FHWA Class 8 Trailer Axle Detector Model distinguishes four refined axle configurations found within the FHWA class 8 data using an MLFF neural network. The overall CCR is 93.6% with class specific CCR between 78.7 and 100.0%. The MAPE in volume is 8.9%. Those vehicles identified as two axle single unit trucks with lift axles and two axle single unit trucks with trailers, are then sent to the body class models for FHWA class 7 and 5 with trailers, respectively. Vehicles identified as two axle small trucks with trailers are terminally identified. Vehicle predicted to be three or four axle semi-tractor trailers are fed into the FHWA class 8 body class model shown in the next section.

5.3.3.7 *FHWA Class 8 Semi-Trailer Body Classification Model*

There were seven unique trailer body classes observed for FHWA class 8 three or four axle semi-tractor trailer combination trucks. Of the seven trailer body classes, five trailer body class groups were formed. Enclosed van trailer are the dominate class accounting for 76% of the training samples and 80% of the test data. Unique minority trailer body classes include beverage, livestock, and agricultural trailers. Aggregate results are shown for the minority classes, e.g. all vehicle classes except vans, since even a simple model predicting every vehicle as a van would be correct at least 76% of the time.

The results of the base classifiers and MCS combining methods are shown in Table 5.20. The MCS with NBC achieves 90.9% and 71.1% CCR for the overall and minority classes, respectively. The majority of cross classification occur between platform and van trailers. If van and platform trailers were to be combined into a single class, the CCR of the combined class would be 97.6%. Low chassis van/platform and beverage trailers had CCR of 77.8 and 100.0%, respectively. Unfortunately agricultural van trailers were not found in the test data set. However, the validation dataset performance shows that the base classifier models were able to predict agricultural van trailers with CCR of 50%. The MCS based model generally produces accurate volume estimates with MAPE of 4.3%. Platforms are the largest source of volume error with APE of 20.0%. The effect of SMOTE was a 0.5% improvement in CCR with an even greater improvement of 5.3% for the minority classes.

Table 5.20 FHWA Class 8 MCS Summary

Trailer Body Class	*Vol.*	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Van	*149*	90.6	99.3	94.0	83.9	63.1	**94.6**	**96.0**
Platform	*20*	45.0	15.0	40.0	60.0	90.0	**45.0**	**55.0**
Low Chassis Van/Platform	*9*	88.9	55.6	77.8	77.8	33.3	**77.8**	**77.8**
Beverage	*9*	100.0	100.0	100.0	33.3	88.9	**100.0**	**100.0**
Agricultural Van	*0*	-	-	-	-	-	**-**	**-**
Overall CCR (%)	*187*	86.1	88.2	87.7	78.6	65.8	**88.8**	**90.9**
Minority Class CCR (%)	*38*	68.4	44.7	63.2	57.9	76.3	**65.8**	**71.1**

5.3.3.8 ***FHWA Class 9 Body Classification Model***

FHWA class 9 semi-tractor trailer combination trucks have the widest diversity of body types compared to all other FHWA classes. The training data consists of 3,205 samples from the Irvine, Willows, Redding, and Fresno data collection sites. The 20 unique body classes were collapsed into 16 body class groups, two of which contain multiple body types: (1) the platform group contains basic platforms, bulk waste transport, and 20ft containers on platforms; (2)the tank group contains liquid, dry bulk, and pneumatic tanks. Grouping of the trailer body types was based on physical and use characteristics as well as cross classifications evident in the training results. Unique body classes include 20ft, 40ft, and 53ft intermodal containers as well as refrigerated vans and containers ('reefer'). Commodity specific classes include tank, automotive transport, livestock, agricultural, and logging trailers.

Table 5.21 summarizes the base classifiers and MCS model combining strategies for the FHWA class 9 trailer body class models. The MCS with NBC achieves 75.5% CCR overall and 77.7% for minority classes while the MV method achieves 73.2% CCR overall and 76.8% for minority classes. The SVM base classifier has the best performance for minority classes (79.2%) but sacrifices classification accuracy for the majority class as a result. Four of the 16 trailer body class groups have CCR above 90%, five between 80 and 90%, and four between 70 and 80% using the MCS with NBC approach. Lower than acceptable classification performance resulted for 53ft containers. Cross classifications (Table 5.22) are common between enclosed vans, reefer vans, and 53ft containers due to their similar length, overhang, and chassis characteristics. Classification accuracy of enclosed vans could be increased to 92.1% CCR by merging these three classes. The model performs exceptionally well for many of the unique minority classes. For example, 40ft containers, 20ft containers, automobile transport, and livestock trailers have CCR above 90% and precision above 70%. The MCS with NBC applied to the test data across all sites results in MAPE of 12.0% and 11.1% for all classes and minority classes, respectively. High APE was observed for 40ft reefer containers and drop frame vans, both of which were overestimated. Commodity specific body classes such as auto transport, logging, livestock, and agricultural van trailers had APE in volume less than 20%.

Overall there is a 0.4% decrease in CCR but a 0.8% increase for minority classes due to the SMOTE technique. The biggest improvements are due to 53ft containers (27.6%) and 20ft containers (38.5%). Because the SMOTE algorithm creates a training dataset with equal sample sizes, the models cannot rely on prior distributions to predict body class, thus the performance of the majority class tends to decrease as observed for the enclosed van trailers.

Table 5.21 FHWA Class 9 MCS Results Summary

Trailer Body Class	***Vol.***	**Base Classifier Models (CCR %)**					**MCS (CCR %)**	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Enclosed Van	2,210	35.8	53.8	74.8	69.3	61.2	**67.7**	**71.9**
Reefer Vans	1,564	64.5	82.4	24.3	72.4	61.0	**73.2**	**74.9**
53ft Box Container	116	69.0	71.6	7.8	59.5	13.8	**51.7**	**55.2**
40ft Container	131	74.0	77.1	66.4	58.8	16.8	**76.3**	**81.7**
40ft Reefer Container	16	87.5	93.8	18.8	81.3	87.5	**87.5**	**93.8**
20ft Container	13	92.3	84.6	100.0	92.3	100.0	**100.0**	**100.0**
Platforms	734	51.0	72.5	89.5	77.4	88.6	**84.2**	**81.3**
Tank	259	65.3	74.1	81.5	76.4	71.8	**77.2**	**78.4**
Open Top Van	152	61.2	79.6	16.4	67.8	33.6	**71.7**	**80.3**
Auto	67	89.6	92.5	94.0	74.6	82.1	**97.0**	**94.0**
Low Boy Platform	166	80.1	81.9	90.4	81.9	88.6	**91.0**	**88.6**
Dump	51	62.7	80.4	41.2	45.1	68.6	**64.7**	**66.7**
Drop Frame Van	43	65.1	76.7	32.6	58.1	58.1	**65.1**	**74.4**
Logging	14	78.6	78.6	85.7	85.7	85.7	**85.7**	**85.7**
Livestock	45	95.6	100.0	64.4	84.4	62.2	**93.3**	**95.6**
Agricultural Van	22	90.9	72.7	4.5	77.3	40.9	**77.3**	**63.6**
Overall CCR (%)	**5,603**	**52.9**	**69.2**	**59.4**	**71.5**	**63.7**	**73.2**	**75.5**
Minority Class CCR (%)	**3,393**	**64.1**	**79.2**	**49.4**	**72.9**	**65.3**	**76.8**	**77.7**

Table 5.22 FHWA Class 9 Cross Classification Table for All Sites

	Enclosed Van	Enclosed Van Reefer	53ft Box Container	40ft Container	40ft Container Reef-er	20ft Container	Platforms	Tank	Open Top Van	Auto	Low Boy Platform	Drop Frame Van	Dump	Logging	Livestock	Agricultural Van	Total	Correct	**CCR (%)**	**SMOTE Difference (%)**
Enclosed Van	1590	419	29			3	45	1	48		12	60	3				2210	1590	71.9	-2.4
Reefer	257	1172		1			61		36			33	4				1564	1172	74.9	-1.3
53ft Container	49	1	64				2										116	64	55.2	27.6
40ft Container		1		107	1		10	2	4				6				131	107	81.7	11.5
40ft Reefer					15								1				16	15	93.8	6.3
20ft Container						13											13	13	100.0	38.5
Platform	16	7		13	13	1	597	22	18	2	21	9	9			6	734	597	81.3	-3.8
Tank				5	3	1	29	203	4		2		11			1	259	203	78.4	3.5
Open Top Van	1			4			14	3	122			1	7				152	122	80.3	4.6
Auto Transport										63	3	1					67	63	94.0	-1.5
Low Boy Platform							4				147	12			3		166	147	88.6	-1.8
Drop Frame Van	1									2	7	32			1		43	32	77.4	4.6
Dump				5	1			11					34				51	34	66.7	5.9
Logging							2							12			14	12	85.7	7.1
Livestock											2				43		45	43	95.6	0
Agricultural Van							1	2	2				7			14	22	14	63.6	18.1
Total	**1914**	**1600**	**93**	**135**	**33**	**18**	**765**	**244**	**234**	**67**	**194**	**148**	**82**	**12**	**47**	**21**	**5603**	**4228**	**75.5**	**-0.4**
Correct	**1590**	**1172**	**64**	**107**	**15**	**13**	**597**	**203**	**122**	**63**	**147**	**32**	**34**	**12**	**43**	**14**				
Precision (%)	83.1	73.3	68.8	79.3	45.5	72.2	78.0	83.2	52.1	94.0	75.8	21.6	41.5	100.0	91.5	66.7				
Volume APE (%)	13.4	2.3	19.8	3.1	106.3	38.5	4.2	5.8	53.9	0.0	16.9	244.2	60.8	14.3	4.4	19.2				

5.3.3.9 *FHWA Class 10 Body Classification Model*

The FHWA Class 10 model was limited by the number of samples available for model training and testing. Due to low sample size, the MCS approach could not be applied and a single SVM model was used for prediction instead. The six unique trailer body classes were collapsed into four groups: 20ft intermodal containers, platforms, low chassis vans and platforms, and enclosed vans. The overall CCR was 100.0% for the test data consisting of a limited set of 10 samples. The model preforms well given the limited training data.

5.3.3.10 *FHWA Class 11 and 12 Body Classification Model*

From the nine unique trailer body classes representing dual semi-trailers, seven groups were created. The majority of samples are enclosed vans, platform, and bottom dump trailers. Minority body types included pneumatic tanks, hoppers, and agricultural vans. The MCS results are shown in Table 5.23 for the test set of 302 samples. The overall CCR for the MCS with NBC was 92.6% compared to the MV approach with CCR of 91.7%. The MLFF neural network base classifier has an overall higher CCR than the NBC method, however, it achieve slightly lower accuracy for bottom dump and tank trailers. CCR values were above 80% for all but one class (Hopper trailers) and precision exceeding 80% for all but one class (Tanks). This is due to cross classifications that occurred between platform and tank trailers. The MAPE in volume of the MCS with NBC was 8.0%. The largest APE in volume results from platforms being misclassified as tanks, all other class specific APE in volume were less than 15%. Lastly, SMOTE greatly increases the CCR of tanks by 33% but results in a 0.6% decrease in overall CCR due to the slight decrease in CCR of the majority class, i.e. platforms.

Table 5.23 FHWA 11 and 12 MCS Summary

Trailer Body Class	Vol.	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Platform	108	92.6	88.9	42.6	77.8	87.0	**90.7**	**91.7**
Van	88	95.5	96.6	87.5	88.6	90.9	**95.5**	**95.5**
Bottom Dump	67	98.5	100.0	98.5	97.0	100.0	**100.0**	**100.0**
Hopper	33	81.8	63.6	45.5	75.8	81.8	**75.8**	**75.8**
Pneumatic Tank	25	88.0	80.0	64.0	72.0	68.0	**84.0**	**88.0**
Tank	3	66.7	66.7	66.7	66.7	33.3	**66.7**	**100.0**
Agricultural Van	2	100.0	0.0	100.0	50.0	0.0	**100.0**	**100.0**
Overall CCR (%)	***326***	***92.9***	***89.3***	***68.7***	***83.7***	***87.7***	***91.7***	***92.6***

5.3.3.11 *FHWA Class 14 Body Classification Model*

The body class model for FHWA class 14 single unit trucks with single trailers consists of five body classes. The body classes represent the truck and trailer body of the vehicle. For example, 'Dump-Dump' refers to a single unit dump truck pulling a single dump trailer. The training set consisted of 145 samples, dominated by 'dump-dump' trucks. Overall the CCR for the test data of 244 samples was 96.7% for the MCS with NBC method compared to 95.9% for the MV method. Dump-Dump, Tank-Tank, and RV-Small trailer classes have CCR and prevision above 90%. Platform-Platform trucks are the only underperforming class due to cross classifications as tank-tank and dump-dump trucks. MAPE in volume of the MCS with NBC was 1.7%. All body classes had APE in volume of less than 2%. Only the Platform-Platform class exceeded 10% APE. The SMOTE training algorithm had an overall positive effect (1.2%) on CCR with significant increase in the CCR of RV-Small trailer (23.5%) and minor decrease in performance for tank-tank trailers.

Table 5.24 FHWA 14 MCS Summary

Trailer Body Class	*Vol.*	Base Classifier Models (CCR %)					MCS (CCR %)	
		MLFF	SVM	CPNN	DT	NB	MV	NBC
Dump-Dump	171	94.7	98.2	83.6	84.2	98.2	**99.4**	**99.4**
Tank-Tank	31	87.1	90.3	71.0	90.3	90.3	**90.3**	**90.3**
RV-Small Trailer	25	92.0	100.0	100.0	88.0	100.0	**100.0**	**100.0**
Platform-Platform	17	64.7	52.9	11.8	52.9	52.9	**64.7**	**76.5**
Livestock-Livestock	0	-	-	-	-	-	**-**	**-**
Overall CCR (%)	244	91.4	94.3	78.7	83.2	94.3	**95.9**	**96.7**

5.3.4 Discussion and Conclusions

Both the results and depth of detailed body classes depicted in these models go well above the capabilities of previous classification models which were limited to at most five body classes using current in-pavement technology (Lu et al., 2011). A major advantage of integrating the WIM site with inductive signature capabilities is that the body classification model is able to predict among body types found within an axle configuration class where-as previous inductive signature based models had the added challenge of predicting among all vehicle body and axle configurations. In all, eight separate body classifications models were developed from an extensive data set of 18,967 truck records distinguishing an un-precedented total of 26 single unit truck, 25 semi-trailer body configurations, and 12 multi-unit trucks as shown in the summary in Table 5.25. Of the 63 body classes, 51 had CCR greater than 70% and 33 had APE in volume less than 10%. Figure 5.16 catalogues the model accuracy in terms of classification error rates (100%-CCR), precision error, and vol-ume APE across all 63 body classes include in the eight models.

