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Using WIM Systems and Tube Counters to Collect and Generate ME Traffic Data for Pavement Design and Analysis: Technical Report

Technical Report 0-6940-R1

Cooperative Research Program

TEXAS A&M TRANSPORTATION INSTITUTE
COLLEGE STATION, TEXAS

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Federal Highway Administration and the
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16. Abstract

Axle load spectra data, typically from permanent weigh-in-motion (WIM) stations, constitute the primary mechanistic-empirical (ME) traffic data input for accurate and optimal pavement design and analysis. However, due to the limited number of available permanent WIM stations (mostly located on interstate highways), most ME pavement designs rely on antiquated estimates, even for the 18-kip equivalent single axle loads (ESALs) that often result in un-optimized and costly designs and/or poor-performing pavement structures with increased maintenance costs or high construction costs due to overdesigning—with high overall life-cycle costs. As a means to address these challenges, this study was initiated, among others, to (a) review the current state-of-the-art methodologies used for estimating ME traffic data inputs, (b) develop clustering algorithms for estimating site-specific ME traffic data, (c) explore the portable WIM as a supplement to the permanent WIM station data, and (d) develop and manage a Microsoft® Access ME traffic data storage system (T-DSS). The scope of work included traffic data collection from numerous WIM stations and development of traffic data analysis macros and clustering algorithms.

Key findings from the study indicated the following: (a) portable WIM is a cost-effective supplement for site-specific traffic data collection – with proper installation and calibration, quality traffic data with an accuracy of up to 90% is attainable; (b) the developed WIM data analysis macros are satisfactorily able to compute and generate ME traffic inputs for both flexible and rigid (concrete) pavements; and (c) the developed clustering algorithms and macros constitute an ideal and rapid methodology for predicting and estimating ME traffic data inputs. Key recommendations are continued portable WIM data collection, particularly in West Texas and on farm-to-market (FM) roads, for population of the T-DSS and improved prediction accuracy of the clustering algorithms.

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USING WIM SYSTEMS AND TUBE COUNTERS TO COLLECT AND GENERATE ME TRAFFIC DATA FOR PAVEMENT DESIGN AND ANALYSIS: TECHNICAL REPORT

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DISCLAIMER

This research was performed in cooperation with the Texas Department of Transportation (TxDOT) and the Federal Highway Administration (FHWA). The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official view or policies of FHWA or TxDOT. This report does not constitute a standard, specification, or regulation.

This report is not intended for construction, bidding, or permit purposes. The researcher in charge of this project was Lubinda F. Walubita.

The United States Government and the State of Texas do not endorse products or manufacturers. Trade or manufacturers' names appear herein solely because they are considered essential to the object of this report.

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TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

LIST OF TABLES

Page

LIST OF SYMBOLS AND ABBREVIATIONS

AADT	Average annual daily traffic
AADTT	Average annual daily truck traffic
AASHTO	American Association of State Highway and Transportation Officials
ADT	Average daily traffic
ADTT	Average daily truck traffic
ALD	Axle load distribution
ALDF	Axle load distribution factor
ALS	Axle load spectra
ATHWLD	Average ten daily heaviest wheel load
CRCP	Continuously reinforced concrete pavement
CST	Construction Division
COV	Coefficient of variance
ESAL	Equivalent single axle load
FHWA	Federal Highway Administration
FM	Farm-to-market road
FPS	Flexible Pavement Design System
G_r	Growth rate
GVW	Gross vehicle weight
HAF	Hourly adjustment factor
HDF	Hourly distribution factor
LEF	Load equivalent factor
LS	Load spectra
LTPP	Long-term pavement performance
MAF	Monthly adjustment factor
MAINT	Maintenance Division
ME	Mechanistic-empirical
M-E PDG	Mechanistic-Empirical Pavement Design Guide
MS®	Microsoft®
NCHRP	National Cooperative Highway Research Program
OW	Overweight
PCA	Principal component analysis
PTT	Pneumatic traffic tube
STDEV	Standard deviation
T-DSS	Traffic data storage system
TF	Truck factor
TCDS	Traffic Count Database System
TPP	Transportation Planning and Programming Division
TSPM	Texas Statewide Planning Map
TxDOT	Texas Department of Transportation
TxCRCP-ME	Texas design program for CRCPs based on ME principles
TxME	Texas Mechanistic-Empirical Flexible Pavement Design System
VBA	Visual Basic for Applications
VCD	Vehicle class distribution
WIM	Weigh-in-motion

CHAPTER 1. INTRODUCTION

Axle load spectra or axle load distribution factors are used as the primary traffic data input for the mechanistic-empirical (ME) pavement design methods for predicting with a higher degree of accuracy the impacts of varying traffic loads on pavements. Ideally, to ensure optimal pavement structural design, site-specific traffic load spectra data—generated from weigh-in-motion (WIM) systems—should be used during the pavement design process. However, due to the limited number of available permanent WIM stations in Texas (mostly located on interstate highways), it is not feasible to generate axle load spectra data for every highway or project from WIM data.

As discussed in this report, one possible alternative method for generating the ME design-ready traffic data is cluster analysis. Cluster analysis is the process of grouping the available WIM traffic data into clusters of similar characteristics, tying project-specific traffic stream characteristics to these clusters, and thereafter estimating the ME traffic data. A second method for generating project-specific axle load spectra data that was successfully explored in this project was to deploy the portable WIM systems to collect site-specific traffic data from the intended highway location to supplement the permanent WIM station data. The third method explored was the use of tube counters to measure and generate traffic volume counts, vehicle speed, and classification data to supplement both the portable and permanent WIM data. All these aspects are discussed and documented in this report.

Currently, the Flexible Pavement Design System (FPS) is used throughout Texas for the structural design of Texas flexible pavements. However, this method often results in poorly performing or over-designed pavement structures due to the use of an antiquated traffic data input mechanism, namely the equivalent single axle load (ESAL) method. The Texas Mechanistic-Empirical Flexible Pavement Design System (TxME) is currently being developed to cover the limitation of the FPS by taking full consideration of axle load spectra. However, successful implementation of the TxME is largely dependent on the availability of project-specific ME-compatible traffic data. Thus, this project was initiated to address some of these challenges and aid in the provision of ready-to-use ME traffic data for both flexible and concrete pavement design and analysis, including the FPS, TxCRCP-ME, TxME, and AASHTOWare.

PROJECT OBJECTIVES

This project collected, assembled, processed, and analyzed traffic data obtained from 50 WIM stations and 15 pneumatic traffic tube (PTT) counter sites. The scope of the research project was to generate statewide site-specific traffic data inputs for ME pavement design and analysis. As a supplement to the limited permanent WIM stations, one of the primary goals of this project was to explore alternate methods for generating ME design-ready traffic data for pavement design. In line with this goal, the specific objectives of the project were as follows:

- Review the state-of-the-practice methodologies used by other agencies and recommend best practices for generating AASHTO/ME design-ready traffic data.
- Develop a clustering approach for predicting site-specific ME-compatible traffic loading data for highway locations where nearby permanent WIM stations are not available.
- Explore the feasibility of applying portable WIM systems for generating project-specific ME-compatible traffic data.
- Identify and recommend mechanisms for delivering the required ME-compatible traffic data, as well as data in the current conventional format, to pavement designers.

To achieve these objectives, the research team implemented a very interactive working approach in collaboration with the Construction Division (CST), Maintenance Division (MAINT), and Transportation Planning and Programming Division (TPP) at the Texas Department of Transportation (TxDOT). As discussed below, the work plan included an extensive review, traffic data collection, analysis, and development of the ME traffic data storage system (T-DSS) using Microsoft (MS)® Access.

RESEARCH TASK AND WORK PLAN

To achieve the research objectives, six tasks were identified and completed. Figure 1 summarizes the project's tasks as well as the main activities pertaining to each task. To ensure a timely completion of the project's activities and deliverables, the tasks were distributed during fiscal year (FY) 2017 and FY 2018, as presented in the timeline in Figure 2.

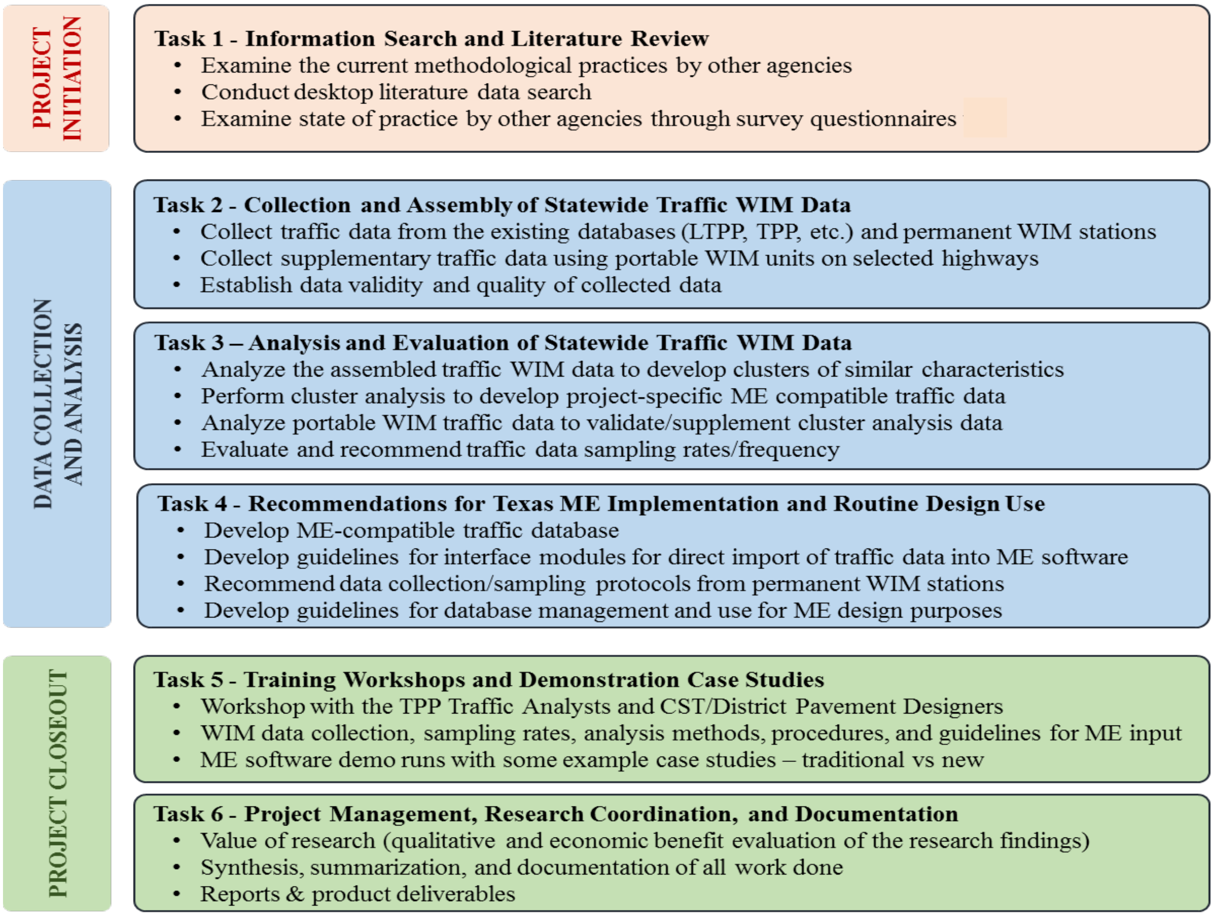


Figure 1. Work Plan Overview.

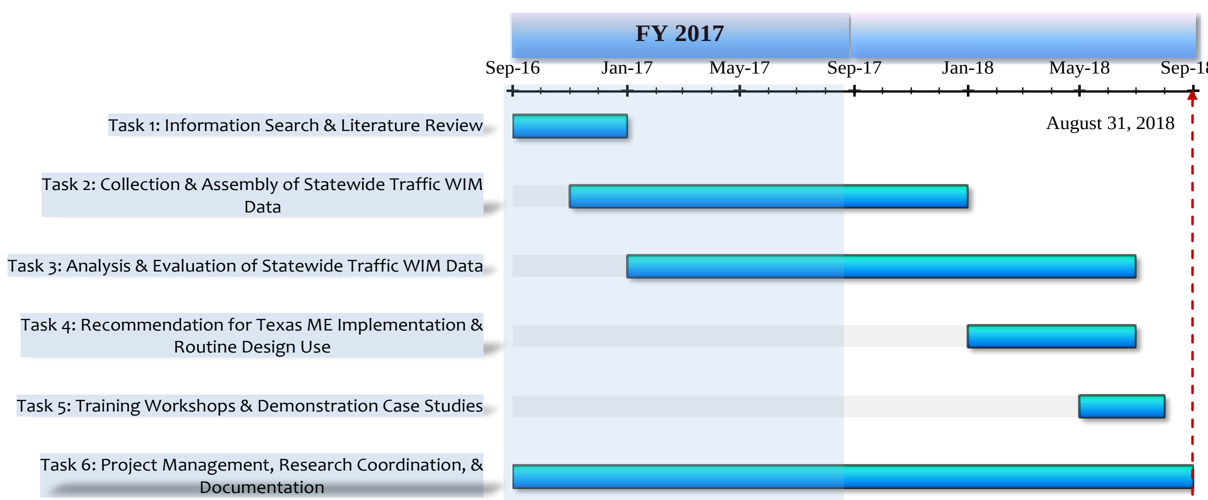


Figure 2. Overview of Project Timeline.

Task 1 was initiated and completed during FY 2017. Task 1 focused on the information search and literature review. Under this task, various activities were carried out, including:

- A literature search and review of relevant studies addressing WIM traffic analyses, axle load spectra, cluster analyses, and so forth.
- A survey of other agencies, including state transportation agencies and private-sector companies, involved in traffic data collection.
- A comparative evaluation of the reviewed methodologies and recommendations of the best option(s) to evaluate in this project.