Table 5.25 WIM-Signature Model Summary

Model	No. Training Samples	No. Testing Samples	No. Body Classes	CCR (%)	Volume APE (%)
FHWA 4	63	62	4	95.2	9.7
FHWA 5 without Trailers	1,172	912	10	75.3	6.8
FHWA 6	215	342	8	80.5	9.2
FHWA 7	72	19	4	100.0	0.0
FHWA 8 Semi Trailers	224	187	5	90.9	4.2
FHWA 9	3,198	5,603	16	75.4	12.2
FHWA 10	17	13	4	92.3	7.7
FHWA 11 and 12	508	326	7	92.7	8.0
FHWA 14	145	244	5	96.7	1.7
Overall	**5,614**	**7,708**	**63**	**52 with CCR > 70%**	**37 with APE < 10%**

The model for FHWA class 4 effectively distinguishes buses from vans and platforms which have been misclassified by WIM controllers into this class. Hence, this model actually improves classification accuracy according to the FHWA scheme since FHWA class 4 is meant to only contain buses. For two axle single unit trucks (FHWA 5), body configurations are extremely heterogeneous, and axle measurements and weights overlap significantly, however the model still effectively separated buses, passenger vans, utility and pickup trucks, bobtails (tractor drive units), and enclosed vans. Models for FHWA classes 6 and 7 differentiated several industry specific categories including concrete, dump, garbage, dumpster transport, and vans. These are important distinctions if one desires to compare possible freight and non-freight related vehicle volumes, since passenger related vehicles like buses or service oriented trucks such as pickups are not freight carriers.

Five axle combination trucks (FHWA 9) possessed the widest diversity of trailer body types. Enclosed vans formed the majority, while several unique and industry specific classes like logging and intermodal containers comprised the minority. Remarkably, the model can even distinguish refrigerated from non-refrigerated vans as well as refrigerated from non-refrigerated 40ft intermodal containers. This level of distinction paves new possibilities for advanced tracking of perishable commodities, especially those that are Port-related. Also, because length is included in the model, 20ft intermodal containers can be classified with high accuracy. Other commodity specific body types such as automobile transport, logging, and livestock trailers had CCR above 85%. Unfortunately, the model is not able to accurately distinguish 53ft intermodal containers from enclosed vans due to overlap in signature and axle configuration features thus it would be appropriate to collapse these classes into one group.

Across all axle configuration groups, the MCS approach which combined five base classifiers – MLP, SVM, CPNN, DT, and NB – using NBC had higher overall CCR than any single base classifier model. While several base classifiers undoubtedly demonstrated adequate performance at predicting certain classes, there was always a tradeoff with low performance of the same classifier on other classes. To illustrate this important facet of MCS, the class specific CCRs less than 60% were highlighted in red in each of the MCS summary tables. Each classifier has a set of classes where it performs quite poorly, hence the need for the MCS method which consequently produced fewer class specific CCRs under 60%.

In the FHWA class 9 model, for example, the SVM base classifier produced more accurate predictions than any base classifier for livestock trailers (100.0%) but had the lowest performance among all base classifier for enclosed van trailers (53.8%). If the SVM model had been applied alone, the accuracy in predicting enclosed vans would have been sacrificed in favor of livestock trailers. But by combining all models, the CCR for enclosed vans was elevated to 71.9%, well above the ability of the SVM model, while still maintaining the high accuracy for livestock trailers (95.6%). Accordingly, for all eight models (FWHA class 4 through 11/12) the overall CCRs were above 75% using the MCS approach. Alternatively, had only the MLFF approach been implemented, for example, only six of the eight models would achieve CCRs above 75%.

Since NBC calculates an array of probabilities for the set of possible body classes based on the joint distribution arising from each base classifier's cross classification matrix, the strengths of each base classifier are captured and weaknesses are controlled. For example, an unknown vehicle could be classified as a reefer by the CPNN model, which had a CCR of only 24% for this class because most reefers were misclassified as enclosed vans. In NBC, the CPNN model will contribute little 'evidence' toward the estimated probability of the vehicle being a reefer (i.e. the number of records that were truly reefers and predicted as such is low) but contribute significant 'evidence' toward the estimated probability of the vehicle being an enclosed van (i.e. the number of records that were truly reefers but classified as enclosed vans is high). In the simplest possible interpretation, this approach allows the best model to be used for each class. Without this approach, there is no way to predetermine which base classifier should be applied to an unknown vehicle.

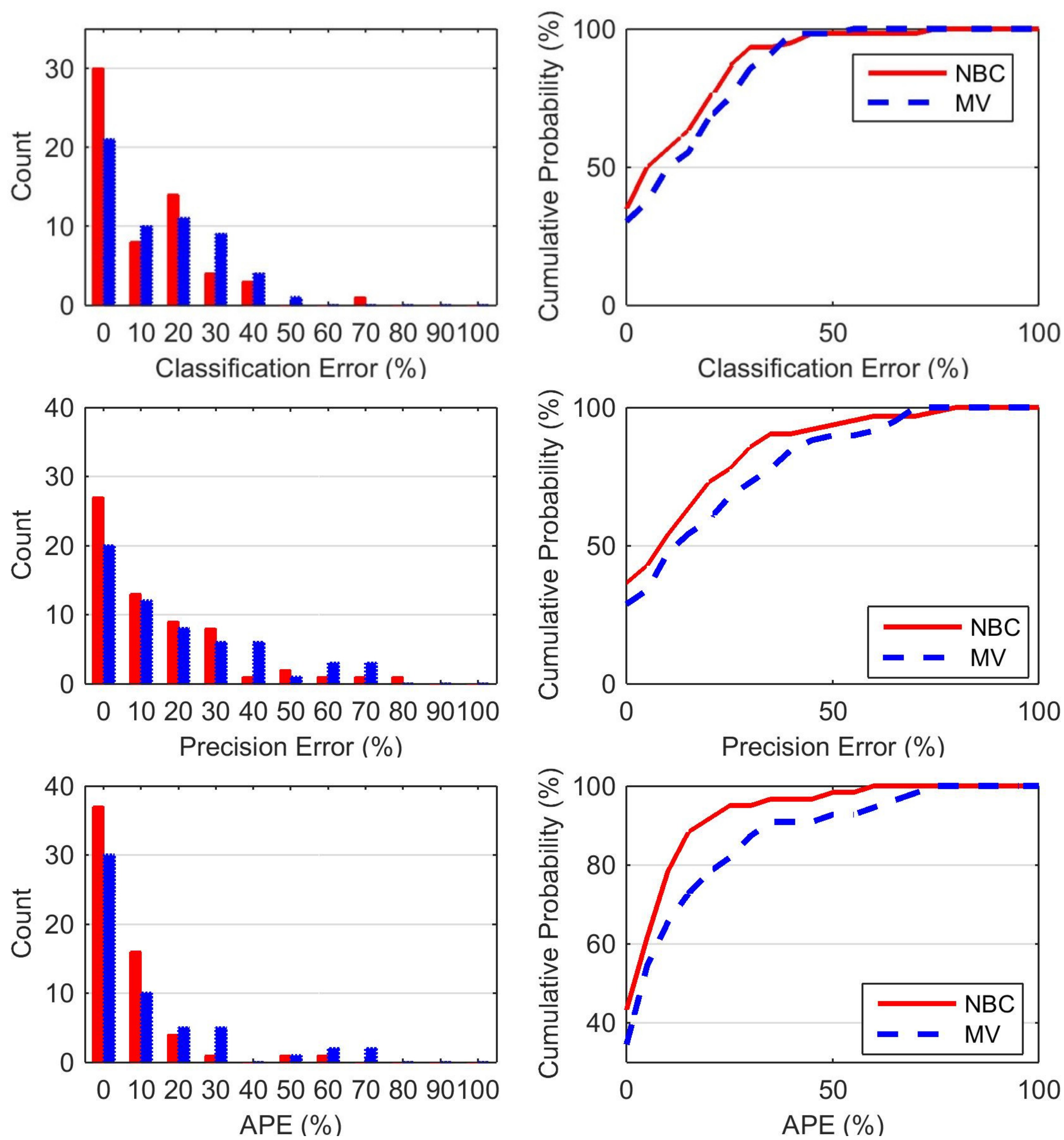


Figure 5.16 Summary of Model Accuracy for Naïve Bayes Combination and Majority Vote MCS Methods for WIM-Signature Models

5.4 Sensitivity Analysis

5.4.1 Spatial Transferability

Spatial transferability analysis was performed for the FHWA class 9 semi-tractor trailer body class model since this model possess the widest array of body classes and spatial differences in body class distributions were observed to be particularly significant for this class of trucks. To assess the spatial transferability of the model, the data from the Irvine data collection site was held out from model training, and then the trained MCS with NBC method was applied to the data collected from the Irvine site.

Table 5.26 displays the CCR and APE in volume for the Irvine data. The CCR of the Irvine data consisting of 589 samples was 64.3% overall and 55.6% for the minority classes. The precision ranges from around 40% to 100%. It should be noted that several body classes reported as 0.0% precision had only one misclassification, i.e. only one vehicle was predicted as that vehicle class. Logging and livestock trailers had 100% precision meaning that neither of these vehicle types were predicted at the Irvine site. The MAPE in volume was 30.4% and 41.3% for the overall and minority classes, respectively. The highest error arises from 53ft containers which had very low CCR.

In all, lower performance resulted from leaving the Irvine data out from the model training, however, this was to be expected because each of the four sites possessed widely different body class distributions. Thus, leaving any site out of the training would mean excluding unique samples from the data. For the most accurate model, data from the Irvine site and potentially other sites around the state should be included to fully encompass the diversity of vehicle types.

Table 5.26 Spatial Transferability Analysis Cross Classification Table for Irvine Data

	Enclosed Van	Enclosed Van Reefer	53ft Box Container	40ft Container	40ft Container Reef-er	20ft Container	Platforms	Tank	Open Top Van	Auto	Low Boy Platform	Drop Frame Van	Dump	Logging	Livestock	Agricultural Van	Total	Correct	**CCR (%)**
Enclosed Van	180	16	5				24	1	4			1					231	180	77.9
Reefer	39	53					11						1				104	53	51.0
53ft Container	33		11														44	11	25.0
40ft Container				4			3		3								10	4	40.0
40ft Reefer					0												0	0	-
20ft Container						0											0	0	-
Platform	4	1		3	1		45	3	1	1		2				1	62	45	72.6
Tank				2		1	7	8			1						19	8	42.1
Open Top Van	6	2					23		25								56	25	44.6
Auto Transport										10	1						11	10	90.9
Low Boy Platform							1				24	2					27	24	88.9
Drop Frame Van										1		9					10	9	90.0
Dump				1				4					10				15	10	66.7
Logging														0			0	0	-
Livestock															0		0	0	-
Agricultural Van																0	0	0	-
Total	**262**	**72**	**16**	**10**	**1**	**1**	**114**	**16**	**33**	**12**	**26**	**14**	**11**	**0**	**0**	**1**	**589**	379	64.3
Correct	**180**	**53**	**11**	**4**	**0**	**0**	**45**	**8**	**25**	**10**	**24**	**9**	**10**	**0**	**0**	**0**			
Precision (%)	68.7	73.6	68.8	40.0	0.0	0.0	39.5	50.0	75.8	83.3	92.3	64.3	90.9	100	100	0.0			
Volume APE (%)	13.4	30.7	63.6	0.0	-	-	83.8	15.8	41.1	9.1	3.7	40.0	26.7	0.0	0.0	-			

5.4.2 Multiple Classifier System Diversity

Diversity among base classifiers is an important consideration in developing a multiple classifier system and should be evaluated as part of the ensemble design. While there are many methods to assess classifier diversity, Kuncheva and Whitaker (2003) suggest using the pairwise Q-statistic (Yule, 1900) averaged over all possible pairs of classifiers in an ensemble due to its ease of calculation and interpretation. For each classifier D_i the output can be represented by an N dimensional binary vector $y_I = [y_{1,i} \ldots y_{N,i}]$ which that y = 1 if D_i correctly classifies record n and 0 otherwise. The pairwise Q-statistic is calculated for a pair of classifiers D_i and D_k as follows:

$$Q_{i,k} = \frac{N^{11}N^{00} - N^{01}N^{10}}{N^{11}N^{00} + N^{01}N^{10}}$$

where N^{ab} is the number of records for which $y_{j,i}$ = a and $y_{j,k}$ = b.

If classifiers are independent then Q is zero. Q ranges from -1 to 1 such that classifiers which recognize the same objects correctly will have a positive Q statistic and classifiers who produce errors on different objects will result in a negative Q statistic. An ensemble with low Q_{av} is said to have greater diversity than an ensemble with higher Q_{av}. For a set of base classifiers, the average Q statistic for the ensemble is the average overall all pairwise Q statistics and is formulated as follows:

$$Q_{av} = \frac{2}{L\,(L-1)} \sum_{i=1}^{L-1} \sum_{k=i+1}^{L} Q_{i,k}$$

where L = number of base classifiers in the ensemble.

An analysis of classifier diversity was carried out to ensure that the set of five base classifiers used in the MCS (MLFF, SVM, CPNN, DT, and NB) provided the highest level of accuracy. The 5,603 test samples from the FHWA Class 9 trailer body classification model were used for diversity analysis.

All possible pairwise Q statistics were calculated for classifier ensembles ranging in size from two to five base classifiers. The pairwise Q statistics were then averaged to obtain Q_{av} for each ensemble combination. There were five possible combinations of base classifiers for an ensemble of four classifiers (e.g. MLFF-SVM-CPNN-NB, MLFF-SVM-CPNN-DT, MLFF-SVM-DT-NB, etc.), 10 combinations for an ensemble of three classifiers, and 10 pairwise combinations representing two classifier ensembles. The Q_{av} statistic for each of the 25 combinations and the MCS with all five base classifiers is shown in Figure 5.17.

The combination of five base classifiers (MLFF-SVM-CPNN-DT-NB) had Q_{av} of 0.585. Paired classifiers exhibiting the most diversity (i.e. lowest Q_{av}) included SVM-CPNN and MLFF-CPNN. Several three and four classifier combinations exhibited higher diversity than the five classifier combination.

Kuncheva and Whitaker (2003) note that although diversity is an important aspect to consider when developing a MCS it is not the only predictor of an ensemble's accuracy. Therefore, the classification accuracy was compared across all ensemble combinations using the NBC model combination approach. Figure 5.18 depicts the overall and minority class CCR for each of the 26 ensemble combinations. The size of the point is based on Q_{av} such that larger circles represent lower values of Q_{av} (i.e. higher diversity). The ensemble with five base classifiers achieves moderate diversity while maintaining the highest overall

CCR and third highest minority class CCR. In summary, the set of five base classifiers achieves an appropriate balance among diversity measures, overall CCR, and minority CCR.

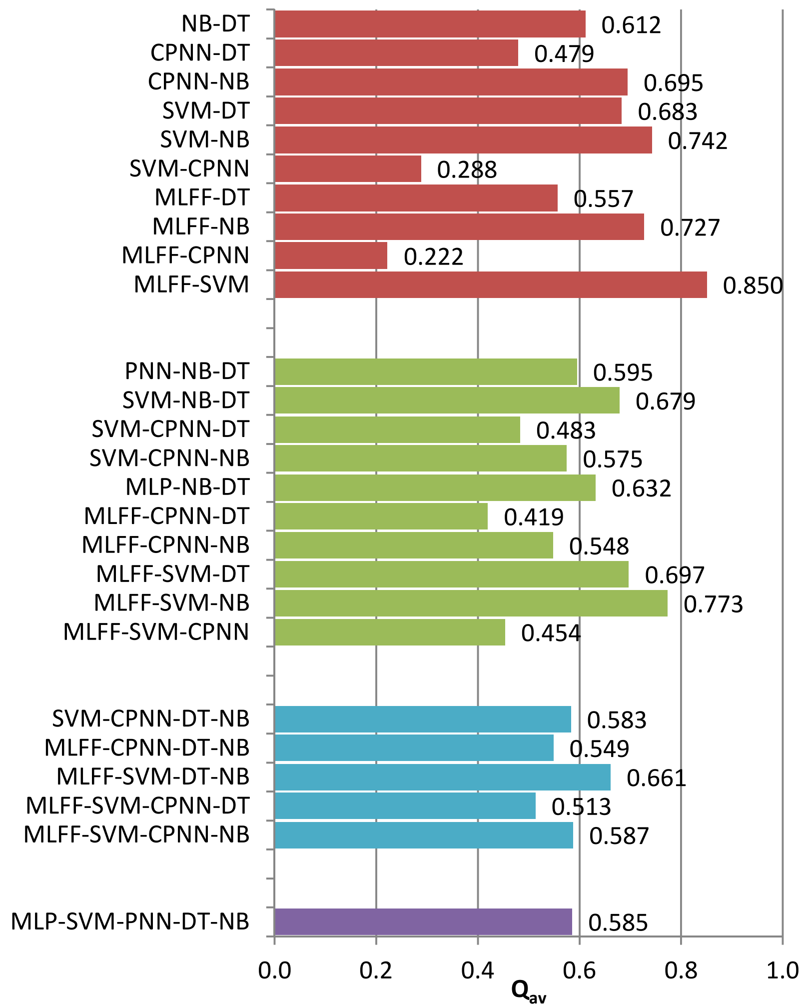


Figure 5.17 Diversity Statistic (Q_{av}) for Various Ensemble Combinations

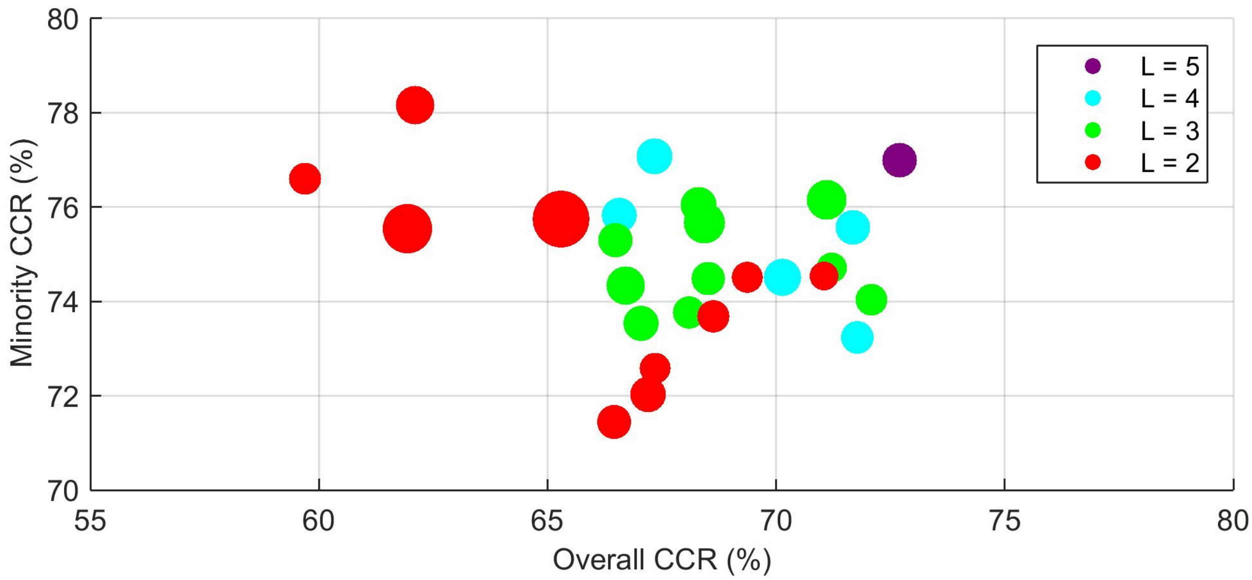


Figure 5.18 Classifier Diversity by Overall CCR and Minority Class CCR for Base Classifier Combinations

5.5 Conclusions

The three models represent increasing levels of detail in the input data and output classification resolution. Beginning with WIM data only, the body type of the tractor and trailer units of five axle semi-tractor trailers (FHWA class 9) was estimated at the aggregate volume level. The models accurately predicted individual classification of two tractor body types and volumes of five trailer body class groups including vans, tanks, platforms, containers, and others. Increasing the input data resolution to incorporate inductive signatures, four body class models were developed distinguishing 47 body classes, 22 of which had classification accuracy of over 70% and 19 of which had volume error less than 10%. Although the inductive signature model separated vehicles into broad axle configuration categories, inductive signatures alone are not the ideal mechanism for distinguishing exact axle configurations. Thus, the next model combined inductive signature and WIM data to distinguish 63 body classes with eight separate body class models- one for each axle configuration class defined by the FHWA scheme. This model represents the highest level of input resolution as it includes axle spacing measures, length, and in some cases axle weights along with inductive signature features. The output resolution is also at the highest among the three models because not only does the model predict body class for each vehicle but each vehicle record also consists of a measured weight and axle configuration.

The MCS approach was superior to any of the five base classifiers when comparing the CCR for each body class. While many of the base classifiers produced more accurate classifications for <u>some</u> classes, no single base classifier was capable of producing accurate classifications across <u>all</u> classes. The MCS approach with NBC combination efficiently and effectively combined the five base classifier predictions by considering the performance of the base classifiers on an independent validation dataset. In this way, the MCS with NBC was able to produce classification accuracy for each class in some cases exceeding the classification accuracy of even the best base classifier. Compared to the MV method of model combining, the NBC method achieved the same or better classification accuracy across all body classes than the MV approach.

Spatial transferability analysis was performed on the model by removing data from the Irvine site from model development and then testing the trained model on that site. Although the overall classification rate was lower than desirable due to cross classification between enclosed vans, reefer vans, and 53ft containers, the model correctly predicted several unique classes including auto transport, low boy platform, drop frame van, and dump trailers. The model accurately depicted the low to non-existent volume of commodity specific body classes including logging, livestock, agricultural, and 40ft reefer containers.

From the spatial testing it is clear that inclusion of a variety of site data is crucial for developing an accurate model. The four sites selected for data collection each possessed a unique array of body classes and were selected based on this diversity, thus leaving any out of model development would result in less than superior performance. Ideally, as demonstrated by the spatial transferability analysis data other sites around the state should be incorporated into the model for more accurate classification.

A comparison of the MCS with five base classifiers (MLFF, SVM, CPNN, NB, and DT) to all other possible combinations of varied ensemble size was carried out to demonstrate the superiority of the chosen set of five base classifiers. The Q-statistic suggested by Kuncheva and Whitaker (2003) was used to assess the diversity of each of the 26 ensemble combinations. While the MCS with five classifiers did not possess the highest diversity, it did achieve the highest overall CCR and third highest minority class CCR. This evidence supports the conclusion that the five base classifiers used in the MCS for all body classification models developed in this dissertation represents the best possible combination.

Further improvements can be made through alternate signature preprocessing methods, further refinement of the body classification scheme within each class, collecting additional data at specific sites within the State and adapting model combining techniques. In terms of model combining, a threshold on the value of support estimated for each class under NBC could be applied to improve performance. Estimated probabilities falling below the threshold could be marked as 'unclassified'. This would introduce a tradeoff between prediction accuracy and the total number of classified records but could be beneficial for applications such as commercial vehicle enforcement, where extremely high accuracy is required.

6 Applications

Three applications of truck body class data are presented in this section including a time of day analysis, average payload estimation, and gross vehicle weight interpolation. The applications highlight specific contributions of this work and suggest ways in which State or Federal agencies might use the integrated data source and resulting models for policy analysis, travel forecasting, and operations.

6.1 Time of Day Analysis

Freight flows are commonly expressed as annual flows while policy decisions (e.g. capacity expansion or design of facilities) are based on daily or hourly flows (NCFRP, 2010). This discrepancy means that annual freight flows should be converted to decision level flows using a simplifying conversion assuming between 295 (about 85% of the working days per year) and 310 working days per year (NCFRP, 2010). By tying together body type with commodity carried, we can determine commodity flows at the hourly, daily, and seasonal aggregation levels to better account for temporal distribution of commodity flows. For emissions modeling, time of day truck count estimates such as what could be provided by implementing the ILD signature based classification model at a VDS site are critically important due to diurnal and seasonal air quality impacts of trucks. Furthermore, temporally continuous truck body classification data at either VDS or WIM sites can allow decision makers to evaluate policies such as time of day shifts targeted toward specific industries such as intermodal shipping since body class can be reasonably tied to certain industries. The current best method to obtain body class data, e.g. VIUS, falls short of accomplishing either of the outlined goals. VIUS does not provide any information on link/route or temporal patterns. Rather, only static proportions of body class can be inferred on the national scale. The next best approach would be to collect site specific classification data through direct observation, although this would be extremely labor intensive and any data collected would have a short lifespan due to seasonal and long term changes in body class proportions.

Using the integrated system we can estimate truck body class for each and every vehicle to produce temporally continuous estimates of body class. To demonstrate, body class volumes estimated from the WIM-Signature body class model are compared (Figure 6.1) against the directly observed volumes from the same time period in which the model was applied (November 7th, 2012) and static proportions gathered from the next day's observations (November 8th, 2012) for a select set of body classes within FHWA class 9 at the Fresno data collection site from 11:00AM to 4:30PM. The predictive model is able to match the volume and track the pattern of each body class more closely than the static based approach.

Likewise, data from the predictive model, observed, and static proportions are shown in Figure 6.2 for select body classes in FHWA class 5 (single unit trucks) for the Irvine site on October 2nd, 2012. For freight modeling it is important to separate freight (e.g. conventional truck) and non-freight (e.g. tow truck and light van/RV) vehicle movements which the WIM-signature model effectively achieved by matching the observed volumes and following the observed pattern more closely than the static proportions.