Task 2 focused on the collection and assembly of statewide traffic WIM data. To achieve this task, the researchers implemented various strategies by:

- Liaising with TPP on permanent WIM-related data (volume, classification, weights, and vehicle speed) to obtain databases for 39 stations across Texas.
- Deploying portable WIM systems on 11 selected highway sections in areas lacking permanent WIM stations to collect at minimum seven-day volume, classification, and weight data as a supplement to permanent WIM data and to aid in populating the ME traffic database and development of the clustering algorithms.
- Deploying PTT counters on 15 selected highways to collect at minimum 48 consecutive hours of traffic volume and classification data to supplement the WIM data.

Task 3 focused on the analysis and evaluation of statewide traffic WIM data. To complete this task, different activities were performed, including:

- Developing user-friendly Excel analysis templates and macros for traffic data analysis.
- Processing and analyzing traffic data (both permanent and portable WIM) to an ME format for the database.
- Formulating and developing the clustering algorithms.

Task 4 focused on recommendations for Texas ME implementation and routine design use. The activities conducted under this task included the following:

- Develop and populate the prototype MS Access ME T-DSS.
- Develop and incorporate the input data into the T-DSS for concrete pavement design.
- Develop and document project's products, including P1 (T-DSS), P2 (guidelines for database), and P3 (guidelines for interface modules).

Task 5 focused on training workshops and demonstration case studies. The workshop aimed to achieve the following goals:

- Demonstrate the methodologies for generating site-specific ME-compatible traffic data for pavement design.
- Present the methodologies and benefits of utilizing ME traffic data for pavement design.
- Highlight relevant key lessons learned from the study.

Task 6 consisted of project management, research coordination, and documentation. The activities performed under this task included, but were not limited to, the following:

- Conducting a kick-off meeting with the project team.
- Conducting progress meetings with the project team to discuss topics such as the status of the research, research results from the work plan, future activities, and issues that might have emerged.
- Conducting a close-out meeting with the project team approximately one month before the end of the research to discuss the final deliverables.
- Preparing and submitting monthly progress reports to summarize activities completed during each month and highlight issues that might have emerged.

REPORT CONTENTS AND ORGANIZATION

This report consists of seven chapters including this one (Chapter 1), which provides the background, research objectives, methodology, and scope of work. Chapters 2 through 5 are the main backbone of this research report and cover the following key items:

- Chapter 2—Literature review.
- Chapter 3—Traffic data collection and assembly.
- Chapter 4—Traffic data analysis.
- Chapter 5—Traffic clustering algorithms.
- Chapter 6—MS Access ME traffic database.

Chapter 7 summarizes the report and includes a list of major findings and recommendations. Some appendices containing important data are also included at the end of the report. The T-DSS and macros are included in the accompanying CD.

SUMMARY

This first chapter of the report presented an overview on the background and the work performed throughout the project. The chapter also provided a brief description of the research tasks, the research methodology, and the structuration of the report contents. Specifically, this report provides a documentation of the work accomplished throughout the whole project period.

CHAPTER 2. LITERATURE REVIEW

An extensive information and literature search was conducted, with the primary goal of reviewing, comparatively evaluating, and documenting the current state-of-the-art methodologies for estimating and predicting project-specific ME-compatible traffic data. The second and third objectives of the literature review task were the following:

- Review and comparatively evaluate different cluster analysis techniques frequently used in transportation studies. These techniques included the methodologies used for grouping the permanent WIM and classification stations into clusters of similar characteristics (e.g., hierarchical clustering and regional clustering). Different algorithms used for tying the project-specific traffic stream characteristics to the developed clusters were also reviewed as part of subtask.
- Review alternative methodologies, including portable WIM systems and tube counters, for generating project-specific ME traffic data.

To achieve the aforementioned objectives, a thorough literature review and data search were performed to identify the methodological practices currently used for generating traffic data for ME pavement design and analysis. As discussed in the subsequent sections, this chapter presents, discusses, and documents the key finding from the literature review task.

OVERVIEW OF ME TRAFFIC DATA GENERATION

Through the extensive information search, a thorough review was conducted on the state of practices in ME traffic data prediction for pavement design and analysis. Although there is a diversity of pavement design software, the traffic input data required are often similar and related to traffic volume, vehicle classification, and load (weight) spectra data. For instance, both the TxME and MEPDG(NCHRP, 2006) require annual load distributions (spectra) for each of the single, tandem, tridem, and quad axles as some of the primary design inputs (Oman, 2010; Walubita et al., 2013). Three commonly used methods that were reviewed in the literature for obtaining ME-compatible traffic data for pavement design and analysis include the following (Faruk et al., 2016; Refai et al., 2014; Kwon, 2012; Lu and Zhang, 2009):

- Direct measurement by permanent roadside WIM stations.
- Cluster analysis estimation of axle load data based on easy-to-obtain traffic volume and vehicle classification distribution (VCD) data from sources such as tube counters.
- Direct measurement by portable WIM systems.

Among these three methods, the traditional direct measurement of traffic data from permanent roadside WIM stations has been the most commonly used method for generating ME-compatible traffic data. However, due to the limited number of available permanent WIM stations in Texas, which are mostly located on interstate highways, it is not feasible to generate a statewide axle load spectra database for every highway or project from WIM data. One possible alternative method for generating ME design-ready traffic data, as reported by several literatures, is cluster analysis (Oh et al., 2015; Sayyady et al., 2010; Lu and Zhang, 2009; Papagiannakis et al., 2006). More recently, however, several research efforts have been conducted to explore the implementation of a portable WIM system for generating site-specific ME-compatible traffic data (Faruk et al., 2016; Refai et al., 2014; Kwon, 2012). Findings from the desktop literature review on these two alternative methods for generating ME design-ready traffic data (i.e., the cluster analysis and the portable WIM method) are discussed in the subsequent text. The detailed literature findings are included in Appendix A.

CLUSTER ANALYSIS AND ME TRAFFIC DATA ESTIMATION

The use of the clustering method is very frequent in multivariate analyses. Indeed, when multiple independent variables are expected to influence a given dependent variable, there is a high chance of collinearity between dependent variables. Thus, cluster analysis is recommended as a variable reduction technique that can be used to create groups of high similarities. In the present project, the cluster analysis was targeted for synthesizing ME-compatible traffic data by combining some easy-to-obtain site-specific traffic data with average regional traffic data obtained from WIM stations located on sites that exhibit traffic properties similar to the specific site being analyzed (Papagiannakis et al., 2006). Essentially, obtaining axle load distribution data for a specific highway through cluster analysis is a three-step process:

1. Collect traffic data from permanent WIM stations and group these data into clusters of similar attributes.
2. Collect some easy-to-obtain traffic data (e.g., VCD) for the specific highway location for which ME traffic data are being sought.
3. Assign the specific site to one of the clusters with matching attributes and use the representative traffic data (e.g., axle load distribution factors) of that cluster.

The most frequently used clustering techniques include *k*-means clustering, hierarchical clustering, principal component analysis (PCA)–based clustering, and entropy-based clustering. However, this literature review emphasizes the first two techniques, which are also the most commonly used methodologies for grouping the available WIM stations to clusters of similar attributes.

The *k*-Means Clustering Method

The *k*-means clustering method predefines the number of clusters (Hardle and Simar, 2003; Lu and Harvey, 2011; Hasan et al., 2016). Given a predefined cluster, *k*-clusters are created by associating every observation with the nearest mean. The centroid of each of the *k*-clusters then becomes the new mean, and the above steps are repeated until convergence has been reached (Hardle and Simar, 2003). Oh (2015) and Walubita et al. (2017) used the *k*-means clustering method to generate site-specific axle load spectra data for several Texas highway sections from traffic volume classification data obtained by pneumatic tubes.

The *k*-means clustering method is beneficial for large amounts of data where the number of clusters desired is known, and some knowledge of the centroid value for each cluster is understood (Norusis, 2008). Although useful for a single variable, such as average annual daily truck traffic (AADTT), this method would not be practical for clustering based only on truck traffic classification, where a single center mean is unintelligible. Due to these shortcomings, this method is less desirable for clustering (Buch et al., 2009; Lu and Zhang, 2009). Indeed, out of the 16 cluster analysis studies reviewed in this task, only two had adopted the *k*-means clustering technique (see Appendix A). However, Wang et al. (2011) compared the hierarchical cluster analysis with the *k*-means analysis method and did not find any significant differences among the generated clusters. Therefore, on the basis of being rapid and the simplest one with the potential to handle large datasets, the *k*-means was selected as the clustering method for this study

The Hierarchical Clustering Method

In the hierarchical approach, the algorithm begins with all sites as individual clusters (Sayyady et al., 2010). A given distance measure is specified for distinguishing how far apart the two sites are and distinguishing a methodology for grouping sites together based on the distances. The algorithm proceeds by grouping sites together based on the distance measure and methodology to form successive clusters until a final single cluster is formed. With this technique, the desired number of clusters does not need to be specified but rather can be selected after the analysis since the output produces clusters at each stage (Norusis, 2008). The hierarchical clustering technique is suitable for smaller data sizes that are numerical in nature and contain multiple values for a given case. The majority of the clustering approaches researched in the literature utilized a hierarchical analysis for grouping traffic characterizations (see Appendix A). The hierarchical clustering algorithm follows four basic steps (Sayyady et al., 2010):

1. Begin with *n* clusters, each consisting of exactly one WIM station.
2. Compare the cluster of WIMs based on the similarity of their attributes to produce individual clusters for axle load distribution factors (ALDFs) and monthly adjustment factors (MAFs).
3. Merge the most similar pair of clusters and reduce the number of clusters by one.
4. Perform Steps 2 and 3 until the best partition that represents the natural structure of the data is found.

The similarity between a pair of WIMs is computed through a dissimilarity coefficient, which is defined as the Euclidean distance between their ALDF and MAF attributes. The algorithm may stop merging clusters further once a significant change in the homogeneity of clusters is observed. A metric introduced by Mojena (1977) is used to explicitly define a significant change in the clustering criterion. Appendix A provides a comparative summary of the hierarchical versus the *k*-means clustering method.

Assigning a Specific Site to a Cluster

Once the WIM stations are grouped into clusters, post-clustering analysis based on local knowledge of traffic and easy-to-obtain traffic parameters is performed to explain the variation among clusters. These observations help form a decision tree that allows locating the correct cluster for a given site-specific traffic stream. Three different examples of decision tree algorithms obtained from the reviewed literature are presented in Appendix A.

In comparison to the *k*-means, hierarchical clustering cannot handle larger datasets. Traffic data are usually bulky with large datasets; hence, it poses a challenge for the hierarchical method. Because it is a linear analysis, the *k*-means clustering analysis is usually simple and fast, unlike the hierarchical method, which is based on quadratic analysis and for which reaching convergence is therefore very time consuming.

USE OF PORTABLE WIM SYSTEMS

While permanent WIM stations have been commonly used by the Federal Highway Administration (FHWA) and state departments of transportation, the portable WIM systems are a fairly new technology, and there are limited studies that have objectively evaluated their applicability, ease of handling, and reliability of the obtained data. Refai et al. (2014) implemented a portable WIM system to collect traffic data on Oklahoma highways and found it at merely 10 percent of the cost to be a viable alternative to permanent systems. Kwon (2012) developed a weigh-pad-based portable WIM system and compared it with permanent WIM stations on Minnesota highways. The corresponding results indicated good correlations between the portable and permanent systems in terms of the gross vehicle weight (GVW), speed, and axle specification data.

Researchers have successfully used the portable WIM system on several Texas highways to collect site-specific ME-compatible traffic data, with an accuracy of 87~90 percent in the data (Faruk et al., 2016). Key contributing factors to this accuracy improvement have been a rigorous on-site calibration regime and improved sensor installation techniques through use of metal plates. However, on highway locations or sites (mostly high-volume roads) where the more accurate permanent WIM stations are available, use of portable WIMs is not necessary unless as a supplement or where site-specific traffic data are needed. Basically, portable WIMs are very practical and ideal for collecting and generating site- or project-specific traffic data in areas where permanent WIM stations are unavailable, such as most of the farm-to-market (FM) roads in Texas.

Nonetheless, permanent WIM stations are considered the most accurate and desired method of generating traffic data. However, the associated costs (e.g., installation, operation, maintenance) are some of the key challenges limiting the statewide installation of permanent WIM stations on most of the state's road network. Portable WIMs, on the other hand, are cheaper, cost-effective, and easy to install at any desired highway location to collect and generate site- or project-specific traffic data with reasonable accuracy (i.e., 87~90 percent), especially on the rural low-volume road network—where in most cases, the costlier permanent WIM stations are unavailable. Thus, portable WIMs serve as a cost-effective and practical supplement for site-specific traffic data collection (volume counts, speed, VCD, and vehicle weight measurements).

USE OF PTT COUNTERS

PTT counters are the cheapest and quickest supplement to collect only traffic volume counts, vehicle speed, and VCD data, and are typically deployed for a minimum period of 48 hours. At a cost of about $2,500 as of 2016, a PTT unit costs over five times less than a portable WIM system and over 25 times less than a permanent WIM system. PTT counters are ideal in situations where vehicle weights and axle load spectra data are not critical. Using clustering analysis, however, the full ME traffic load spectra data can easily be generated and estimated from the PTT's traffic volume counts and VCD data.

SUMMARY

This chapter reviewed and presented various methods of generating ME traffic data. While permanent WIM stations are the preferred methods, installation and operational costs limit the statewide installation of permanent WIMs on the state's road network. Portable WIMs are a cost-effective and practical supplement for site-specific traffic data collection (volume counts, speed, VCD, and vehicle weight measurements). Portable WIMs were used in this study to supplement permanent WIM data. Similarly, PTT counters were used in this study to supplement the traffic volume counts, vehicle speed, and VCD data as well as supplement the input data for clustering analysis. On the basis of being rapid and the simplest one with the potential to handle large datasets, the *k*-means was selected as the clustering method for this study—see the summary comparison with the hierarchical method in Table 1.