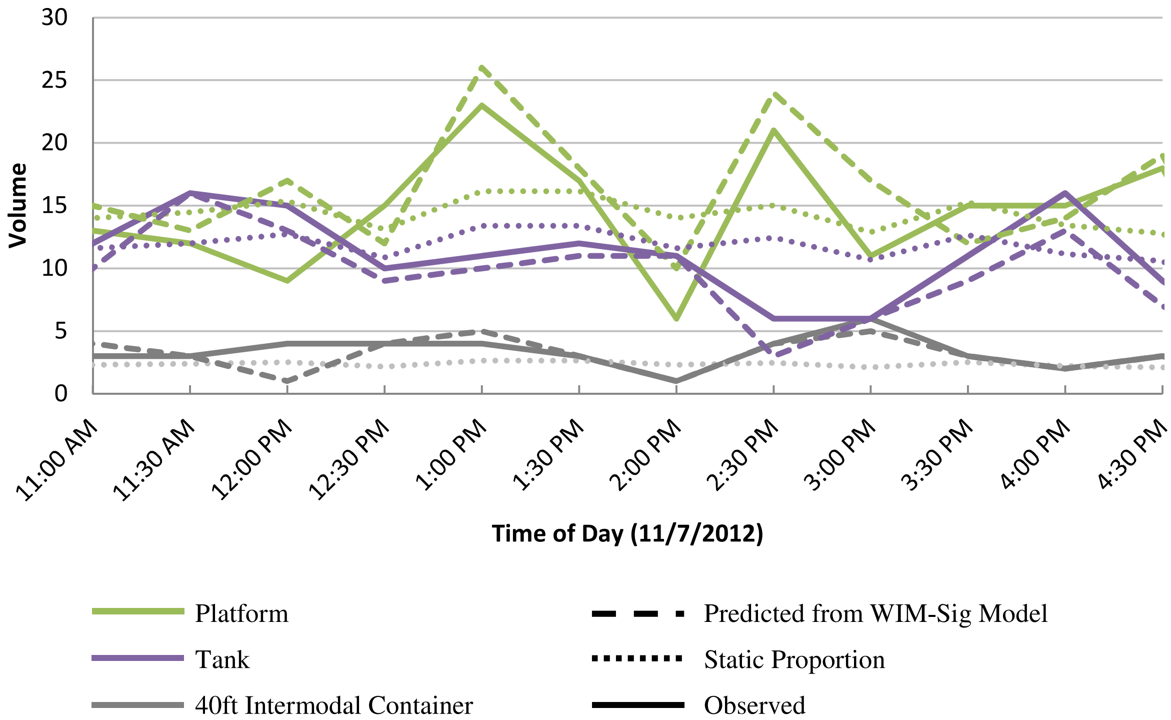


Figure 6.1 Time of Day Plot for Select Body Classes in FHWA Class 9 for Fresno

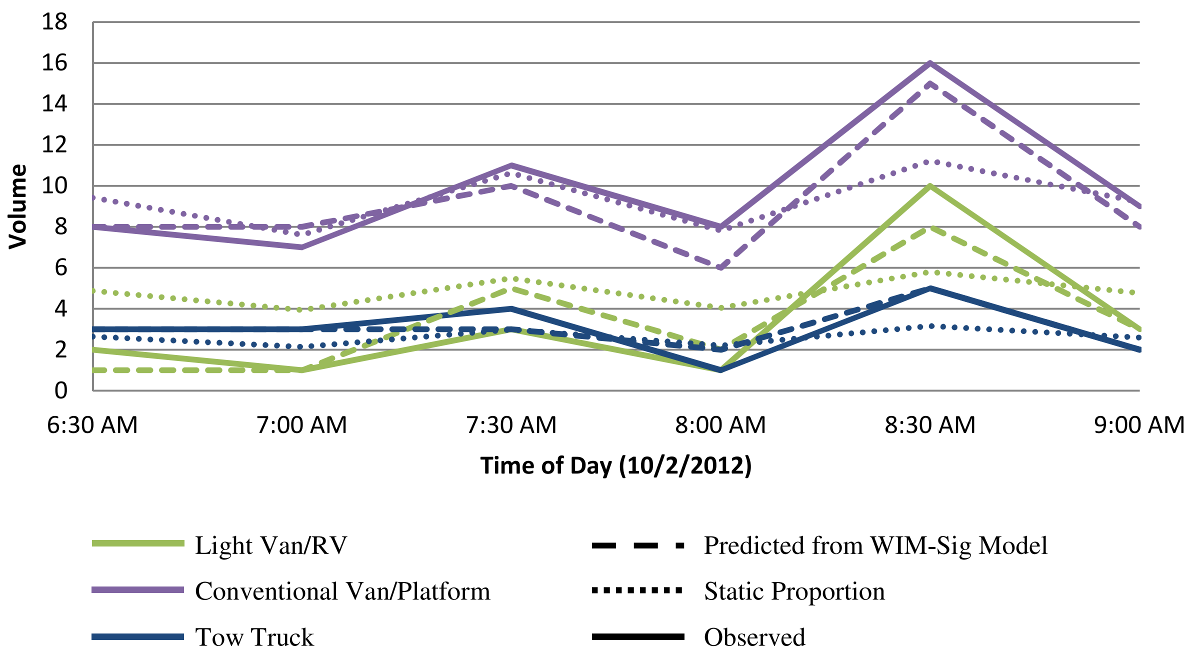


Figure 6.2 Time of Day Plot for Select Body Classes in FHWA Class 5 for Irvine

6.2 Average Payload Estimation

Determination of average payloads are a particularly useful application of the body class models developed with WIM and ILD signature data. Average payload refers to the weight of the commodity carried by a truck and is calculated by subtracting the unloaded weight of the truck from the loaded weight. Average payloads are typically computed for each State by body class and commodity group. For example, the Freight Analysis Framework (FAF) computes average payloads for nine body classes within the five axle semi-tractor trailer axle configuration group, and for 51 commodity groups.

Several different types of freight models exist ranging from simple truck flow factoring methods to more complex models based on economic, lane use, and transportation interactions (Chow et al., 2010). Commodity based freight forecasting models such as the California Statewide Freight Forecasting Model (CSFFM) first predicts the flow of commodities (in tons) across the State's freight analysis zones and subsequently converts commodity flows to truck trips using payload estimates. After assigning the predicted truck volumes to the highway network, the model is validated against WIM truck count data. Thus, payloads estimated from observed data would be useful as would truck count data by body type at both WIM and VDS stations. Beyond California, in developing a nationally recommended architecture for freight model development, the National Cooperative Freight Research Panel (NCFRP) highlighted two stages at which truck body class data could supplement modeling efforts: Estimation of payload and temporal factors and generation of service/non-freight trucks. NCFRP Report 8 (2010) also suggested that more detailed vehicle classification can assist in determining more general research areas such as truck trip chaining and distance based classification.

Commodity based freight forecasting models use surveys such as VIUS to develop factors to convert commodity tons to truck volumes (NCHRP, 2008). However, when compared to WIM data contained in the Vehicle Travel Information System (VTRIS), VIUS derived estimates of average payload and empty weights are often much higher than those recorded in VTRIS (Alam and Rajamanickam, 2007). Alam and Rajamanickam (2007) report this discrepancy across all 50 states, body classes, weight classes, and axle configurations. Unfortunately, because WIM data is limited to axle based class resolution comparisons to VIUS estimates can only be undertaken at a very aggregate level, e.g. for all FHWA class 9 trucks rather than by body type. VIUS derived data are prone to some error as respondents are asked to report their average empty weight, truck body type, and commodity transported over the course of an entire year. Deriving average payloads by commodity and body type can be somewhat erroneous as a result since a trucker can report combinations of commodity and body type that are inconsistent. For example, the payload equivalency factors derived from VIUS which are used by FAF provide a conversion for tons of 'live animals and live fish' to a platform trucks (Battelle, 2007). Furthermore, VIUS does not provide intermodal container truck information, and thus cannot be used to determine average payloads for container traffic. In FAF, where average payloads are used to determine payload equivalency factors by vehicle body type, the source of discrepancy between average payloads in observed WIM data and reported VIUS data are attributed to misclassifications of smaller, non-freight-related trucks into freight truck axle categories (FAF, 2012). For example, the FHWA Class 9 five axle truck category may contain three axle pickup trucks pulling larger two axle trailers which are not freight-related and due to their lower weight, skew the gross vehicle weight distribution of FHWA Class 9 trucks. In FAF, no adjustments are undertaken to account for the noted discrepancy.

Since truck body type is a general indication of the type of commodity transported, it could be used to derive average payloads. For instance, truck body types for trucks in FHWA class 9 (five axle semi-tractor trailers) such as logging, open top vans, hoppers, agricultural vans, specific tank types, cement/concrete, and refrigerated vans or containers tend to transport specific commodities. From the proposed integrated system body type can be predicted and truck weight is measured. Examples of such an application are demonstrated in this section for FHWA class 9 and 11/12 semi-tractor trailer combination trucks.

First, in order to determine the empty truck weight by body type, the gross vehicle weight (GVW) distribution is modeled as a Gaussian Mixture Model (GMM) of two or three components. A GMM is a linear composition of individual Gaussian distributions combined via a mixing parameter as follows (Hastie et al., 2009).

$$f(x) = \sum_{m=1}^{M} p_m \cdot \mathcal{N}(x; \mu_m, \Sigma_m)$$

where

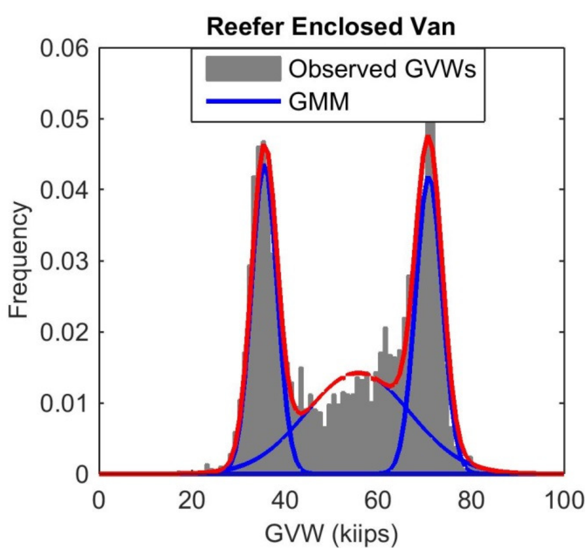
m = number of mixture components

$\mathcal{N}(\mu_m, \Sigma_m)$ = Gaussian distribution with mean μ and covariance matrix Σ

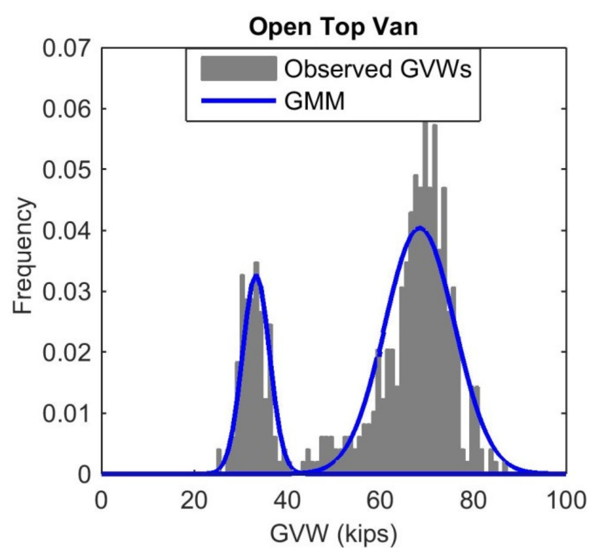
p_m is the mixing proportion

With three components (Figure 6.3(a)), the first component is assumed to represent the empty trucks, the second represents partially loaded trucks, and the third component represents the fully loaded trucks. For mixtures of two components (Figure 6.3(b)), the first component represents the distribution of empty weight while the second represents the distribution of loaded weight. Trucks of certain body classes tend to follow either tri-modal or bimodal GVW distributions. For example, tank trailers travel either fully loaded or empty for safety purposes related to the movement of liquids under partially loaded conditions.

The average payload is measured by subtracting the mean weight of the empty trucks from the mean weight of the loaded trucks. This follows the methodology used in VIUS and VTRIS for estimating average payloads. Thus, for the observed body class GVW data mixtures of only two components were calculated. In this case, the mean weight of the loaded trucks represents both the partially and fully loaded trucks. The average payload was then calculated from the observed data by subtracting the mean of the empty trucks from the mean of the partial and loaded trucks combined.



(a) Three component GMM



(b) Two component GMM

Figure 6.3 Examples of GMM for Van and Open Top Van Trailers

FAF estimates of the average payload by body type at the national level were compared against estimated payload factors from the groundtruthed data across all four data collection sites in California for the following body class groups:

1. Vans (basic enclosed, drop frame, insulated non-refrigerated, curtainside, beverage)
2. Platform (flatbed, lowboy, stake, and platform)
3. Bulk (dump, open top van, hopper)
4. Reefer
5. Logging

Estimated average payloads from the integrated WIM-Signature system were systematically lower than the VIUS estimates as shown in Figure 6.4 perhaps due to higher weight regulations allowed in many states whereas California has an 80,000lb weight limit. This highlights the fact that using nationally derived payloads might not be appropriate for state level analysis. A major contribution of the body class data derived from the integrated data source can provide more spatially disaggregate average payload estimates.

A second comparison of average payloads is made for body types that correspond to specific commodity groups. For example, agricultural vans are assumed to carry ‘all other agricultural products’ commodities and open top vans are assumed to carry ‘all other waste and scrap’. Note that average payloads of containers are reported in VIUS only for the commodity labeled ‘empty shipping containers’. For this commodity/body type combination, only the average weight of the unloaded (left most GMM distribution) was used. Again, the payloads estimated from VIUS tend to be higher than those from the integrated system for the same hypothesized reasons.

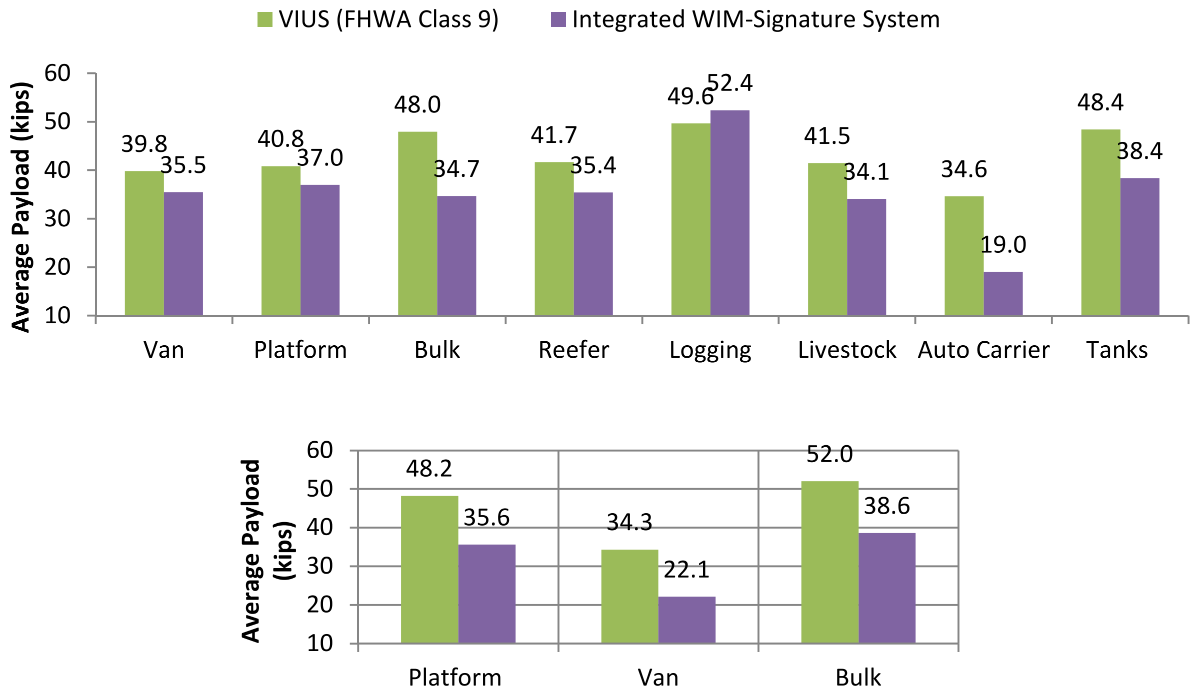


Figure 6.4 Average Payloads by VIUS Body Class estimated from VIUS and the Integrated WIM-Signature System

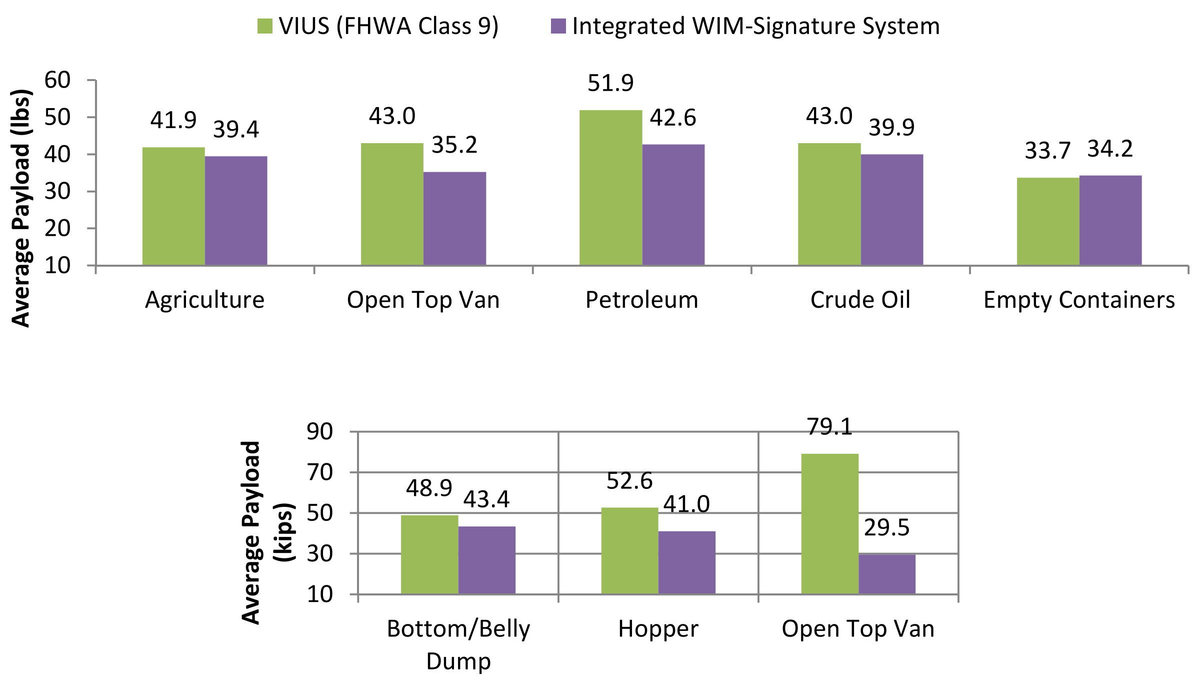


Figure 6.5 Average Payloads by VIUS Commodity estimated from VIUS and the Integrated WIM-Signature System

6.3 Gross Vehicle Weight Interpolation

Truck weight data is key for pavement management, emissions estimation, and freight modeling but is not widely collected since it requires WIM or static scales. VDS, even those equipped to collect ILD signatures, do not measure weight nor do GPS based tracking methods. However, if weight measurements can be obtained at VDS then truck weight data will be available at more than just the sparse WIM locations thus providing valuable data for the abovementioned applications. The objective of this section is to estimate gross vehicle weight (GVW) distributions at loop detector stations using a combination of body class volume and spatial relationships between VDS and WIM detectors.

6.3.1 Methods

The overarching premise to this analysis is that GVW distributions can be modeled as GMM as shown in Section 6.2. Each site is assumed to possess a GVW distribution following a GMM comprised of three components represented by three means, three variances, and three mixing proportions as follows:

$$f(x) = p_1 \cdot \mathcal{N}(x; \mu_1, \Sigma_1) + p_2 \cdot \mathcal{N}(x; \mu_2, \Sigma_2) + p_3 \cdot \mathcal{N}(x; \mu_3, \Sigma_3)$$

where

$\mathcal{N}(\mu_m, \Sigma_m)$ = Gaussian distribution with mean μ and covariance matrix Σ

p_m is the mixing proportion

To estimate a GMM at a new site, nine parameters (p_m, μ_m, Σ_m) need to be determined. To determine these parameters, two approaches are suggested.

First, each body class exhibits a uniquely shaped GVW distribution such that the overall GVW at a site is a mixture of the GVW distributions for each body class at that site. This means that the overall GVW distribution at a site is the volume weighted combination of each body classes' individual GVW distribution. To demonstrate, each of the five body class groups shown in Figure 6.6 consists of a three component mixture model that have been combined via a GMM of 5 by 3 (i.e. 15) components weighted by their corresponding volume to produce the overall GVW distribution shown in the bottom right of the figure. Moreover, certain body classes such as tanks and platforms exhibit unique GVW patterns. For example, tanks travel either loaded or empty for safety purposes resulting in GVW distributions with two clear peaks. Under these principles, a regression model was developed to relate body class volumes at each site to the GMM parameters (p_m, μ_m, Σ_m) for m = 1:3. Nine regression models were estimated, one for each dependent variable (i.e. each GMM parameter) using the volumes of vans, tanks, platforms, container, and 'other' trailer body class volumes as independent variables. The linear regression model takes the following form:

$$p_m = \beta_{m,0} + \sum_{b=1}^{B} \beta_{m,b} X_b$$

$$\mu_m = \beta_{m,0} + \sum_{b=1}^{B} \beta_{m,b} X_b$$

$$\Sigma_m = \beta_{m,0} + \sum_{b=1}^{B} \beta_{m,b} X_b$$

where m = the m^{th} GMM component (m = 1…3)

$\beta_{m,0}$ = constant

$\beta_{m,b}$ = regression coefficient for mth GMM component for body class b

X_b = body class volumes for body class b

To produce a GVW distribution, the estimated component parameters would be combined in a final mixture as follows:

$$f_j(x) = \sum_{m=1}^{3} p_m \cdot \mathcal{N}(x; \mu_m, \Sigma_m)$$

where

$\mathcal{N}(\mu_m, \Sigma_m)$ = the mth Gaussian distribution for site i with mean μ and covariance matrix Σ

p_m = mixing proportion

To apply the model, body class volumes at a VDS site would be estimated via the ILD signature classification model and used to predict each of the nine mixture model components. This model assumes a linear relationship between body class volume and GMM parameters and also assumes a static relationship between body class volume and GMM parameters across space. The latter is a simplifying assumption to be accounted for by the second approach.

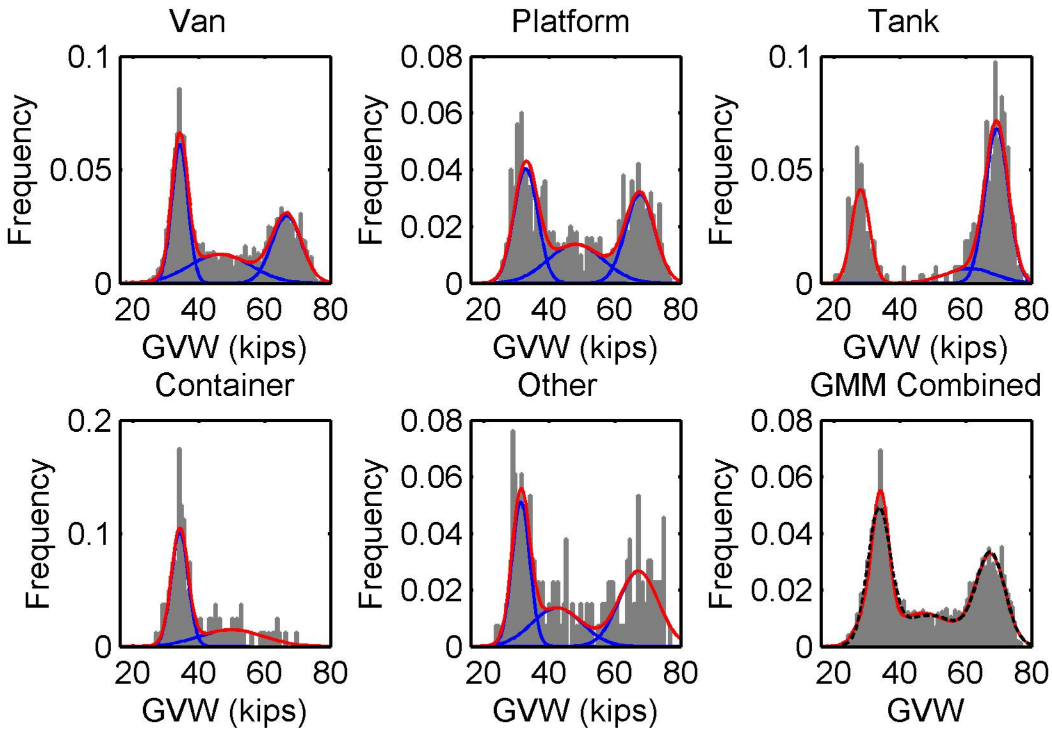


Figure 6.6 Example of GVW distribution by Body Class Group Contributing to Overall Site GVW Distribution

Second, GVW distributions are related spatially such that sensors along the same route in the same direction within the same region see similar GVW distribution patterns. Figure 6.7 shows a small subsample of GVW distributions for FHWA class 9 trucks at four WIM sites in Northern California in the southbound direction along I-5 and SR-97. Each of the sites has a significant volume of loaded trucks. This is due to shared trips along common routes and commodity flow patterns within a region. Given a reasonable assumption about spatial relationships between sites, a GMM can be estimated at a VDS by combining the GMMs at each of the sites that are spatially related to the VDS site using the assumed spatial distances as weights in the mixture model. Thus, for site j, the GMM components μ and Σ can be estimated as follows:

$$f_j(x) = \sum_{i=1}^{N} \sum_{m=1}^{3} W_{i,j} \cdot \mathcal{N}\left(x; \mu_{1,i}, \Sigma_{1,i}\right)$$

where

N = number of neighboring sites, i = 1…N

$\mathcal{N}(\mu_{m,i}, \Sigma_{m,i})$ = the mth Gaussian distribution for site i with mean μ and covariance matrix Σ

$W_{i,j}$ = spatial distances between sites i and j used as a mixing proportion

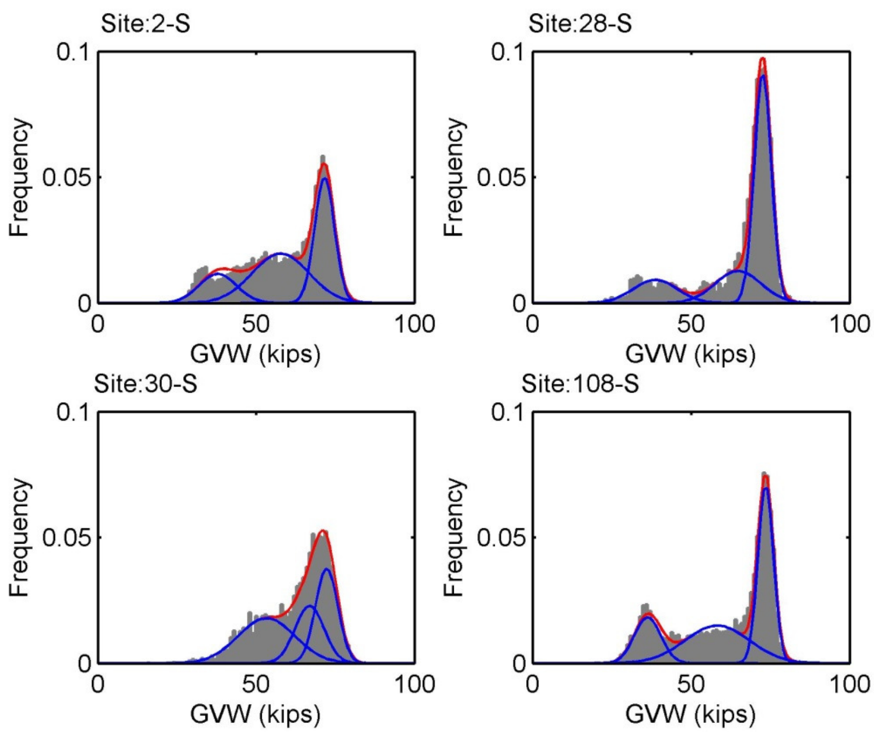


Figure 6.7 GVW Distributions along Southbound I-5 and SR-97 in Northern California

A common method to assess spatial relationships is to use coordinate locations, however this fails for directional data where sites of opposite directions share the same coordinate but tend to have very different GVW distributions. For example, at the port of Long Beach, most incoming container traffic in the westbound direction is heavily loaded while the outgoing container traffic in the eastbound direction is empty. Using route based distances would also not account for bi-directional sites, nor would it accurately capture the spatial relationship for trucks. For example, I-5 and SR-99 are parallel routes in the central valley and sites located at Willows along I-5 and Chico along SR-99 are only 90 miles apart by highway routes but would never reasonably see the same trucks and therefore might not have the same GVW weight distribution patterns.

In order to derive reasonable spatial relationships between sites, GPS data from the American Trucking Research Institute (ATRI) was used to assess the number of shared trips between sites. The sampling period and sampling frame of the ATRI GPS data are limited. The samples were obtained from four two-week periods from the month of February, May, August and November in 2010, and were limited to trucks that subscribe to the program. Trucks in ATRI tend to travel long distance, hence, there might be bias in the spatial patterns learned from the ATRI data. Still, ATRI GPS data can be used to evaluate the number of shared trips between WIM and VDS sites.

6.3.2 Data

A spatially diverse set of WIM sites with GVW data was needed to model the proposed two solutions described above. The data collected for body classification modelling consisted of only four sites spread across California and was therefore not dense enough to use to estimate a reasonable model. Instead, archived WIM data from 2010 was used. Since

WIM data contains GVW, axle spacing, and vehicle length measures but not body class, the WIM-only body class volume model (Section 5.1) was applied to estimate body class volumes of FHWA class 9 trucks. In summary, GMM parameters (p_m, μ_m, Σ_m) representing the GVW distribution and body class volumes (vans, platforms, tanks, containers, other) were estimated for all 114 sites included in the archived WIM data for the year 2010.

The time aggregation level was determined by examining the time of day (off peak, AM peak, midday, and PM peak), day of week (Monday through Friday), and seasonal (fall, spring, summer, winter) changes in GVW distribution parameters. For exposition purposes, the models were developed for data disaggregated to the midday (10am to 2PM) time period on Wednesdays in the Fall season.