Table 1. Summary Comparison of the *k*-Means and Hierarchical Clustering Methods.

***k*-Means**	**Hierarchical**
▪ Predefined cluster, *k*-clusters are created by associating every observation with the nearest mean. ▪ The centroid of each of the *k*-clusters then becomes the new mean, and iterations are repeated until convergence.	▪ Begins with *n* clusters and assumes each station/site is cluster. ▪ Groups based on similar attributes, i.e., ALDF, ADT, MAF, etc. ▪ Hierarchical clustering and iterations repeated to convergence.
- Simple and fast - Linear analysis - Ideal for large datasets - *k*-clusters predefined	- Ideal for multi-variables - Quadratic analysis - Limited to small datasets - A bit complex and more time consuming

CHAPTER 3. TRAFFIC DATA COLLECTION

Three main sources were used for measuring, collecting, and assembling traffic data for this study: permanent WIM stations, portable WIM units, and PTT counters. The specific objectives for the traffic data collection task were threefold:

- Assemble traffic data from the available permanent WIM stations for the development of traffic data clusters.
- Supplement where needed and on selected highways the permanent WIM station data with portable WIM traffic data collection from sites lacking permanent WIM stations.
- Collect easy-to-obtain traffic data (e.g., pneumatic tube volume classification data) where needed and on selected highways (without permanent WIM stations) to aid in validating the clustering algorithms and supplementing the WIM volume and vehicle classification data.

The type of traffic data measured, collected, and generated included traffic volume counts, vehicle classification, vehicle speed, and weight data. Specifically, the permanent and portable WIM systems provided the following minimum type of traffic data:

- Traffic volume counts.
- Vehicle classification.
- Vehicle speed.
- GVW and individual axle loads.
- Number of axles and axle spacing.

In addition to the detailed per vehicle measurements, the WIM systems also provided traffic volume and vehicle classification data, including the per hour number of vehicles for different vehicle classes. By contrast, PTT counters provided only traffic volume counts, vehicle speed, axle spacing, and vehicle classification—but no vehicle weight data. The three data sources (WIM, portable WIM, and PTT counters) along with the traffic data types are discussed in the subsequent sections of this chapter.

TRAFFIC DATA SOURCE 1—PERMANENT WIM STATIONS

Raw traffic data from permanent WIM stations was collected from and provided by TxDOT's TPP division. These raw traffic data were traffic volume counts, vehicle classification, vehicle speed, and vehicle weight data. The raw data provided included 365 days of continuous traffic data per year over a 3-year period from 2013 to 2016 to aid in the computation of the traffic growth rates (G_r).

Figure 3 shows an example of a permanent WIM station on SH 121 (Paris District) that is operated and maintained by TxDOT's TPP division. These permanent WIM data are measured and collected continuously during the year. For this reason, permanent WIM stations are classified as long-term traffic data collectors.

Figure 3. Permanent WIM Station—SH 121 (Paris District).

TRAFFIC DATA SOURCE 2—PORTABLE WIM UNITS

Portable WIM units were deployed by these researchers on selected highways (without permanent WIMs) to supplement the permanent WIM stations to aid in the effective development of the ME traffic clusters and population of the T-DSS. Like permanent WIM stations, the portable WIM measures traffic volume counts, vehicle classification, vehicle speed, vehicle weight data, and so forth. The portable WIM data were collected by these researchers through short-term deployment (minimum seven days) of portable WIM units on selected highway sites around the state of Texas. Figure 4 shows an example of a portable WIM setup using piezo-electric (PZT) sensors, metal-plates, silicon adhesives, and pocket/road tapes.

Figure 4. Portable WIM Setup—SH 114 and FM 468.

As shown in Figure 4, a pair of PZT sensors are placed 8 ft apart in the outer wheel path and then connected to the WIM unit that applies an in-built multiplication factor of two to generate the full one-lane traffic data. The effective 69-inch PZT sensor length completely covers half of the traffic lane to account for any possible lateral wandering of the wheel-tire. The width of a typical US truck dual-tire is about 29-inch, which is only 42 percent of the total sensor length and is therefore, sufficiently covered within the 69-inch sensor span. The setup and installation process comprise of placing the PZT sensors inside the pocket tapes on the metal-plates and then, the metal-plates (6 or 8 ft long by 6-inch wide by 0.04-inch thick) are attached to the pavement surface using quick setting silicon adhesives and road tapes. The metal-plates also aids in providing a stable flat surface for improved sensor accuracy and data quality. On seal coat roads, nails are also used as additional anchorage of the metal-plates onto the pavement. On asphalt and concrete roads, metal-plates, silicon adhesives, and road tapes have proved to be adequately sufficient.

Typically, the portable WIM data are measured and collected for a minimum period of seven consecutive days up to a maximum of one year for low volume roads, with routine periodic maintenance (i.e., adding new tape, re-taping the sensors/plates) including PZT sensor replacement. In particular, sensor replacement is strongly recommended for continuous traffic data measurements after cumulative passes of about 300,000 vehicles; above this cumulative count, the PZT sensors tend to decay and lose accuracy/sensitivity and/or get damaged.

Onsite calibration with a Class 9 truck of known varying weights at multiple speeds and different pavement temperature conditions (i.e., morning versus afternoon), is strongly recommended prior to actual traffic data measurements. The portable WIM units used in the study had a manufacturer error/accuracy rating of ±15 percent. With good installation, calibration, and maintenance practices, traffic data accuracy of up to 92.5 percent is attainable.

TRAFFIC DATA SOURCE 3—PTT COUNTERS

Unlike the WIM system, which also measures vehicle weights, PTT counters are installed to measure and collect only traffic volume counts, vehicle speed, axle spacing, and vehicle classification—but with no vehicle weight data. PTT counters are particularly used in situations where vehicle weights and load spectra data are not very critical (i.e., where only volume counts, vehicle speed, and VCD data are needed). In this study, PTT counters were used to aid in validating the clustering algorithms and to supplement the WIM volume and vehicle classification data. Figure 5 shows an example of a PTT counter setup on US 59.

Figure 5. PTT Counter Setup—US 59 (ATL).

PTT counters are traditionally deployed for short-term periods of at least 48 hours up to seven days. Beyond seven days, the tube counters generally lose hold of the pavement due to the nature of installation, which includes tape and nails; and may actually become a safety hazard to motorists. Thus, like portable WIM units, PTT counters are categorized as short-term traffic data collectors. With good site selection, installation, and setup, traffic data accuracy of up to 97 percent is achievable with PTT counters.

TRAFFIC STATIONS AND HIGHWAY SITES

In total, traffic data were collected, measured, and assembled for over 65 highway sites around the state. These 65 traffic stations and highway sites included the following:

- 39 permanent WIM stations.
- 11 portable WIM sites.
- 15 PTT counter sites.

Figure 6 shows the location of these traffic stations and highway sites. As evident in Figure 6, most of the WIM stations and highway sites are located in East Texas, with very little in West Texas. Additionally, it is also clear that most of the WIM stations are located on major and interstate highways, with very few on rural networks, such as FM roads. Therefore, any future traffic data collection studies to enhance the traffic clusters and populate the ME traffic database should focus on West Texas. Appendix B gives some examples of selected WIM stations and highway site locations.

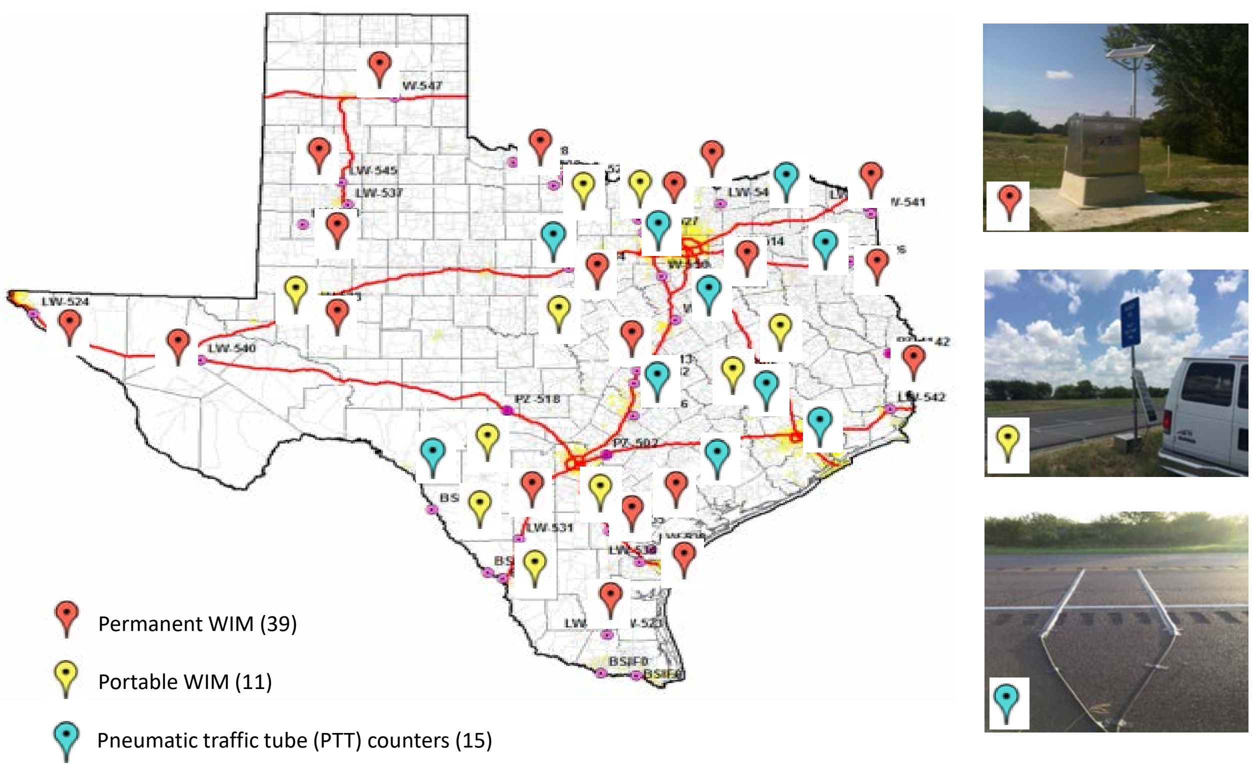


Figure 6. Map Location for Traffic Stations and Highway Sites Evaluated in this Study.

TRAFFIC DATA COLLECTED

Table 2 gives an overview of the traffic data collected and generated from each source. As previously mentioned, unlike WIM systems, PTT counters do not measure vehicle weights and load spectra data—only volume counts, speed, and VCD data. Also, unlike the permanent WIM stations, both the portable WIM systems and PTT counters are short-term data collectors and therefore cannot be used to generate G_r data (instead default values are used—typically 3 or 4 percent).

Table 2. Traffic Data Collected and Generated.

Type	Traffic Parameter	Permanent WIM	Portable WIM	PTT Counters
Traffic Volume	Average Annual Daily Traffic (AADT)	✓	✓	✓
	Average Annual Daily Truck Traffic (AADTT)	✓	✓	✓
	Truck Percentage	✓	✓	✓
	Axles per Truck	✓	✓	
Classification	Vehicle Classification Distribution (VCD)	✓	✓	✓
Adjustment Factors	Monthly Adjustment Factor (MAF)	✓		
	Hourly Distribution Factor (HDF)	✓	✓	✓
Growth Rate	Yearly Volume Growth Rate (G_r)	✓	X	X
Weight	Gross Vehicle Weight (GVW)	✓	✓	X
	Axle Load Distribution Factor (ALDF) or Axle Load Spectra (ALS)	✓	✓	X

SUMMARY

This chapter presented and discussed the traffic data sources (WIMs and PTT counters) used in this study and the type of traffic data measured, collected, and generated from respective sources. With good site selection, installation, calibration, and maintenance practices, the portable WIM has proved to be a cost-effective and practical supplement to the permanent WIM station data, with an attainable accuracy of up to 92.5 percent. PTT counters, with an attainable accuracy of up to 97 percent, were found to be very cheap and rapid supplements for traffic volume, vehicle speed, and VCD data only—no weight data. Since most of the current WIM stations and PTT highway sites are located in East Texas, any future traffic data collection studies should focus on West Texas—this focus is critical to enhance the ME traffic clusters and populate the T-DSS.

CHAPTER 4. TRAFFIC DATA ANALYSIS

The collected raw traffic data were processed and analyzed to generate the general traffic parameters and ME traffic inputs. The computed traffic parameters are listed below and summarized in Table 3.

- The average daily traffic (ADT), which is computed as the total number of vehicles (all classes) recorded divided by the duration of record (i.e., number of days).
- The average daily truck traffic (ADTT), which is calculated as the total number of trucks (Classes C4–C13) recorded divided by the duration of record (i.e., number of days).
- The percentage of truck = ADTT/ADT (percent).
- The VCD, the percentage of each vehicle class in the ADT.
- The average vehicle speed and the percentage of over-speeding vehicles estimated relative to the speed limit at the highway section in question.
- The axle per truck inputs, computed as the average number of single/tandem/tridem/quad axles per truck.
- The total 20-year and 30-year 18-kip ESALs, estimated using the load spectra of trucks and the annual traffic growth rate.
- The average ten daily heaviest wheel loads (ATHWLD).
- The daily GVW distribution, the daily single/tandem/tridem/quad load distribution.
- The daily overweight (OW) vehicles, estimated based on the recorded GVW values and the consideration of 80 kip as the limit allowed for GVW.
- The daily OW axles, estimated based on the different axle threshold loads (e.g., 20 kip for single axles, 34 kip for tandem axles, 42 kip for tridem axles, and 50 kip for quad axles).
- Axle load distribution (ALD), estimated through the load spectra (LS) analysis.
- FPS and ME traffic inputs for TxCRCP-ME, TxME, TxACOL, TxCrackPro, MEPDG, PerRoad, and AASHTOWare (replaced DARWin-ME) software.
- Truck factor (TF), estimated as the ratio of the total 18-kip ESALs for all the weighed/measured trucks divided by the total number of trucks weighed/measured; which is also essentially the “daily 18-kip ESALs divided by the ADTT.

Table 3. Traffic Parameters Computed.

General Traffic Parameters			ME Traffic Inputs and Software	
Traffic volume	1)	AADT	1)	FPS
	2)	AADTT	2)	TxCRCP-ME (concrete)
	3)	Truck percentage	3)	TxME
	4)	Axles per truck	4)	TxACOL
	5)	Volume distributions, such as hourly and daily	5)	TxCrackPro
Classification	6)	VCD	6)	M-E PDG
Adjustment factors	7)	MAF	7)	AASHTOWare (DARWin-ME)
	8)	HDF	8)	PerRoad
Growth trends	9)	Traffic G_r—mostly from permanent WIM data		
Weight	10)	GVW		
	11)	ALD		
	12)	Weight distributions, i.e., hourly and daily		
	13)	ALDF or ALS		
	14)	18-kip ESALs		
	15)	Accumulated ESALs (18 kip), e.g., 20-year 18-kip ESALs for flexible pavements and 30-year 18-kip ESALs for concrete pavements		
	16)	Average of the ATHWLDs		
	17)	Truck OW data (GVW and axles), i.e., overweight and overloading statistics		
	18)	LEFs		
Others	19)	Truck factor (TF)		

As shown in Table 3, the generated ME traffic inputs for various pavement design and analysis software include flexible and concrete pavements. These ME traffic input data were computed and generated for the most commonly used pavement software in Texas (e.g., FPS, TxCRCP-ME) and at the U.S. national level (e.g., AASHTOWare). While the primary objective of the study was to generate the ME-compatible traffic inputs, general traffic parameters were also computed, as listed in Table 3, to provide a full spectrum of the traffic loading on a given highway. These valuable general traffic parameters can be used for various applications, including but not limited to the following: VCD characterization, planning purposes, truck overloading and pavement damage assessment, overweight quantification, and speed quantification. As discussed in the subsequent text, easy to use MS Excel macros were developed to automate the traffic data processing and analysis.

WIM DATA ANALYSIS MACROS

To ensure consistency and accuracy and to be able to rapidly handle the massive traffic raw data, particularly from the permanent WIM stations, data analysis macros were developed using Visual Basic for Applications (VBA) to automate the processing, analysis, and generation of the required general traffic parameters and ME inputs. The two macros—the permanent WIM macro and portable WIM macro—are managed in the MS Excel VBA platform because MS Excel is able to support various computing methodologies required for the data analysis and is compatible with most computers.

Portable WIM Data Analysis Macro

Once the raw data from the portable WIM unit are downloaded, they can be quickly parsed to several MS Excel files, each representing a one-day data set. These daily raw data will usually still be in an unorganized state and do not represent any meaningful or interpretable data. The purpose of the portable WIM macro is to obtain the MS Excel raw data and then generate the ME-compatible traffic data for pavement design and analysis. Figure 7 shows the portable WIM macro main screen.

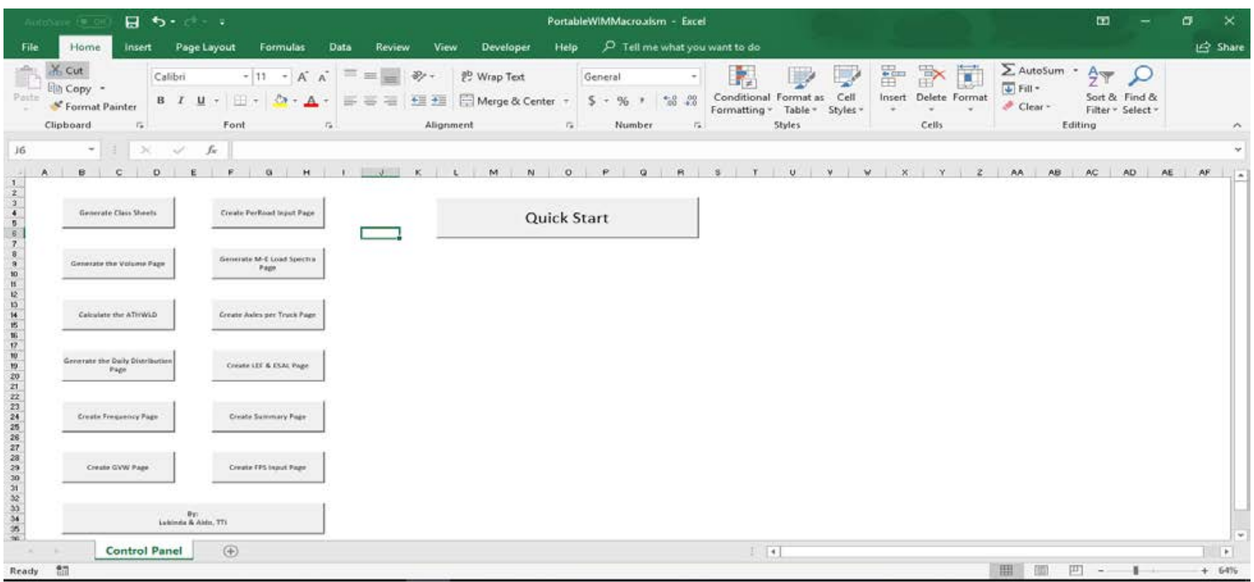


Figure 7. Portable WIM Macro Main Screen.

To execute the portable WIM macro, the user can simply click on the Quick Start button, pick the destination folder where the result of the macro will be saved, and then pick the raw data files to be analyzed. It is recommended to have at least seven days of data to ensure complete weekly data analysis. Additionally, the user can also generate specific desired outputs from one of the 12 buttons on the left side of the control panel.

The macro running time ranges from 5 minutes to 30 minutes depending on a highway's traffic volume and data quantity. Example output data from portable WIM macro analyses are included in Appendix C. In addition to the MS Excel output results, PowerPoint (PPT) slides were manually prepared for each WIM station and highway section. The portable WIM macro is included in a CD accompanying this report.

Permanent WIM Data Analysis Macro

The permanent WIM data analysis macro has a similar purpose to the portable WIM macro, but it is custom designed specifically for permanent WIM data analysis. Both permanent WIM and portable WIM systems have two different formats of raw data; thus, two separate macros were created for each system. Figure 8 shows the permanent WIM macro's main screen.

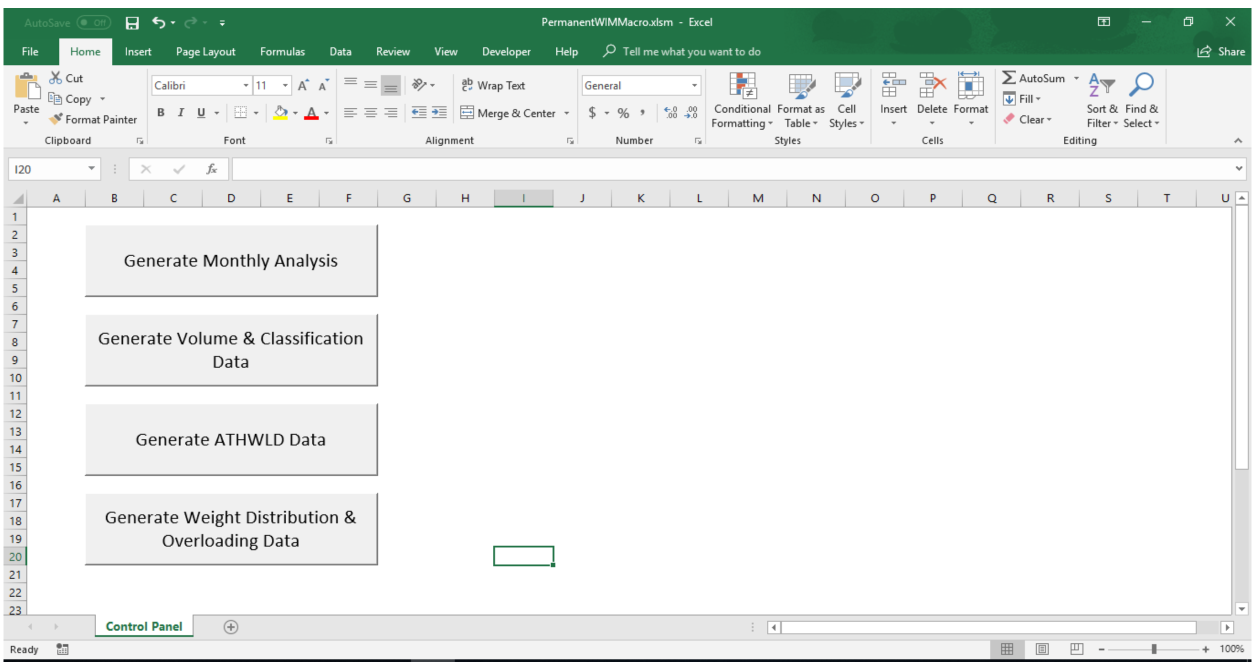


Figure 8. Permanent WIM Main Screen.

Due to the huge data size and different format of the permanent WIM station raw data, the permanent WIM macro has a slightly different methodology than the portable WIM macro. Users can click on the Generate Monthly Analysis button, pick the destination folder for monthly analysis, then select all of the raw data that need to be analyzed. This will generate an analyzed version for each raw data type selected. These types of files are the ones needed for the subsequent three analysis outputs: volume analysis, weight analysis, and class analysis. Each of the outputs can be generated from the Generate Volume & Classification Data, Generate ATHWLD Data, and Generate Weight Distribution & Overloading Data buttons, respectively.

The minimum macro running time is about8 hours and can go over 48 hours depending on the WIM station's data quantity—the larger the traffic dataset, the longer the processing time. Example output data from portable WIM macro analyses are included in Appendix C. In addition to the MS Excel file outputs, PPT slides were manually prepared for each WIM station and highway section. The portable WIM macro is included in a CD accompanying this report.

LOAD SPECTRA DATA AND TRAFFIC GROWTH RATE

For the LS data analysis, the weight data for each category of the axle (e.g., steering, other single, tandem, tridem, and quad) are addressed separately for each truck classification (e.g., C4, C5, …, C13). The results are reported for individual months of the year (e.g., January, February, …, December) and then organized to generate the ALD input files for the ME software, including TxME, MEPDG, and AASHTOWare. Along with the traffic parameters listed in Table 3, historical traffic volume data and predominantly permanent WIM data were utilized to compute the MAF and the annual traffic Gr. In general, the latest three consecutive years' traffic volume data are needed to accurately generate the MAF and G_r data for a given highway section. In the event the minimum three-year data requirement is not met, then default values are used for G_r—typically 3 or 4 percent.

Note that in addition to serving as ME inputs for the software listed in Table 3. Traffic Parameters Computed.the LS estimates are useful for designing and quantifying the damage on pavement structures. Thus, this study provided 18-kip ESAL estimates for both flexible and concrete pavements. Example traffic results are illustrated in Appendix C and include FPS/ME inputs, WIM/PTT data, GVW, axle weight distribution data, truck OW data, and overloading statistics.

TRAFFIC DATA ACCURACY AND SYSTEM COMPARISON

To verify the validity, reliability, and accuracy of the portable WIM units, traffic data comparisons and sensitivity analyses were conducted against the permanent WIM station data. The sensitivity analysis and accuracy assessment were accomplished through three methodological approaches:

- Comparisons of traffic data analysis (ADT) with those computed by TxDOT's TPP for the same highway location/site. The TPP traffic data (ADT) were pulled from the online databases, namely the TCDS and TSPM.
- Installation of a portable WIM unit adjacent to a permanent WIM station on the same highway location and then making a direct comparison of the traffic data measured/collected during the same time period by the two WIM systems—portable and permanent. This was done on SH 114 (FTW, Wise County) in July 2016.
- Variability analysis of the portable WIM data based on the Class 9 steering axle weight, with 10.5 kip as the reference datum and ±15 percent as the unit accuracy/error rating.

The results of these analyses (sensitivity and accuracy assessment) are shown in Tables 4 and 5 and Figures 9 and 10, respectively. In comparison with TxDOT TPP's results, Table 4 shows that these researchers' traffic data analysis has a comparable accuracy of up to 98.02 percent—the average absolute difference is only 1.88 percent. Meanwhile, Table 5 shows that the portable WIM data measurements have a comparable accuracy of 94.14 percent relative to TxDOT TPP's data.

Table 4. Comparison of ADT Data Analysis.

Station#	District	ADT Counts		
		Researchers' Results	TxDOT TPP Results	Absolute Difference (%)
W523 (US 281)	PHR	14,527	14,403	0.86%
W524 (IH 10)	ELP	24,445	25,027	2.33%
W527 (SH 114)	FTW	15,260	15,869	3.84%
W531 (IH 35)	LRD	17,681	17,685	0.02%
W541 (FM 3129)	ATL	1,121	1,150	2.52%
W547 (IH 40)	AMA	11,976	12,187	1.73%
			Average difference (%)	1.88%

Table 5. ADT Comparisons—Portable WIM, TxDOT TPP, and PTT Results.