Finally, WIM system measurements can contain systematic measurement error due to sensor calibration issues. Although there are sophisticated methods (Jeng et al., 2015) by which to assess calibration issues, a simple approach of normalizing each vehicles GVW measurement by the weight of the steering axle was employed for this analysis. The steering axle has a relatively static weight across locations and body types so it can be used as a reference for calibration error. All GVWs displayed in the following tables and figures reference the normalized GVW.

ATRI GPS pings converted to truck trip trajectories have poor resolution due to the 15 minutes between consecutive pings. As a result, truck trip trajectories (shown as green lines in Figure 6.8) could not be directly "snapped" to the road network and linked to WIM sites to derive the spatial weight matrix. Instead, screenlines were manually drawn at each of the sites for each direction to capture the truck trip trajectories passing through a site. After placing screenlines, the number of truck trip trajectories that passed through each pair of WIM sites were counted and converted into a directional spatial weight matrix (a sub-sample shown in Table 6.1) with cells(i,j) representing the number of shared trips from WIM site i to WIM site j. Figure 6.9 shows an example of the resulting spatial relationships arising from the screenline capture approach for the northbound Lodi WIM site located along I-5 in the Sacramento area. The site with the most shared trips is WIM site number 105 with 969 shared trips.

Figure 6.8 ATRI Truck Trip Trajectories

Table 6.1 Directional Spatial Weight Matrix from GPS Truck Trip Trajectories

Row Labels	1_N	1_S	10_N	10_S	100_S	101_N	102_N	102_S	1
1_N		0	70	0	0	0	135	0	
1_S	0		0	64	0	0	0	128	
10_N	70	0		0	0	0	1611	0	
10_S	0	64	0		0	0	0	1506	
100_S	0	0	0	0		0	0	0	
101_N	0	0	0	0	0		0	0	
102_N	135	0	1611	0	0	0		0	
102_S	0	128	0	1506	0	0	0		

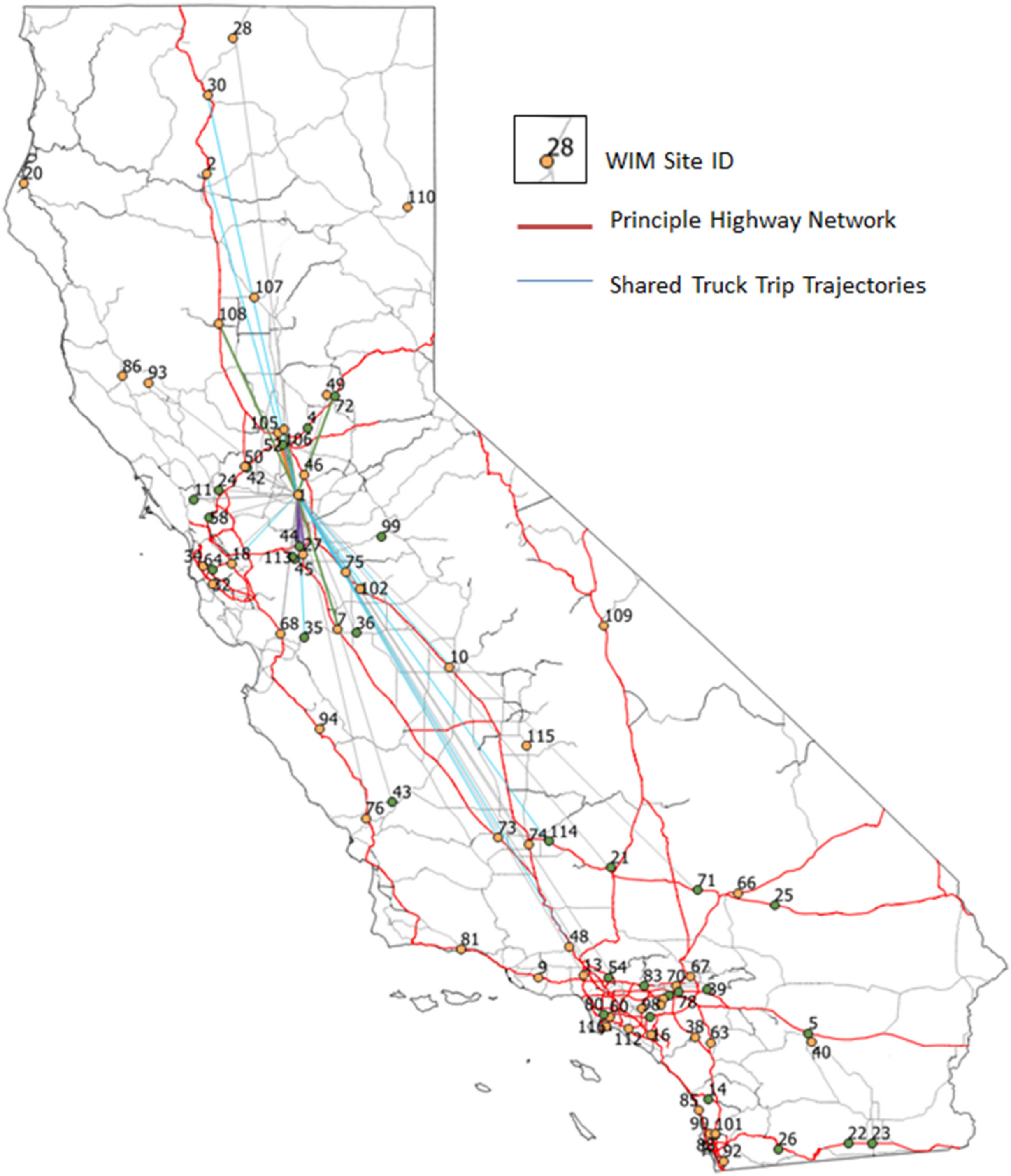


Figure 6.9 Shared Truck Trip Trajectories with the Lodi Northbound WIM Site as an origin

6.3.3 Results

The Kolmogorov-Smirnov (KS) test was used to assess the fit of the GVW distributions resulting from the regression and spatial weight based methods. The null hypothesis was that the estimated distribution is from the same continuous distribution as the observed GVW data. The alternative hypothesis was that the estimated distribution is from a different continuous distribution than the observed GVW data. Testing was performed by holding out one site from model development (i.e. estimation of the regression coefficients) and then applying estimated model to the data from the held out site. This process was repeated for all 112 of the sites in the dataset. Two sites were identified as outliers based on their observed GVW mean and variance, leaving 110 viable samples for modeling. In total, 93 stations had shared truck trajectories from which a GMM based on spatial weights could be estimated. For the regression based approach, 65.2% of the sites failed to reject the null hypothesis ($\alpha = 0.05$). This means that for 72 of the 110 sites their estimated GVW distributions matched their observed GVW distribution. For the spatial weight based approach, 67.7% of the sites failed to reject the null hypothesis ($\alpha = 0.05$) meaning that for 63 of the 93 sites the estimated GVW distribution matched the observed distribution.

Lastly, the regression and spatial weight based models were combined to produce a final GMM model for each site by weighting each of the models equally. For the combined model approach, 65.2% of the sites failed to reject the null hypothesis. Detailed results show that for some cases, where both the regression and spatial weight models failed to match the observed data, the combined model provided a suitable match.

Results for a sample of directional GVW distributions are shown in Figure 6.10 for WIM sites 10 north and southbound along I-5 in Fresno in central California and sites 22 east and westbound along I-8 near the southern California- Mexico border. The observed GVW distributions at each of these sites are quite different however for all except the regression model at the 22W site, the models produced statistically significant matches to the observed data.

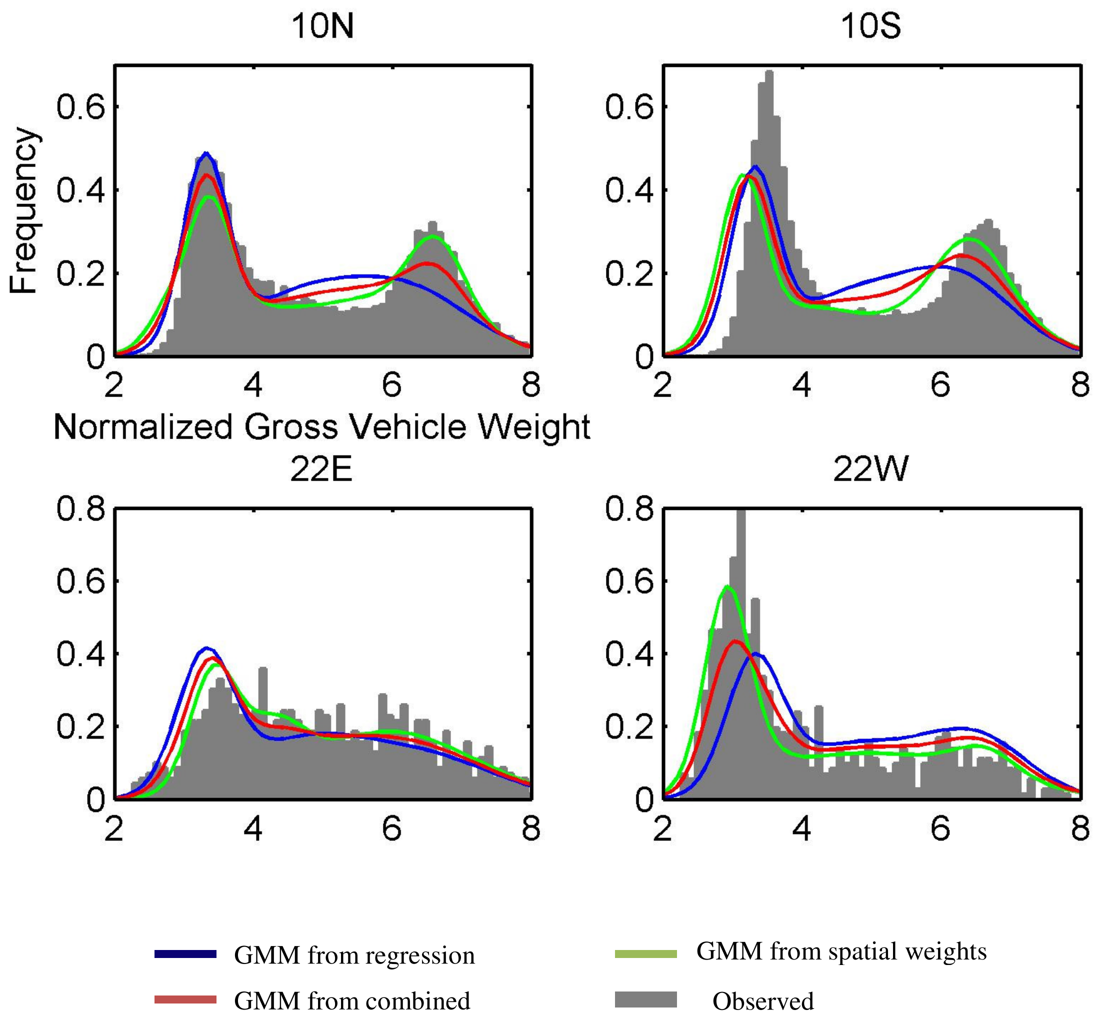


Figure 6.10 Spatial Interpolation of GVW Distributions Results

6.3.4 Conclusions

The spatial interpolation of GVW distributions is an example of the type of analysis that can be performed with knowledge of weight data. The results indicate that by combining body class volume estimates and incorporating spatial relationships between WIM sites, GVW distributions can be estimated with relative accuracy. This application serves as a baseline for what can be accomplished in regards to weight interpolation.

Several key areas for improvement should be undertaken in future studies. First, a more advanced normalization approach should be applied to the GVW data at each site prior to determining GMM parameters. Second, an obvious improvement will arise by predicting body class volumes based on ILD signature data rather than WIM data alone. With more accurate classification data, more accurate GVW distributions should be possible. Also, with the WIM-Signature based body classification method, GVW distributions can be stratified by body class, so that the spatial weight combination method can pull from the stratified GVW distributions rather than the overall distribution. Third, rather than using a global regression model, spatially based regression approaches could be evaluated.

7 Closing Remarks

7.1 Contributions

The method presented in this dissertation to integrate WIM and ILD signature technologies and the resulting models developed to predict detailed truck body class will uniquely fill the existing gaps in freight and air quality monitoring data sources by providing complete, temporally continuous, and spatially diverse truck characters data along major truck corridors. In this work, two methods were introduced to overcome the limitations of previous ILD signature based vehicle classification studies. First, a Multiple Classifier System (MCS) approach which combined the predictions of five independent classifiers including a multilayer feed forward neural network, a probabilistic neural network, a support vector machine, a decision tree, and a naïve Bayes classifier combined using Naïve Bayes Combination (NBC) was used to improve classification generalization. The MCS with NBC proved to be more accurate than any single classifier used in the ensemble and in some cases exceeded the accuracy of even the best classifier in the ensemble. Second, to account for class imbalance during model development the Synthetic Minority Oversampling Technique (SMOTE) algorithm which generates additional samples of minority class feature sets was used to induce higher classification accuracy for minority classes. Through the SMOTE algorithm body classes with low sample counts realized increased classification accuracy as high as 43% while only diminishing the performance of the majority class by at most 4%. Comparisons to previous classification models using ILD signature are difficult to make due to the low number of commercial vehicle samples used in previous efforts, however, the number of body classes depicted in this dissertation far exceed any found in existing research. In regards to this point, previous vehicle classification problems suffered from a lack of a comprehensive set of commercial vehicle data. In this dissertation, models were developed from around 33,000 commercial vehicle records representing over 60 body classes. The data itself is a valuable asset for truck characteristics analysis as it contains a very diverse array of body types, time periods, and locations.

Even though state transportation planning and air quality monitoring agencies would benefit most from the work described in this dissertation as shown in the Applications section (Chapter 6), there are many additional applications and potential uses. The table below outlines the major expected contributions of the proposed work.