Site#	Hwy	District	ADT Counts			Absolute Difference		
			Portable WIM	Nearest Site on TxDOT TPP Website	PTT	Portable WIM vs. TPP	PTT vs. TPP	Portable WIM vs. PTT
TS001	US 83	LRD	4,687	5,130	4,619	8.64%	9.96%	1.47%
TS002	SH 7	BRY	2,692	2,518	2,525	6.91%	0.28%	6.61%
TS003	SH 7	BRY	2,050	1,913	2,118	7.16%	10.72%	3.21%
TS007	SH 114 (EB outside lane)	FTW	4,511	4,873	4,230	7.43%	13.20%	6.64%
TS005	US 281	CRP	10,310	10,239	N/A	0.69%	N/A	N/A
TS006	SH 6	BWD	2,118	2,085	N/A	1.58%	N/A	N/A
TS004	FM 468	LRD	1,976	1,757	N/A	12.46%	N/A	N/A
TS008	FM 1787	ODA	2,521	2,552	N/A	1.21%	N/A	N/A
TS009	US 83	LRD	3,520	3,769	3,506	6.61%	6.98%	0.40%
					Average difference (%)	5.86%	8.23%	3.67%
					Relative accuracy (%)	94.14%	91.77%	96.33%

Legend: N/A = Not applicable (means PPT counters were not installed on this particular highway site)

WIM Type	Permanent WIM	Portable WIM	PTT
Highway	S114, EB outside lane, FTW district, Wise County (July2016)		
Site ID#	W527	TS0007	TTI00002
Unit#	LW-527	TRS-3	PTT-1
ADT (EB outside lane)	4,802	4,511 (6.06%)	4,230
%Trucks (EB outside lane)	32.9%	39.8%	29.2%
ADTT (EB outside lane)	1,572	1,561 (0.70%)	1,235
18-kip ESALs	39.4 million	38.7 million (1.78%)	35.3 million
Comment			ESALs estimated using Haung Book

Figure 9. Validation of Portable WIM against Permanent WIM Station on SH 114.

In comparing the portable WIM to the permanent WIM station, the results in Figure 9 show that the portable WIM unit on SH 114 attained an accuracy of up to 93.94 percent (i.e., 100 percent − 6.06 percent) relative to the permanent WIM station data. With respect to the 18-kip ESALs, the difference does not exceed 2 percent (i.e., 1.78 percent)—thus validating the reliability and accuracy of the portable WIM unit.

The Class 9 truck's front axle weight is typically used as an indicator of the system (portable WIM) accuracy and reliability and as the datum reference for calibrating the portable WIM unit. The industry standard for Class 9 front axle weight is 10~11 kip, so a value of 10.5 kip was used as the reference datum in this study. The manufacturer-specified error rating of the portable WIM system used in this study is ±15 percent, and all the coefficient of variance (COV) values shown in Figure 10 are less than 15 percent. Thus, the data variability was less than 15 percent. This validates that with proper site selection, installation, calibration, and maintenance practices, repeatable portable WIM data with an accuracy of up to 92.5 percent are attainable. Overall, Figure 10 indicates an average accuracy and reliability level of about 88.67 percent for the portable WIM system used in this study, with a maximum accuracy of up to 92.5 percent.

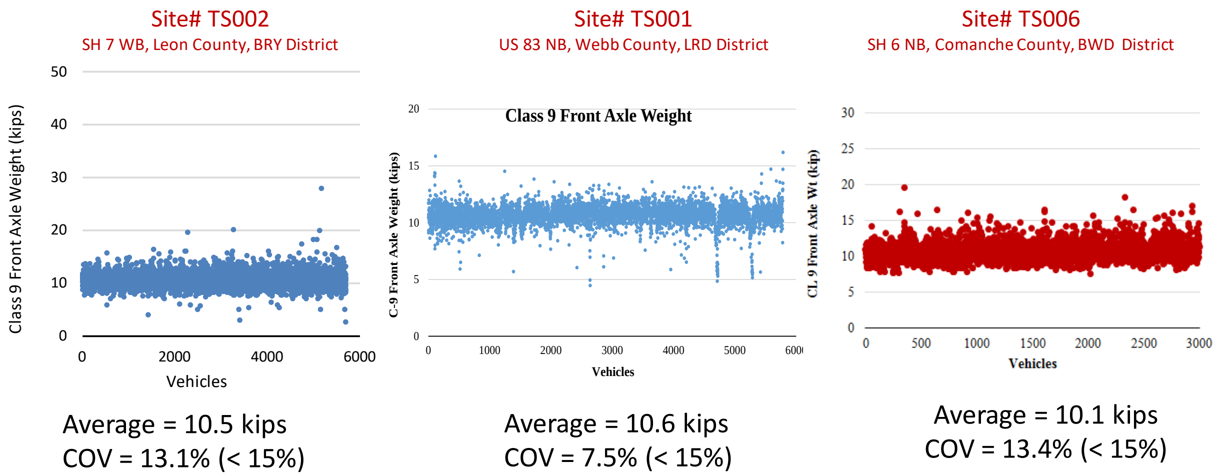


Figure 10. Portable WIM Data Variability Analysis (Class 9 Steering Axle-Wheel Weight).

SUMMARY

This chapter presented the methodology used for processing and analyzing the raw traffic data, including the generated traffic parameters and ME inputs. Although, the generated ME traffic input data was primarily focused on the Texas pavement design software—namely FPS, TxCRCP-ME (concrete), and TxME—other software such as MEPDG, AASHTOWare, and PerRoad were included in the matrix. Two MS Excel-based macros—the permanent WIM macro and portable WIM macro—were developed for automated processing, analyzing the raw data, and generating the traffic output parameters and ME inputs.

A sensitivity analysis and validation study of the portable WIM data against the permanent WIM station data indicated that the portable WIM is a fairly reliable system with an attainable accuracy of up to 92.5 percent. Key aspects to obtaining good-quality, repeatable, and reliable portable WIM data with low variability is proper site selection, installation, calibration, and maintenance practices.

CHAPTER 5. TRAFFIC CLUSTERING ALGORITHMS

As defined in Chapter 2, cluster analysis is a process of synthesizing ME-compatible traffic data by combining some easy-to-obtain site-specific traffic data with average regional traffic data obtained from WIM stations located on sites that exhibit traffic properties similar to the specific site being analyzed. To reiterate from Chapter 2, the following generalized three-step process for clustering analysis was executed in this study:

- Step 1—collecting traffic data from WIM stations and grouping these data into clusters of similar attributes. Both permanent and portable WIM data were used for this step, with Class 9 tandem axle load as the principal input.
- Step 2—collecting or assembling some easy-to-obtain traffic data (e.g., VCD, ADT) and/or percentage trucks for the specific highway location for which ME traffic data are being sought. These traffic data (e.g., VCD, ADT, percent truck) can be obtained from various sources, including PTT counters, existing traffic databases (e.g., DSS, TCDS, TSPM), historical experience, and empirical estimates—as was the case in this study.
- Step 3—assigning the specific site to one of the clusters with matching attributes and using the representative traffic data (e.g., ALDF) of that cluster to estimate the required ME traffic inputs.

The *k*-means method of clustering, following the concepts illustrated in Figure 11, was used. In the figure, Example 1 illustrates datasets grouped into six clusters, while Example 2 exemplifies two clusters. That is, data points close to a particular centroid with the nearest mean and least statistical STDEV/COV are grouped together to form a cluster.

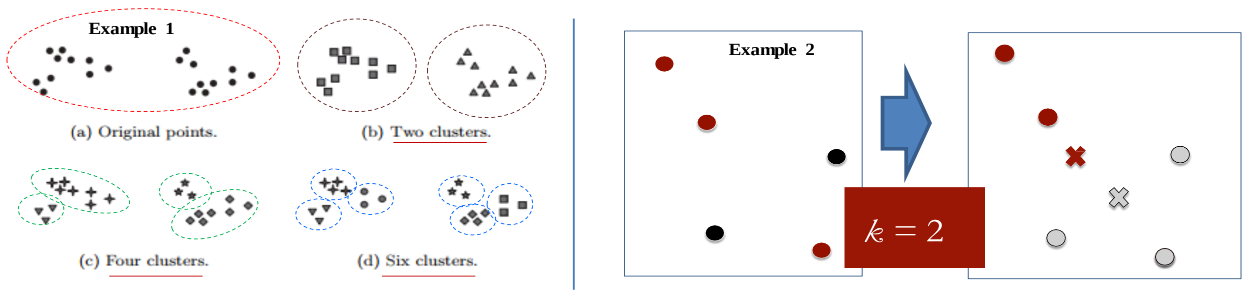


Figure 11. Clustering Concept.

TEXAS CLUSTERS

Using the *k*-means method and clustering concept illustrated in Figure 11, the permanent and portable WIM data generated in Chapter 4 were evaluated into groups of similar characteristics. Based on the Class 9 truck tandem axle load spectra, six clusters shown in Figure 12 were generated. Class 9 and tandem axles are the most common and most overloaded truck type/axle configuration on the Texas roads. Therefore, this truck type/axle configuration was used as the basis for creating the clusters in this study.

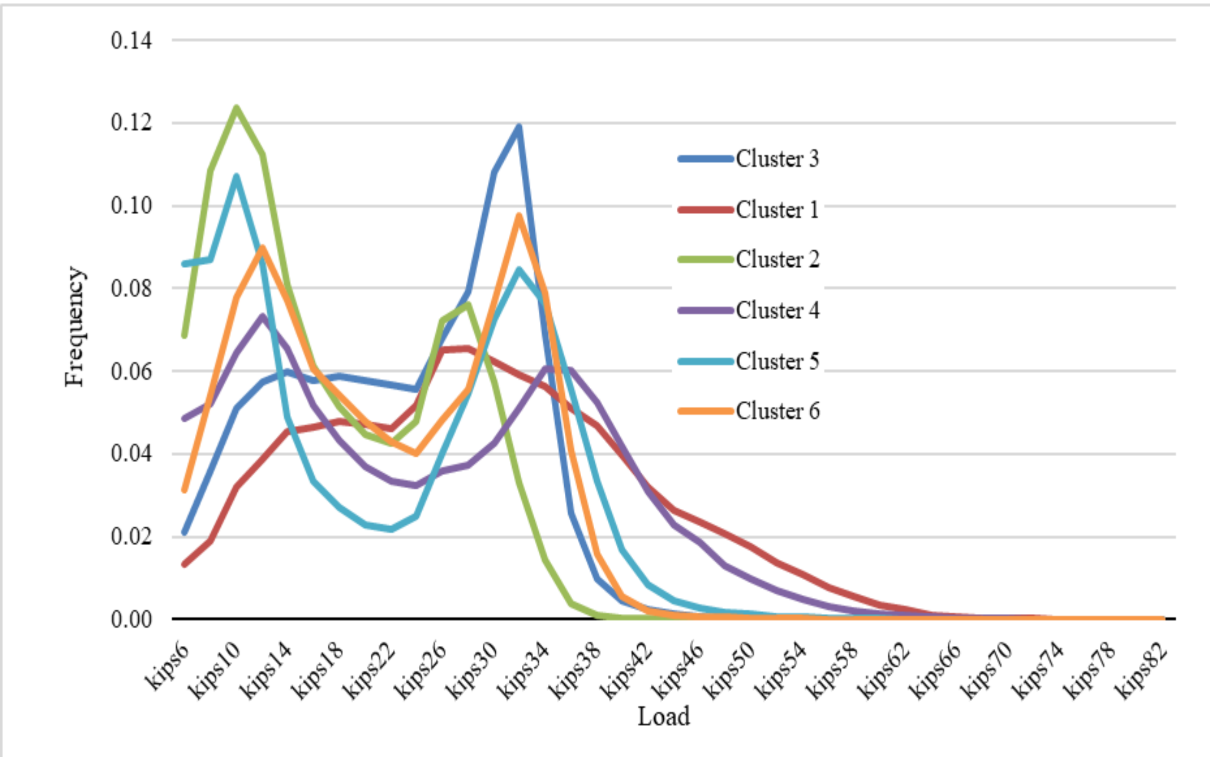


Figure 12. Texas's Six Traffic Clusters Based on Class 9 Truck Tandem Axle Load.

Figure 12 shows the six tandem axle load spectra clusters for Texas, with almost all the clusters exhibiting peaks at 10 and 32 kip, respectively. From the figure, it is also evident that Cluster 3 is associated with a higher percentage of 32-kip tandem axle loading than the other clusters. Cluster 1, on the other hand, appears to be associated with more tandem axle loading, while Cluster 5 has the least (22-kip) tandem axle loading.

In general, Figure 12 implies that any highway traffic loading in Texas would theoretically exhibit a Class 9 truck tandem axle loading similar to one of the clusters shown in Figure 12. Ultimately, this allows for clustering analysis to be able to predict the axle load spectra data for any given highway site with only simple VCD, ADT, and percentage trucks as the input because each of the six clusters is associated with specific VCD, ADT, ADTT, and percentage trucks data.

CLUSTERING ALGORITHM

Using the six clusters in Figure 12, a clustering analysis macro (in MS Excel) was developed to predict and estimate the ME axle load spectra data for any given highway by iteratively outputting a closest match with the available WIM data. During execution, the macro basically performs an automated two-step functional operation:

- Computes and predicts the cluster group in terms of the Class 9 truck tandem axle load spectra clusters shown in Figure 12.
- Iteratively scans the available WIM data to find the closest matching WIM stations and highways. The greater the number of WIM station data, the greater the prediction. At minimum, five ranked WIM stations and highways will be given as the output.

For execution, the current version of the clustering macro requires only simple-to-obtain traffic data, namely highway functional class (e.g., FM, IH, SH, US), ADTT, percent truck, and C5/C9 ratio. The C5/C9 ratio is the ratio of the Class 5 to Class 9 trucks, representing the most common truck types on the Texas roads—that is, Class 9 is the most common truck, followed by Class 5 trucks as the next most common.

Once the simple inputs are entered and the prediction analysis is executed, the macro will analyze the data and suggest WIM stations with the most similar axle load attributes based on the estimated clustering group in Figure 12 and a percentage score matching system. As of now, the clustering macro database comprises 50 WIM stations—furthers addition of WIM station data will definitely improve the prediction accuracy of the macro. Figure 13 shows the main screen of the clustering macro and example output resulting in a rank order from 1 through 5.

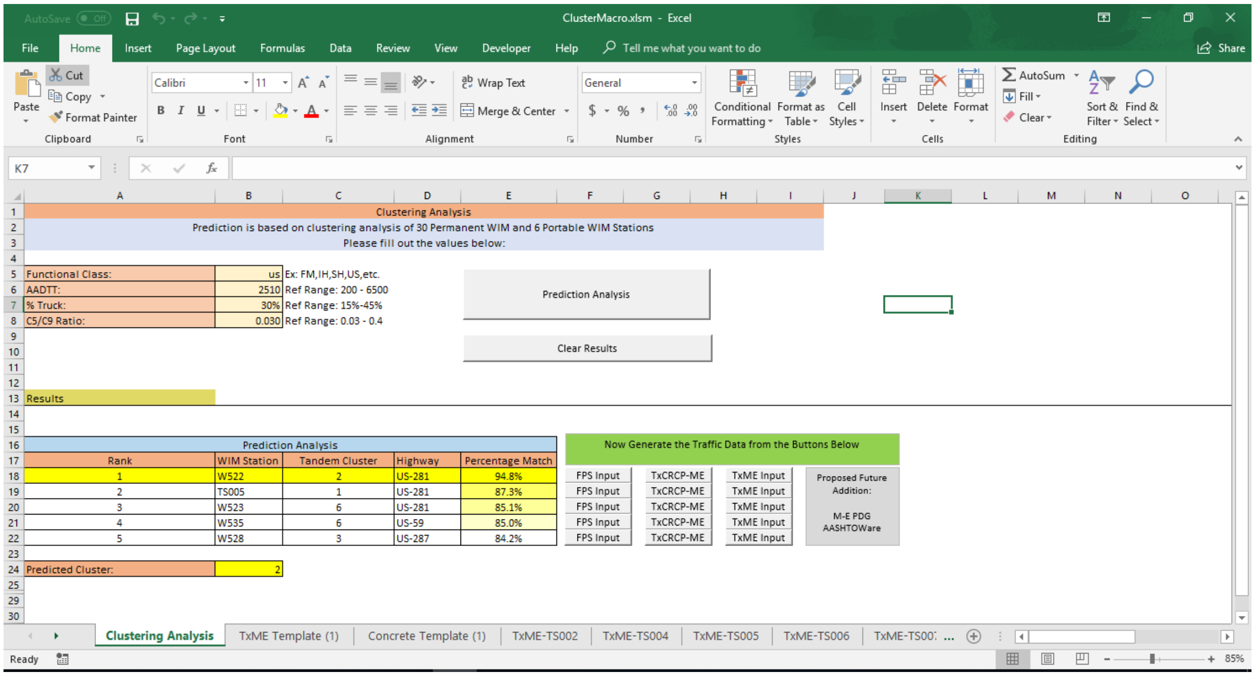
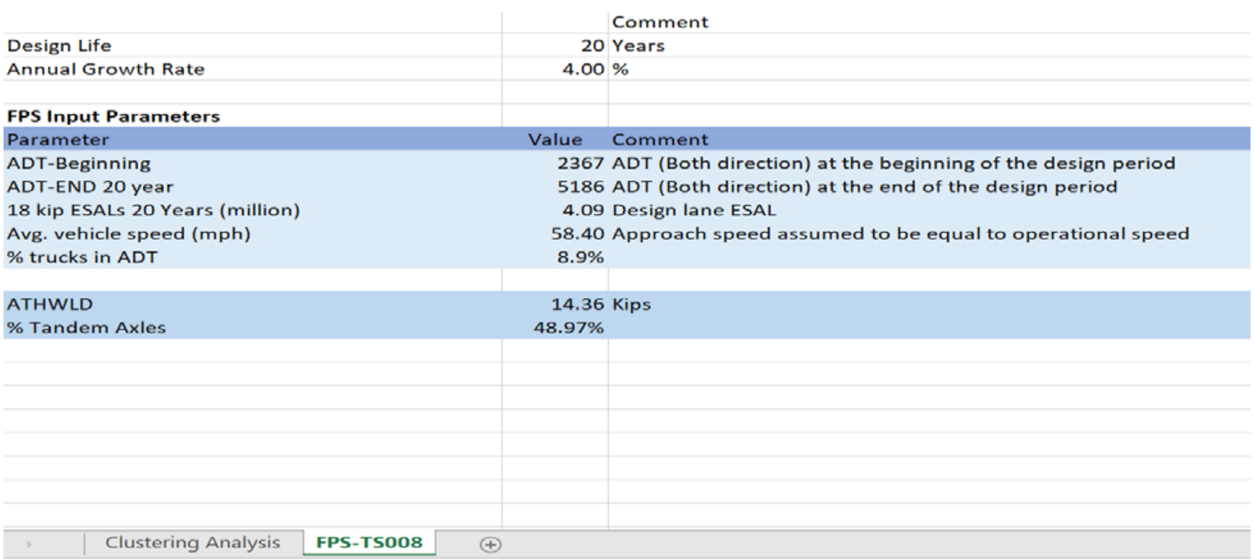


Figure 13. Clustering Macro Main Screen with Results.

As shown in Figure 13, the cluster macro outputs the five most matching WIM stations and highways as a function of a percentage score-ranking criteria. The actual output ME traffic data estimates are FPS, TxCRCP-ME (concrete), TxME, AASHTOWare, and TF. The user can then select his/her preference and generate the required ME traffic data, as exemplified in Figure 14 and Figure 15. Running time of the current clustering macro version is less than 5 minutes.



		Comment
Design Life	20	Years
Annual Growth Rate	4.00	%
FPS Input Parameters		
Parameter	Value	Comment
ADT-Beginning	2367	ADT (Both direction) at the beginning of the design period
ADT-END 20 year	5186	ADT (Both direction) at the end of the design period
18 kip ESALs 20 Years (million)	4.09	Design lane ESAL
Avg. vehicle speed (mph)	58.40	Approach speed assumed to be equal to operational speed
% trucks in ADT	8.9%	
ATHWLD	14.36	Kips
% Tandem Axles	48.97%	

Figure 14. Cluster Analysis Results—FPS Input Data.

Concrete - Inputs (Based on Flex PVMNT Daily ESAL)	Value	Comment
Design Life	30	Years
Annual Growth Rate	4.00	%
Number of Lanes in one direction	1	
18 kip ESALs 30 Years (million)	8.16	

Concrete - Inputs (Based on Concrete Daily ESAL)	**Value**	**Comment**
Design Life	30	Years
Annual Growth Rate	4.00	%
Number of Lanes in one direction	1	
18 kip ESALs 30 Years (million)	12.53	

Clustering Analysis | TxCRCP-TS008 | FPS-TS008

Figure 15. Cluster Analysis Results—TxCRCP-ME (Concrete) Input Data.

SUMMARY

This chapter presented and discussed the clustering analysis macro developed using the *k*-means method of clustering for predicting and estimating axle load spectra data. From the evaluated permanent and portable WIM data, six Texas tandem axle load spectra clusters were created. When executed, the clustering macro outputs the five most matching WIM stations/sites and highways as a function of a percentage score-ranking criteria for FPS, TxCRCP-ME (concrete), TxME, and AASHTOWare traffic input data including the TF. The clustering macro is included in a CD accompanying this report.

However, one current challenge is the limited number of WIM stations/sites (50 in the clustering macro database), which tends to inhibit the prediction accuracy of the macro. Continued population of the traffic data, through deployment of portable WIM units around the state, is thus strongly warranted to aid in the enhancement and prediction accuracy improvement of the clustering macro. Also, continuous traffic data updates of the latest WIM measurements are imperative.

CHAPTER 6. THE ME TRAFFIC DATABASE

The T-DSS was developed and is being maintained and managed in the user-friendly MS Access platform to provide ME traffic data support for the FPS, TxCRCP-ME (concrete), TxME, and other ME software such as the AASHTOWare. Microsoft products are compatible with most computers, and almost all engineering professionals are conversant with MS Office/Access; thus, this was selected as the platform for the T-DSS. As shown in Figure 16, the data are arranged and stored in tabular format along with zipped attachments such as PDF, MAF, and ALD files.

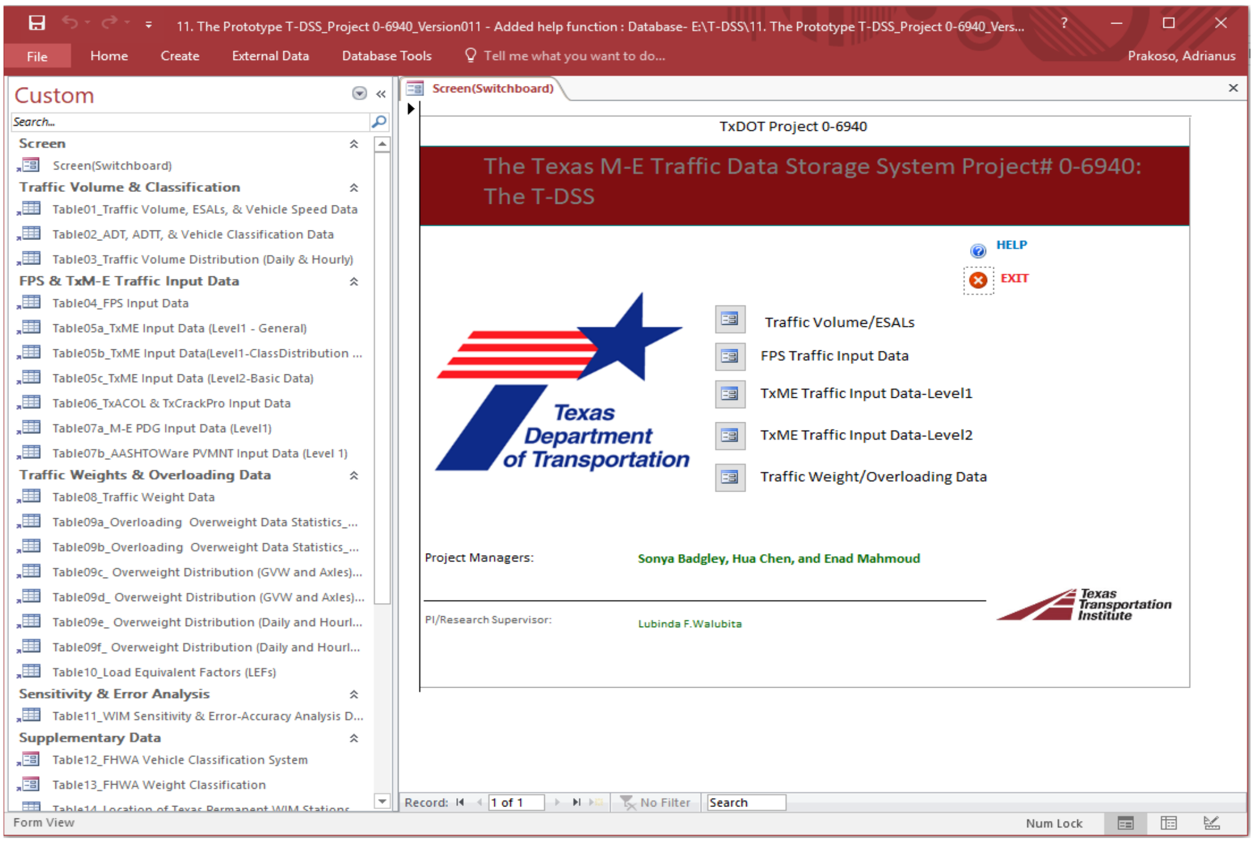


Figure 16. T-DSS Main Screen.

As discussed in the subsequent text, the T-DSS tables are organized in the following main groups or categories: traffic volume and classification, FPS and ME traffic input data, traffic weight and overloading data, and supplementary data.

TRAFFIC VOLUME AND CLASSIFICATION DATA TABLES

Tables in this category of general traffic data include the following: (a) Table01—traffic volume, ESALs, and vehicle speed data; (b) Table02—ADT, ADTT, and classification data; and

(c) Table03—traffic volume distribution, including hourly and daily distributions. PPT slides with the complete data analysis output and results for each highway site and WIM station are also included as zipped PDF attachments to Table01.

FPS AND ME TRAFFIC INPUT DATA TABLES

Tables in this category comprise the ME traffic input data, including FPS, TxCRCP-ME, TxME, TxACOL, TxCrackPro, MEPDG, and AASHTOWare. For TxME, MEPDG, and AASHTOWare Level 1, the tables also include attachments of zipped MAF and ALD files. The TxME includes separate tables for both Levels 1 and 2 ME traffic input data.

TRAFFIC OVERWEIGHT AND OVERLOADING DATA TABLES

Tables in this category comprise general traffic weight and overweight statistics for truck loading, including the LEFs. The OW data include GVW, axle loading, and hourly and daily distribution for all trucks, as well as for Class 9 trucks only. These data are tailored to provide the user with the truck weight data, among others, to aid in the quantification and assessment of any potential pavement damage.

SUPPLEMENTARY DATA TABLES

Tables in this category comprise supplementary data including but not limited to the following: FHWA vehicle classification, FHWA weight classification, location of Texas permanent WIM stations, and a map of Texas's permanent WIM stations.

T-DSS DATA ACCESS, EXPORTING, EMAILING, AND DOWNLOADS

Accessing the T-DSS data is typically achieved through the MS Access External Data function that exports the data (selected table and/or data) into various desired formats, including MS Excel, text, and PDF. MS Access also provides direct emailing of the T-DSS data once the desired table or set of data is selected. This is exemplified in Figure 17 through Figure 19. The zipped attachments can simply be downloaded by double-clicking the attachment icon on any table that has the zipped attachments.

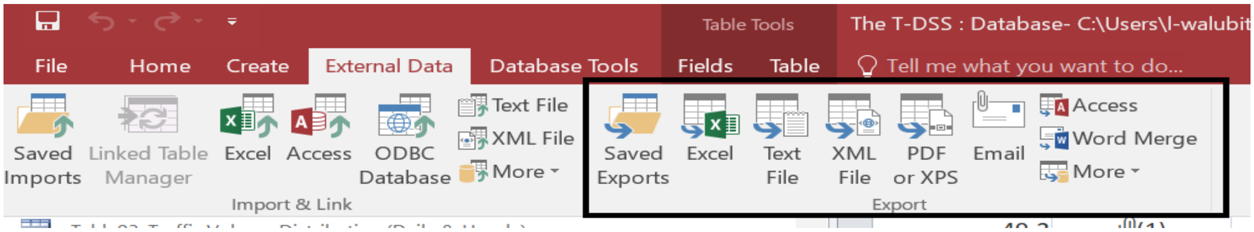


Figure 17. MS Access Tools for T-DSS Data Export.