Table 7.1 Summary of Contributions by Application Area

Application	Potential Use
Freight Modeling	• Payload factors that are typically estimated from VIUS can be supplemented, replaced, and/or corrected with observed truck body type volumes. • The ability to distinguish freight from non-freight trucks, the percentage of empty movements, and long and short haul trucks can be used for validation of freight forecasting models. • Seasonal and hourly traffic by truck body and commodity type can be used to convert annual flows to daily flows at the commodity and industry level.
Emissions Estimation	• Body class data can contribute to the development of more detailed emissions models which currently rely on broad weight or axle categories to estimate vehicle emissions. • Agencies can design policies and programs to reduce emissions that are aimed at specific industries that produce those commodities.
Operations and Management	• Infrastructure Management: The spatial weight interpolation method would allow for weight information to be available at a wider spatial and temporal range of state highways. This could allow for better monitoring of pavement damage. • Safety: The types of crashes by body type could be important since body type may be a predictor of accident severity and delay time. For instance, a tanker involved accident may cause more damage, be more dangerous, and cause more delay, then say an intermodal container involved accident since a tanker is more likely to be carrying fuel or other corrosive liquid. • Calibration: WIM stations can be evaluated for systematic measurement errors by considering truck body type and how body type relates to the occurrence of calibration errors

7.2 Future Work

While the work in this dissertation can fill many of the exiting gaps identified for freight forecasting, emissions modeling, and infrastructure management, there are several paths for improvement as well as additional applications that can be investigated. First, although the body classification scheme is very comprehensive it can be expanded by collection of additional data in regions of the state that may possess vehicles of different body types. This could improve the spatial transferability of the model and also provide additional data for body classes with low samples. Second, the MCS with NBC method employed a simple set of five base classifiers but, as shown in the diversity analysis, classification accuracy of the majority and minority classes benefited from incorporating an increased number of classifiers. Future work could investigate alternate sets of classifiers with increasing complexity of each base classifier as well as the architecture under which the base classifiers are designed. For example, one could employ a gating model such as a neural network to fuse the outputs of the base classifiers in the ensemble. Third, alternate feature sets and pre-processing methods could be developed to further improve classification accuracy. The methods in this dissertation relied on an interpolation approach to smooth signatures followed by extraction of inductive magnitudes and differences between interpolated magnitudes. A method such as that proposed by Tok (2008) to smooth distorted signatures prior to feature extraction could help with the spatial and temporal transferability under congested conditions. Lastly, the fusion of data at the feature level was only carried out for FHWA class 9 tractor trailers by parsing the inductive signature into tractor and trailer portions. Future work can focus on more advanced fusion algorithms as well as develop alternate architectures for data fusion. For example, the model could be multi-tiered with different WIM and/or ILD signature feature sub-sets used at each tier, or if using the MCS approach, different feature sub-sets could be used in each base classifier.

In terms of applications, the method outlined to spatially interpolate total vehicle weights at VDS from surrounding WIM data showed potential but suffered from lack of body class data. If body class data resulting from the body class models developed in this dissertation are available at a large number of sites, spatial weight interpolation could be performed by body class rather than the aggregate level allowing for more detailed and potentially more accurate total weight distributions. Also, the spatial relationship matrix can be augmented by other types of vehicle tracking data. Besides GPS records, vehicle re-identification techniques using inductive signature and WIM data separately or in conjunction has the potential to produce truck OD patterns. The OD patterns could then be used to spatially relate WIM and VDS sites.

7.3 Conclusions

By leveraging existing infrastructure, a novel, readily implementable approach to integrate two exceptionally complementary data collection devices, WIM systems and advanced ILDs, to produce high resolution truck data was developed in this dissertation. For each vehicle traversing a WIM site, an ILD signature was collected along with WIM measurements such as axle spacing and weight which were then used as inputs to a series of truck body classification models that encompass all truck classes in the axle-based FHWA classification scheme. A MCS with NBC was adopted for classification while the SMOTE algorithm was implemented for pre-processing model training data to account for class imbalance.

Three families of classification models were developed showcasing increased levels of output class resolution at increased levels of input data resolution. The WIM only model which uses only WIM variables as input can be used for historical body class volume analysis given only historical WIM measurement data. This would allow for freight model validation to backcast years. A major benefit of the ILD signature model is that it is intended to be implemented at VDS sites thus converting simple traffic count stations into classification stations. As an application, a method to interpolate vehicle weight distributions at VDS sites based on surrounding WIM sites and body class characteristics was outlined to further demonstrate the potential of the ILD signature model. Knowledge of weight distribution at VDS sites is extremely useful for emissions modeling and pavement infrastructure planning and maintenance. Finally, the most complex model, which integrated WIM measurements and ILD signatures, was able to classify over 63 body types across the eight axle configuration groups. The main benefit of this model is not only increased body classification resolution, but the ability to associate each body class with axle and total vehicle weight measurements, which allows for better prediction of several freight model parameters including average payload estimation by body class and for some commodities.

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Appendix A1: WIM-Only Body Classification Model Results

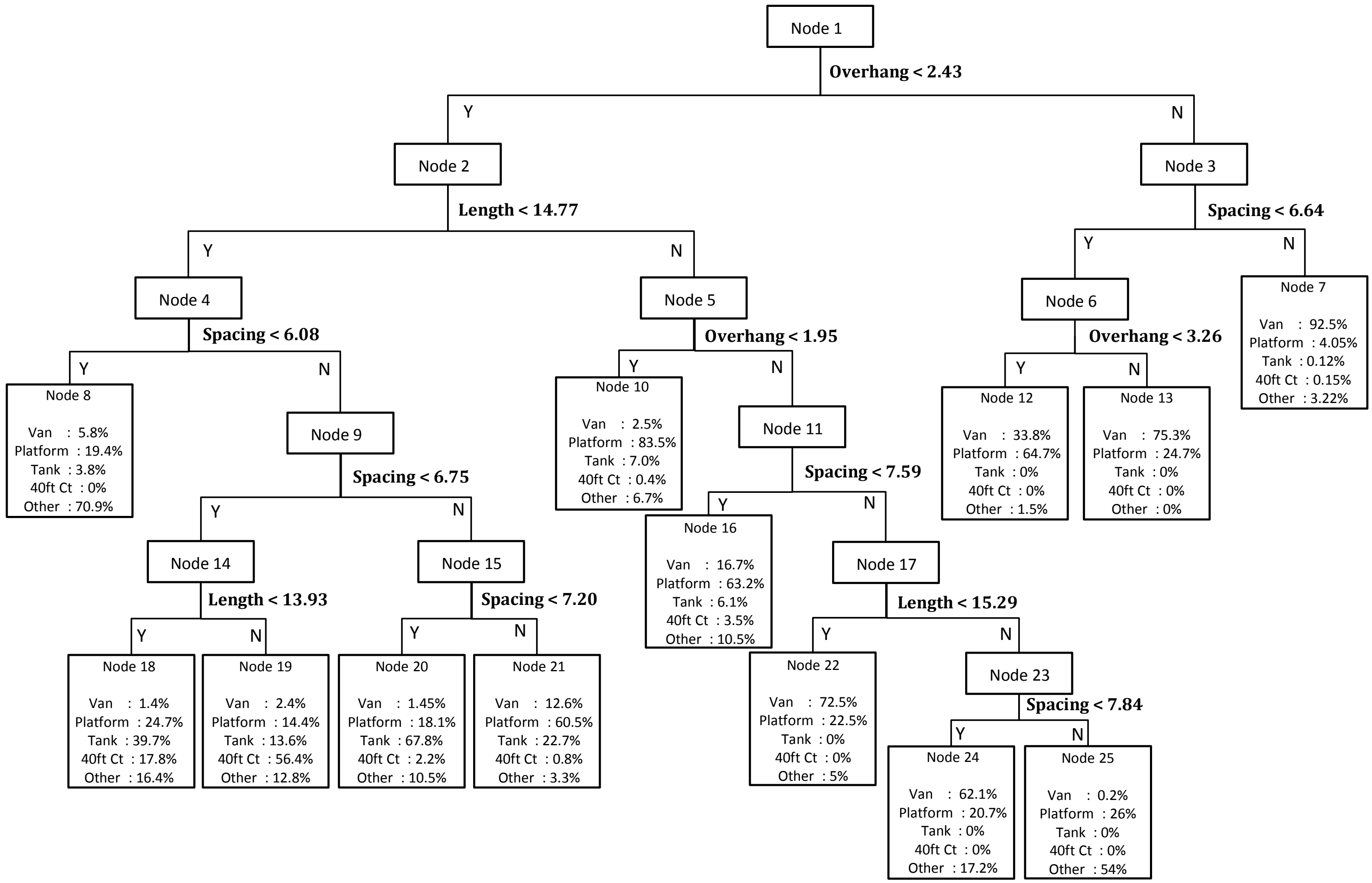

Figure A-1 Adapted Decision Tree Model for WIM-Only Trailer Body Classification

Table A1-1 Results of the WIM-Only Trailer Body Classification Model for Fresno, Redding, and Willows

Site		Van	Platform	Tank	40ft Container	Other	Overall APE (%)
Overall	Actual Volume	2353	515	208	108	139	3323
	APE (%)	**1.7%**	**5.4%**	**21.2%**	**31.5%**	**22.3%**	**5.3%**
Fresno	Actual Volume	1131	286	160	61	72	1710
	Estimated Volume	1151	294	131	47	87	
	Difference	20	8	-29	-14	15	86
	APE (%)	**1.8%**	**2.8%**	**18.1%**	**23.0%**	**20.8%**	**5.0%**
Redding	Actual Volume	223	53	11	4	29	320
	Estimated Volume	224	60	9	3	25	
	Difference	1	7	-2	-1	-4	15
	APE (%)	**0.4%**	**13.2%**	**18.2%**	**25.0%**	**13.8%**	**4.7%**
Willows	Actual Volume	999	176	37	43	38	1293
	Estimated Volume	980	189	50	24	50	
	Difference	-19	13	13	-19	12	76
	APE (%)	**1.9%**	**7.4%**	**35.1%**	**44.2%**	**31.6%**	**5.9%**

Table A1-2 APE comparisons of observed site specific proportions and ADT approaches by Site and Body Group

Site		Van	Platform	Tank	40ft Container	Other	Overall APE (%)
Overall	Actual Volume	2353	515	208	108	139	3323
	APE (%)	**4.8%**	**13.2%**	**14.9%**	**25.9%**	**27.3%**	**8.4%**
Fresno	Actual Volume	1131	286	160	61	72	1710
	Estimated Volume	1077	308	188	51	86	
	Difference	-54	22	28	-10	14	128
	APE (%)	**4.8%**	**7.7%**	**17.5%**	**16.4%**	**19.4%**	**7.5%**
Redding	Actual Volume	223	53	11	4	29	320
	Estimated Volume	240	51	10	3	19	
	Difference	17	-2	-1	-1	-10	31
	APE (%)	**7.6%**	**3.8%**	**9.1%**	**25.0%**	**34.5%**	**9.7%**
Willows	Actual Volume	999	176	37	43	38	1293
	Estimated Volume	957	220	39	26	52	
	Difference	-42	44	2	-17	14	119
	APE (%)	**4.2%**	**25.0%**	**5.4%**	**39.5%**	**36.8%**	**9.2%**

Table A1-3 APE comparisons of VIUS proportions and ADT approaches by Site and Body Group

Site		Van	Platform	Tank	40ft Container	Other	Overall APE (%)
Overall	Actual Volume	2353	515	208	108	139	3323
	APE (%)	**22.3%**	**54.8%**	**52.4%**	**100.0%**	**306.5%**	**43.6%**
Fresno	Actual Volume	1131	286	160	61	72	1710
	Estimated Volume	941	410	68	0	291	
	Difference	-190	124	-92	-61	219	686
	APE (%)	**16.8%**	**43.4%**	**57.5%**	**100.0%**	**304.2%**	**40.1%**
Redding	Actual Volume	223	53	11	4	29	320
	Estimated Volume	176	77	13	0	54	
	Difference	-47	24	2	-4	25	102
	APE (%)	**21.1%**	**45.3%**	**18.2%**	**100.0%**	**86.2%**	**31.9%**
Willows	Actual Volume	999	176	37	43	38	1293
	Estimated Volume	711	310	52	0	220	
	Difference	-288	134	15	-43	182	662
	APE (%)	**28.8%**	**76.1%**	**40.5%**	**100.0%**	**478.9%**	**51.2%**

Appendix A2: Inductive Signature Only Body Classification Model Results

Table A2-1 Inductive Signature Only Model Tier 3 Single Unit Truck with Trailer Cross Classification Table

	SU small trailer	Tow Truck w/ towed vehicle	Platform-Platform	Dump-Dump	Tank-Tank	RV w/ Towed Vehi-cle	Concrete w/Lift Axle	Dump w/ Lift Axle	**Total**	**Correct**	**CCR (%)**	**SMOTE Result (%)**
SU small trailer	496	2	2	1		10		4	515	496	96.3	-0.4
Tow Truck w/ towed vehicle	1	6				1			8	6	75.0	25.0
Platform-Platform	1		13	3	3				20	13	65.0	15.0
Dump-Dump				87					87	87	100.0	0.0
Tank-Tank			7		23				30	23	76.7	-6.6
RV w/ Towed Vehicle	4	3				42			49	42	85.7	-10.2
Concrete w/Lift Axle							34		34	34	100.0	0.0
Dump w/ Lift Axle							1	2	3	2	66.7	0.0
Total	502	11	22	91	26	53	35	6	**746**	**703**	**94.2**	*-0.6*
Correct	496	6	13	87	23	42	34	2				
Precision (%)	98.8	54.5	59.1	95.6	88.5	79.2	97.1	33.3				
Volume APE (%)	2.5	37.5	10.0	4.6	13.3	8.2	2.9	100.0				

Table A2-2 Inductive Signature Only Model Tier 3 Multiple Semi Tractor Trailer Combination Trucks Cross Classification Table

	Enclosed Van	Platform/Tank	Dump	Pneumatic Tank	Hopper	Agricultural Van	Low Chassis Van/Platform	**Total**	**Correct**	**CCR (%)**	**SMOTE Result (%)**
Enclosed Van	235	10					8	253	235	**92.9**	2.0
Platform/Tank	10	109	1	1				121	109	**90.1**	0.8
Dump		3	114		8		1	126	114	**90.5**	5.6
Pneumatic Tank		2		27	7			36	27	**75.0**	0.0
Hopper			3		42	1		46	42	**91.3**	13.0
Agricultural Van						2		2	2	**100.0**	0.0
Low Chassis	3						17	20	17	**85.0**	-5.0
Total	248	124	118	28	57	3	26	**604**	**546**	**90.4**	3.0
Correct	235	109	114	27	42	2	17				
Precision (%)	94.8	87.9	96.6	96.4	73.7	66.7	65.4				
Volume APE (%)	2.0	2.5	6.3	22.2	23.9	50.0	30.0				