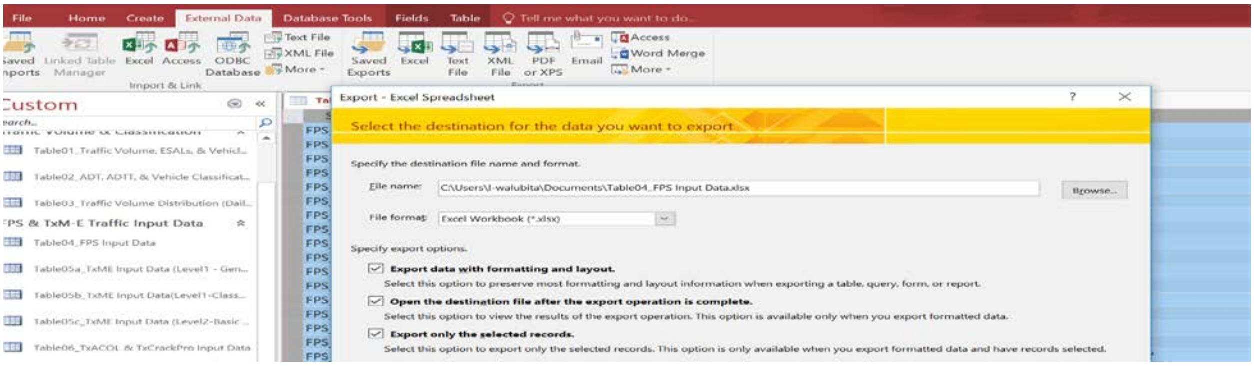


Figure 18. T-DSS Data Export (External Data ⇒ Excel).

HWY	LaneDirection	ADTbegin	ADTend-20Yr	20Yr 18-kips ESALs (millions)	Avg Vehicle Speed (mph)	%Trucks in ADT	ATHWLD (kips)	%age Tandem Axles (%)
IH 35	NB	6113	23001	39.08	65.00	47.00%	14.34	55.50%
IH 35	NB	2699	10155	5.49	65.00	13.00%	11.78	51.06%
IH 35	SB	6213	23377	40.11	65.00	51.00%	12.25	57.91%
IH 35	SB	2656	9994	5.76	65.00	14.00%	12.74	54.87%
US 281	NB	2124	6473	1.79	65.00	14.00%	13.03	46.84%
US 281	SB	2150	6552	1.69	65.00	17.00%	12.86	46.73%
FM 3129	SB	504	910	0.44	65.00	33.00%	12.8	60.12%
SH 7	WB	1902	3435	5.31	67.10	20.50%	15.5	49.12%
FM 468	EB	1977	3571	12.74	64.80	54.00%	15.5	57.78%
US 281	NB	1354	2445	37.31	33.70	77.00%	20.51	56.42%
US 281	SB	3801	6865	18.90	35.20	32.00%	15.29	56.15%
SH 6	NB	2118	3825	2.25	69.00	22.40%	12.68	45.61%
IH 35	NB	6113	23001	39.08	65.00	47.00%	14.34	55.50%
IH 35	NB	2699	10155	5.49	65.00	13.00%	11.78	51.06%
IH 35	SB	6213	23377	40.11	65.00	51.00%	12.25	57.91%
IH 35	SB	2656	9994	5.76	65.00	14.00%	12.74	54.87%

Figure 19. Example Data Export from The T-DSS (FPS Input Data).

THE HELP FUNCTION

The Help function comprises, in zipped and PDF file formats, documents designed to help users navigate the T-DSS. The information and documents include the user's manual, MPRs, tech memos, project deliverables, research reports, and the ME software associated with the T-DSS data. Specifically, users are recommended to read the user's manual for easy T-DSS navigation and data access.

SUMMARY

This chapter provided an overview of the T-DSS that is used to store and manage the ME traffic data. The T-DSS is a user-friendly MS Access platform and is included in the CD accompanying this report. For continued population and update of the T-DSS, traffic data collection through statewide deployment of the portable WIM on selected highway sites, particular FM roads without permanent WIM stations, is strongly recommended.

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

This technical report presented and documented the two-year work done to collect, process, and analyze WIM data to generate ME traffic inputs. Specifically, the portable WIM was explored to supplement the permanent WIM station data. The scope of work included development of data analysis macros for automated processing and analysis of the traffic data followed by development of the MS Access T-DSS for storing and managing the traffic data. A clustering analysis macro was subsequently developed for predicting and estimating ME traffic data (in the absence of actual field measurements). The key findings and recommendations are discussed in the subsequent text.

KEY FINDINGS

In total, traffic data were sourced from 65 WIM station and PTT highway sites. Using the developed macro, these data were analyzed to generate ME traffic inputs and develop the T-DSS and clustering algorithms. Key findings from the study are summarized as follows:

- Portable WIM is a cost-effective, reliable, and practical supplement for site-specific traffic data collection (volume counts, speed, VCD, and vehicle weight measurements). With proper site selection, installation, calibration, and maintenance, traffic data accuracy of up to 92.5 percent is attainable with the portable WIM.
- Pneumatic tube counters are a cheap and quick supplement for traffic volume counts, vehicle speed, and VCD data only. PTT counters are ideal in situations where vehicle weights and axle load spectra data are not critical.
- The developed WIM data analysis macros are satisfactorily able to compute and generate ME traffic inputs for both flexible and rigid (concrete) pavements.
- The developed clustering algorithms and macros constitute an ideal and rapid methodology for predicting and estimating ME traffic data inputs (in the absence of costly permanent WIM field measurements).
- The T-DSS is a viable, user-friendly, and readily accessible MS Access storage platform for the storage and management of ME traffic data.

RECOMMENDATIONS

As was discussed in Chapter 3, most of the collected WIM station data predominantly came from East Texas, with very few stations in West Texas (see Figure 20). Thus, for project continuation and/or implementation, the following recommendations are made:

- More statewide traffic data collection with the portable WIM, particularly in West Texas (circled areas in Figure 20) and on FM roads, is strongly recommended for continued population of the T-DSS. More traffic data are very critical for the improved prediction accuracy of the clustering macro.
- Continued improvements, refinement, and enhancements of the clustering algorithms are needed to make the macro more robust, accurate, and user friendly.

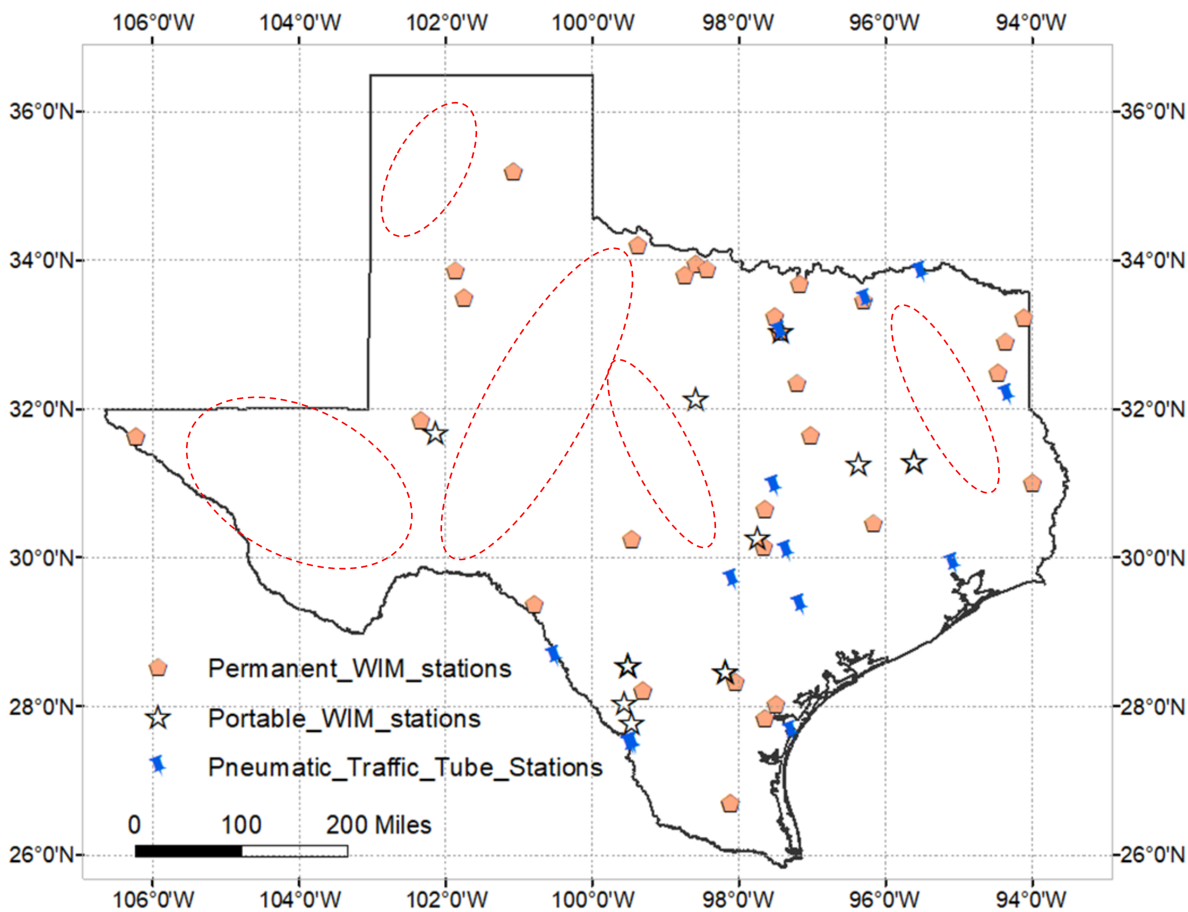


Figure 20. Map Location for the Circled Areas Needing Portable WIM Data.

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APPENDIX A. LITERATURE REVIEW RESULTS

Table A-1. Summary of Literature Review Findings.

Number	1			2	
Paper ID	Lu et al. 2009			Oh et al. 2015	
State/Country	California, USA			Texas, USA	
Clustering Technique Used	Hierarchical/ Euclidian distance			*k*-means/ Mean square error	
Parameters Used for Clustering	Level-1 Tandem Axle Load Distribution	Level-2 Single Axle Load Distribution	Level-1 Tridem Axle Load Distribution	Vehicle Class Distribution	Class 9 Tandem Axle Load Spectra
Parameters Used for Assigning Hwys to Clusters	Geographic location, AADT, AADTT, Truck %, Ratio of Classes (4–8)/(9–15)			Truck class distribution	
Number of WIM Sites Considered	108			29	
Number of Clusters	3	4	8	6	
Key Conclusion	Cluster analysis performed better than regression analysis for developing traffic input for ME pavement design.			*k*-means clustering was found to be an appropriate methodological approach to group the WIM sites.	

Table A-1. Summary of Literature Review Findings (Continued).

Number	3			4	
Paper ID	Sayyady et al. 2010			Papagiannakis et al. 2006	
State/Country	North Carolina, USA			Washington, USA	
Clustering Technique Used	Hierarchical/ Euclidian distance between attributes			Hierarchical/ Euclidian distance between attributes	
Parameters Used for Clustering	Level-1 Tandem Axle Load Distribution	Level-2 Single Axle Load Distribution	Level-1 Tridem Axle Load Distribution	Tandem Axle Load Distribution	Vehicle Class Distribution
Parameters Used for Assigning Hwys to Clusters	Geographic location, AADTT, Truck %, Ratio of Classes 5/9, Ratio of Classes (4-7)/(8-13)			—	
Number of WIM Sites Considered	44			17	
Number of Clusters	5	7	7	3	3
Key Conclusion	To generate ALD and MAF inputs, hierarchical clustering analysis and post-clustering analysis using local knowledge of the design road and easy-to-obtain traffic parameters must be used.			Accepting a lower level of dissimilarity (i.e., a lower value of Euclidean distance as threshold) would yield a larger number of groups, each involving fewer sites of higher similarity.	

Table A-1. Summary of Literature Review Findings (Continued).

Number	5		6	
Paper ID	Papagiannakis et al. 2006		Papagiannakis et al. 2006	
State/Country	Connecticut, USA		Indiana, USA	
Clustering Technique Used	Hierarchical/ Euclidian distance between attributes		Hierarchical/ Euclidian distance between attributes	
Parameters Used for Clustering	Tandem Axle Load Distribution	Vehicle Class Distribution	Tandem Axle Load Distribution	Vehicle Class Distribution
Parameters Used for Assigning Hwys to Clusters	—		—	
Number of WIM Sites Considered	4		14	
Number of Clusters	3	1	3	3
Key Conclusion	The findings from the cluster analysis study based on the Washington long-term pavement performance (LTPP) sites were extended to 178 LTPP WIM sites in 7 states.			

Table A-1. Summary of Literature Review Findings (Continued).

Number	7		8	
Paper ID	Papagiannakis et al. 2006		Papagiannakis et al. 2006	
State/Country	Michigan, USA		Minnesota, USA	
Clustering Technique Used	Hierarchical/ Euclidian distance between attributes		Hierarchical/ Euclidian distance between attributes	
Parameters Used for Clustering	Tandem Axle Load Distribution	Vehicle Class Distribution	Tandem Axle Load Distribution	Vehicle Class Distribution
Parameters Used for Assigning Hwys to Clusters	—		—	
Number of WIM Sites Considered	11		18	
Number of Clusters	3	1	3	3
Key Conclusion	The findings from the cluster analysis study based on the Washington LTPP sites were extended to 178 LTPP WIM sites in 7 states.			

Table A-1. Summary of Literature Review Findings (Continued).