Appendix A3: WIM-Signature Body Classification Model Result

Table A3-1 FHWA class definition with body class unit modeled and number of body classes

FHWA Class	FHWA Class Description	Number of Body Classes
FHWA 4	2 or 3 axle Buses	4
FHWA 5	2 axle, 6 tires (dual rear tires)	10
	2 axle with small trailer	5
FHWA 6	3 axle	8
FHWA 7	4 or more axles	4
FHWA 8	3 or 4 axles	5
FHWA 9	5 axles	16
FHWA 10	6 or more axles	4
FHWA 11	5 or less axles	7
FHWA 12	6 axles	
FHWA 13	7 or more axles	-
FHWA 14	5 axles	5

Table A3-2 FHWA Class 4 Model Training Data

Body Class	Volume
Van or Platform	33
30ft Bus with tandem rear axle (30ft Bus Tandem)	19
30ft Bus with single rear axle (30ft Bus Single)	9
RV	2
TOTAL	**63**

Table A3-3 FHWA Class 4 Cross Classification Table

Body Class	Van or Platform	30ft Bus Tandem	30ft Bus Single	RV	**Total**	**Correct**	**CCR (%)**	**SMOTE Difference (%)**
Van or Platform	24		2		26	24	**92.3**	3.8
30ft Bus Tandem		10	1		11	10	**90.9**	-9.1
30ft Bus Single			25		25	25	**100.0**	0.0
RV				0	0	0	**-**	-
Total	24	10	28	0	**62**	**59**	**95.2**	0.2
Correct	24	10	25	0				
Precision (%)	**100.0**	**100.0**	**89.3**	**100.0**				
Volume APE (%)	**7.7**	**9.1**	**12.0**	**-**				

Table A3-4 FHWA Class 5 Trailer Axle Detection Model (Tier 2) Cross Classification Table

Axle Group	No trailer	Trailer	Total	Correct	CCR (%)
No trailer	913	3	916	913	**99.7**
Trailer	4	27	31	27	**87.1**
Total	917	30	947	940	**99.3**
Correct	913	27			
Precision (%)	***99.6***	***90.0***			

Table A3-5 FHWA Class 5 without Trailer Training Data

Body Class	Volume	Body Class Group
Conventional Van (Conv. Van)	163	Conv. Van/Platform
Cab Over Van	159	Cab Over Van/Platform
Utility	131	Utility/Platform/Pickup
Pickup	98	Utility/Platform/Pickup
Light Van	87	Light Van/RV
Cab Over Platform (Type 1)	74	Cab Over Van/Platform
20ft Bus	65	
12 Pass Van	55	
30ft Bus	49	
Conventional Platform (Type 2)	45	Conv. Van/Platform
Platform for Autos (Type 3)	44	Tow Truck/ Platform
Pick-up type Platform (Type 0)	35	Utility/Platform/Pickup
Multi-stop van	33	Cab Over Van/Platform
Tow Truck	23	Tow Truck/ Platform
Bobtail	22	
RV	22	Light Van/RV
Wrecker	22	Utility/Platform/Pickup
Crane/Winch	16	Utility/Platform/Pickup
Dump	13	Other
Tank	12	Other
Garbage	4	Other
TOTAL	**1,172**	***10 Groups***

Table A3-6 FHWA Class 6 Training Data

Body Class	Count	Body Class Group
Dump	25	
Dumpster Transport	33	
Garbage	39	
Concrete	14	
Platform	22	Platform/Van/Tank/Other
Tank	10	Platform/Van/Tank/Other
Van	3	Platform/Van/Tank/Other
Crane/Winch	10	Platform/Van/Tank/Other
Bobtail	48	
Wrecker	1	Platform/Van/Tank/Other
30ft Bus	1	
Platform w/ Trailer	2	FHWA 6 w/ trailer
Van w/Trailer	1	FHWA 6 w/ trailer
Passenger Car w/Trailer	5	FHWA 6 w/ trailer
Crane/Winch w/Trailer	1	FHWA 6 w/ trailer
TOTAL	**215**	**8 Groups**

Table A3-7 FHWA 6 Cross Classification Table

	Dumpster	Bobtail	Plat-form/Van/Tank/Other	Dump	Garbage	Concrete	FHWA 6 w/ trailer	Bus	Total	Correct	CCR (%)	SMOTE Differ-ence (%)
Dumpster	75		8	4	7	1			95	75	78.9	-4.2
Bobtail		86	7	1					94	86	91.5	4.3
Platform/Van/Tank/Other	9		65	8	6	1			89	65	73.0	11.2
Dump	1	4	13	69	1				88	69	78.4	1.1
Garbage	4		2		23				29	23	79.3	-6.9
Concrete			5			11			16	11	68.8	-12.5
FHWA 6 w/ trailer			1				13		14	13	92.9	0.0
Bus								1	1	1	100.0	0.0
Total	89	90	101	82	37	13	13	1	**426**	**343**	**80.5**	1.4
Correct	75	86	65	69	23	11	13	1				
Precision (%)	84.3	95.6	64.4	84.1	62.2	84.6	100.0	100.0				
Volume APE (%)	6.3	4.3	13.5	6.8	27.6	18.8	7.1	0.0				

Table A3-8 FHWA Class 7 Training Data

Body Class	Count
Dump Tandem w/ Lift Axle	33
Concrete Tandem w/Lift Axle	14
Dump Triple	13
Garbage Triple	12
TOTAL	**72**

Table A3-9 FHWA Class 8 Trailer Axle Detection Model (Tier 2) Cross Classification Table

	FHWA 7	FHWA 3	FHWA 5	FHWA 8	Total	Correct	CCR (%)	Volume APE (%) [MAPE]
Two axle single unit truck with lift axle (FHWA 7)	2				2	2	100.0	0.0
Two axle small trucks with trailers (FHWA 3)		12		2	14	12	85.7	7.1
Two axle single unit truck with trailer (FHWA 5 w/ trailer)		2	48	11	61	48	78.7	19.7
Three or four axle semi-tractor trailer trucks (FHWA 8)		1	1	188	190	188	98.9	5.7
Total	2	15	49	201	**267**	**250**	**93.6**	**[8.9]**
Correct	2	12	48	188				
Precision (%)	100.0	80.0	97.9	93.5				

Table A3-10 FHWA Class 8 Training Data

Trailer Body Class	Volume	Trailer Body Class Group
Enclosed Van	171	Van
Basic Platform	25	Platform
Drop frame Van	11	Low Chassis Van/Platform
Beverage	7	
Low Boy Platform	6	Low Chassis Van/Platform
Agricultural Van	2	
Livestock	2	Low Chassis Van/Platform
TOTAL	224	**5 Groups**

Table A3-11 FHWA Class 8 Cross Classification Table

	Van	Platform	Low Chassis Van or Platform	Beverage	Agricultural Van	Total	Correct	CCR (%)	SMOTE Difference (%)
Van	143	3	2	1		149	143	96.0	-0.7
Platform	8	11	1			20	11	55.0	10.0
Low Chassis Van/Platform		2	7			9	7	77.8	0.0
Beverage				9		9	9	100.0	0.0
Agricultural Van					0	0	0	-	-
Total	151	16	10	10	0	**187**	**170**	**90.9**	**0.5**
Correct	143	11	7	9	0				
Precision (%)	94.7	69.8	70.0	90.0	100.0				
Volume APE (%)	1.3	20.0	11.1	11.1	100.0				

Table A3-12 FHWA Class 9 Training Data

Trailer Body Class	Volume	Trailer Body Class Group
Enclosed Van	1218	
Enclosed Van Reefer	811	
Platform	380	Platform
Tank	166	Tank
Open Top Van	138	
Low Boy Platform	120	
53ft Container	94	
40ft Container	43	
Automotive Transport	42	
End Dump or Bottom/Belly Dump	41	Dump
Drop Frame Van	30	
Livestock	24	
Agricultural Van	22	
Pole/ Logging/ Pipe	20	Logging
40ft Container Reefer	19	
Pneumatic Tank	14	Tank
Bulk Waste Transport	7	Platform
20ft Container	6	
20ft Container on 40ft Chassis	5	Platform
Container Chassis	4	Platform
20 Body Classes	3,205	16 Groups

Table A3-13 FHWA Class 10 Training Data

Trailer Body Class	Volume	Trailer Body Class Group
20ft Box Container	1	
20ft Container on 40ft Chassis	5	Platform
Basic Platform	5	Platform
Drop Frame Van	1	Low Chassis
Enclosed Van	1	
Low Boy Platform	4	Low Chassis
6 body classes	**17**	**4 Groups**

Table A3-14 FHWA Class 10 Cross Classification Table

	Platform	Container	Van	Low Chassis	Total	Correct	CCR (%)
Platform	2				2	2	100.0
Container		3			3	3	100.0
Van			2		2	2	100.0
Low Chassis				3	3	3	100.0
Total	2	3	2	3	**10**	**10**	**100.0**
Correct	2	3	2	3			
Precision (%)	100.0	100.0	100.0	100.0			
Volume APE (%)	0.0	0.0	0.0	0.0			

Table A3-15 FHWA 11 and 12 Training Data

Body Class	Volume	Body Class Group
Enclosed Van	205	
Platform	110	
Bottom Dump	89	
Pneumatic Tank	37	
Hopper	27	
Drop Frame Van	17	Van
Open Top Van	11	Platform
Tank	10	
Agricultural Van	2	
9 Body Classes	**508**	**7 Groups**

Table A3-16 FHWA 11 and 12 Cross Classification Table

	Platform	Van	Bottom Dump	Hopper	Pneumatic Tank	Tank	Agricultural Van	Total	Correct	CCR (%)	SMOTE Result (%)
Platform	99	4				5		108	99	91.7	-2.8
Van	2	84	1	1				88	84	95.5	1.1
Bottom Dump			67					67	67	100.0	0.0
Hopper			7	25	1			33	25	75.8	0.0
Pneumatic Tank				3	22			25	22	88.0	-4.0
Tank						3		3	3	100.0	33.3
Agricultural Van							2	2	2	100.0	0.0
Total	101	88	75	29	23	8	2	326	302	**92.6**	**-0.6**
Correct	99	84	67	25	22	3	2				
Precision (%)	98.0	95.5	89.3	86.2	95.7	37.5	100.0				
Volume APE (%)	6.5	0.0	11.9	12.1	8.0	166.7	0.0				

Table A3-17 FHWA 14 Training Data

Training Data	Count
Dump Truck with Dump Trailer (Dump-Dump)	73
Tank-Tank	32
RV with Small Trailer (removed from FHWA 8)	24
Platform-Platform	12
Livestock-Livestock	4
Total	**145**

Table A3-18 FHWA 14 Cross Classification Table

	Dump	Tank	RV	Platform	Livestock	Total	Correct	CCR (%)	SMOTE Result (%)
Dump-Dump	170	1				171	170	**99.4**	**0.6**
Tank-Tank	1	28		2		31	28	**90.3**	**-6.5**
RV-Small Trailer			25			25	25	**100.0**	**23.5**
Platform-Platform	2	2		13		17	13	**76.5**	**0.0**
Livestock-Livestock					0	0	0	**-**	**-**
Total	173	31	25	15	0	***244***	***236***	***96.7***	1.2
Correct	170	28	25	13	0				
Precision (%)	**98.3**	**90.3**	**100.0**	**86.7**	**100.0**				
Volume APE (%)	**1.2**	**0.0**	**0.0**	**11.8**	**0.0**				

Table A3-19 Cross Classification Table for FHWA Class 9 Body Class Model at Irvine

	Enclosed Van	Enclosed Van Reefer	53ft Container	40ft Container	40ft Container Reefer	20ft Container	Platforms	Tank	Open Top Van	Auto	Low Boy Plat-form	Dump	Drop Frame Van	Logging	Livestock	Ag. Van	Total	Correct	CCR (%)
Enclosed Van	180	16	5				24	1	4				1				231	180	77.9
Enclosed Van Reefer	39	53					11					1					104	53	51.0
53ft Container	33		11														44	11	25.0
40ft Container				4			3		3								10	4	40.0
40ft Reefer Container					0												0	0	
20ft Container						0											0	0	
Platforms	4	1		3	1		45	3	1	1			2			1	62	45	72.6
Tank				2		1	7	8			1						19	8	42.1
Open Top Van	6	2					23		25								56	25	44.6
Auto										10	1						11	10	90.9
Low Boy Platform							1				24		2				27	24	88.9
Dump				1				4				10					15	10	66.7
Drop Frame Van										1			9				10	9	90.0
Logging														0			0	0	
Livestock															0		0	0	
Agricultural Van																0	0	0	
Total	262	72	16	10	1	1	114	16	33	12	26	11	14	0	0	1	589	379	64.3
Correct	180	53	11	4	0	0	45	8	25	10	24	10	9	0	0	0			
Precision (%)	68.7	73.6	68.8	40.0	0.0	0.0	39.5	50.0	75.8	83.3	92.3	90.9	64.3	100.0	100.0	0.0			

Table A3-20 Volume APE for FHWA Class 9 Body Class Model at Irvine

Body Class	Training Data		Test Data Vol.	Predicted Volume		APE (%) [MAPE]	
	Vol.	Prop. (%)		Prop.	MCS	Prop.	MCS
Enclosed Van	869	37.5	231	221	262	4.3	13.4
Enclosed Van Reefer	614	26.5	104	156	72	50.2	30.8
53ft Container	40	1.7	44	10	16	76.9	63.6
40ft Container	35	1.5	10	9	10	11.0	0.0
40ft Container Reefer	13	0.6	0	3	1		
20ft Container	5	0.2	0	1	1		
Platform	291	12.6	62	74	114	19.4	83.9
Tank	156	6.7	19	40	16	108.9	15.8
Open Top Van	70	3.0	56	18	33	68.2	41.1
Automotive Transport	22	1.0	11	6	12	49.1	9.1
Low Boy Platform	82	3.5	27	21	26	22.7	3.7
Dump	32	1.4	15	8	11	45.7	26.7
Drop Frame Van	20	0.9	10	5	14	49.1	40.0
Logging	20	0.9	0	5	0		0.0
Livestock	24	1.0	0	6	0		0.0
Agricultural Van	22	1.0	0	6	1		
Overall	**2,315**	**100**	**589**	**589**	**589**	**[32.5]**	**[30.4]**