Number	9		10	
Paper ID	Papagiannakis et al. 2006		Papagiannakis et al. 2006	
State/Country	Mississippi, USA		Vermont, USA	
Clustering Technique Used	Hierarchical/ Euclidian distance between attributes		Hierarchical/ Euclidian distance between attributes	
Parameters Used for Clustering	Tandem Axle Load Distribution	Vehicle Class Distribution	Tandem Axle Load Distribution	Vehicle Class Distribution
Parameters Used for Assigning Hwys to Clusters	—		—	
Number of WIM Sites Considered	22		5	
Number of Clusters	3	2	2	1
Key Conclusion	The findings from the cluster analysis study based on the Washington LTPP sites were extended to 178 LTPP WIM sites in 7 states.			

Table A-1. Summary of Literature Review Findings (Continued).

Number	11				12
Paper ID	Wang et al. 2007				Abbas et al. 2014
State/Country	Arkansas, USA				Ohio, USA
Clustering Technique Used	Hierarchical/ Euclidian distance between attributes				Group average clustering/ Euclidian distance between attributes
Parameters Used for Clustering	Gross Vehicle Weight	Vehicle Class Distribution	Hourly Distribution Factor	Monthly Adjustment Factor	Vehicle Class Distribution
Parameters Used for Assigning Hwys to Clusters	Region attributes (geographical considerations), GVW, VCD, HDF				—
Number of WIM Sites Considered	10				50
Number of Clusters	3	3	2	3	5
Key Conclusion	Also conducted clustering analysis using *k*-means and fuzzy cluster analysis method and did not find significant differences among the three methods.				Functional classification and truck traffic classification (TTC) grouping systems do not effectively represent the prevailing truck class pattern in Ohio.

Table A-1. Summary of Literature Review Findings (Continued).

Number	13	14
Paper ID	Buch et al. 2009	Hasan et al. 2016
State/Country	Michigan, USA	New Mexico, USA
Clustering Technique Used	Hierarchical/ Euclidian distance between attributes	*k*-means clustering/ Sum of squared error
Parameters Used for Clustering	TTC	VCD
Parameters Used for Assigning Hwys to Clusters	Truck %, Geographic Information, AADTT, Class 5%, Class 9%, Functional Class of Hwy	—
Number of WIM Sites Considered	44	10
Number of Clusters	3	3
Key Conclusion	Hierarchical clustering is suitable for smaller data size and the *k*-means method is beneficial for large amount of data.	The VCD and axle load spectra vary depending on their location and surrounding infrastructure, so the ME design traffic inputs need to be adjusted accordingly.

Table A-1. Summary of Literature Review Findings (Continued).

Number	15	16
Paper ID	Darter et al. 2013	Swan et al. 2008
State/Country	Arizona, USA	Ontario, Canada
Clustering Technique Used	Hierarchical/ Euclidian distance between attributes	Hierarchical/ Euclidian distance between attributes
Parameters Used for Clustering	Tandem axle load distribution	Tandem axle load distribution
Parameters Used for Assigning Hwys to Clusters	Geographic information, TTC	Geographic information
Number of WIM Sites Considered	21	—
Number of Clusters	3	3
Key Conclusion		Commercial vehicle survey data were used; no WIM data were considered.

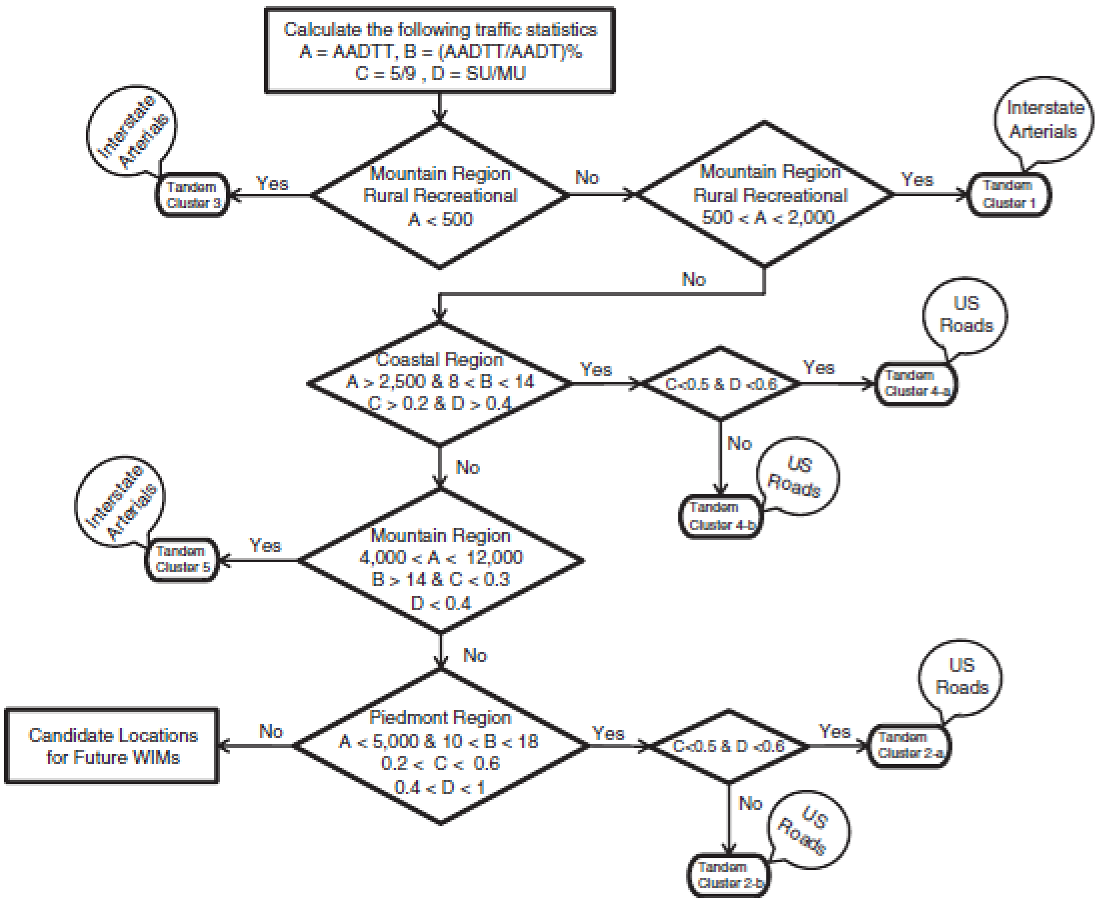


Figure A-1. Decision Tree to Assign Highway Locations in North Carolina to Representative Clusters (Sayyady et al., 2010).

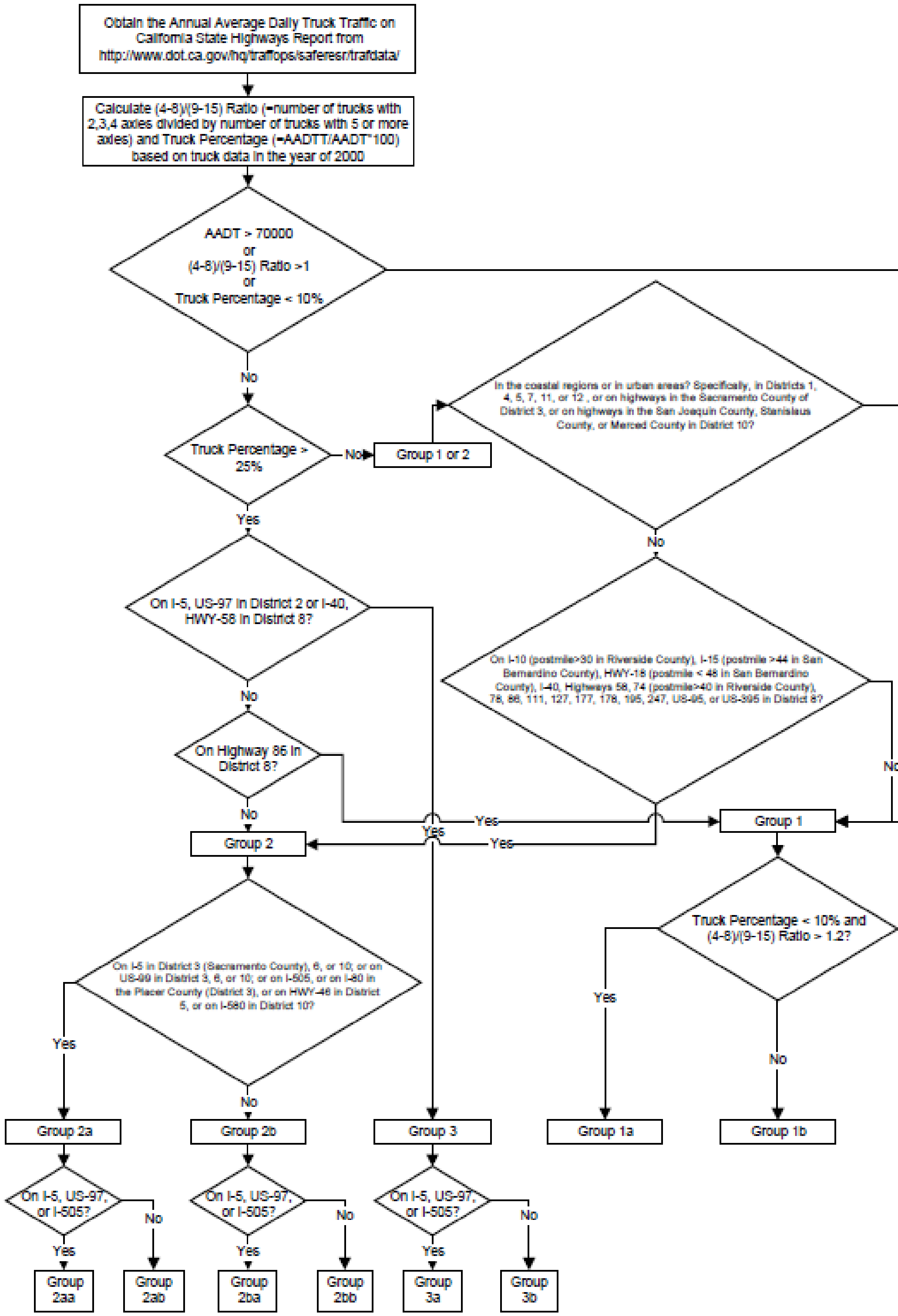


Figure A-2. Flowchart for Grouping California Highways Based on Axle Load Spectra (Lu and Zhang, 2009).

Parameter	Cluster number	Cluster definition	WIM Stations
GVW	1	Dominance of heavy fully loaded trucks	170064, 460006, 580236
	2	Dominance of empty light trucks	71813, 230001, 720034, 740035, 430038, 600870
	3	High percentages of empty light and fully loaded heavy trucks	480037
CDF	1	Higher frequency of Class 5 than Class 9 vehicles	171651, 670027, 680032, 750010
	2	Roughly equal frequencies of Class 5 and Class 9 vehicles	281983, 430037, 460006, 481524, 580236, 680025, 740035
	3	Higher frequency of Class 9 than Class 5 vehicles	71813, 170064, 180002, 230001, 290002, 430038, 460286, 480037, 600870, 720034, 730068
HDF	1	Relative higher frequency of trucks during daytime	430037, 481524, 580236, 680025, 180002, 170064, 460006, 730068
	2	Relative lower frequency of trucks during daytime	71813, 281983, 720034, 290002, 740035, 480037, 230001, 460286, 600870, 750010, 670027, 430038, 171651, 680032
MAF	1	Roughly equal frequencies of vehicles of all months	430037, 481524, 580236, 720034, 480037, 670027, 171651, 180002
	2	Relatively lower frequency of vehicles in June (summer)	680025, 730068, 460286, 600870,
	3	Relatively higher frequency of vehicles in February (winter)	71813, 281983, 290002, 740035, 170064, 460006, 230001, 750010, 430038, 680032

Figure A-3. Identifying Clusters for ME Traffic Data (Wang et al., 2011).

k-Means Clustering Method	Hierarchical Clustering Method
▪ Predefined cluster, *k* clusters are created by associating every observation with the nearest mean. ▪ The centroid of each of the *k* clusters then becomes the new mean, and iterations repeated until convergence	▪ Begins with *n* clusters and assumes each station/site is cluster ▪ Then groups based on similar attributes, i.e., ALDF, ADT, MAF, etc ▪ Hierarchical clustering & iterations repeated to convergence
- Simple and fast - Linear analysis - Ideal for large datasets - *K-clusters* predefined	- Ideal for multi-variables - Quadratic analysis - Limited to small datasets - A bit complex and more time consuming

Figure A-4. Comparison of Clustering Methods (*k*-Means versus Hierarchical).

APPENDIX B. EXAMPLE WIM STATIONS AND PTT HIGHWAY SITE LOCATIONS

#	Station ID#	District (County)	Climatic Region	Hwy	Lane Direction	Mile Marker	GPS Coordinates
1	W513	WAC(Bell)	Moderate	IH 35	All (NB & SB)	276-280	N 30° 51' 36" W 97° 35' 18"
2	W523	PHR(Hidalgo)	Moderate	US 281	All (NB & SB)	750-748	N 26° 41' 09" W 98° 06' 53"
3	W524	ELP(El Paso)	Dry-Warm	IH 10	All (EB &WB)	40-41	N 31° 37' 59" W 106° 13' 08"
4	W527	FTW(Wise)	Wet-Cold	SH 114	All (NB & SB)	582	N 33° 02' 11" W 97° 25' 56"
5	W531	LRD(La Salle)	Dry-Warm	IH 35	All (NB & SB)	50-55	N 28° 13' 05" W 99° 18' 10"
6	W534	CRP(Corpus Christi)	Moderate	IH 69	All (NB & SB)	145	N 27° 50' 23" W 97° 37' 59"
7	W541	ATL(Cass)	Wet-Cold	FM3129	NB (L1) & SB(L1)	232-230	N 33° 13' 32" W 94° 05' 56"
8	W542	BMT(Western Orange	Wet-Warm	IH 10	All (EB &WB)	860-865	N 30° 07' 35" W 94° 01' 25"
9	W547	AMA (Potter)	Dry-Cold	IH 40	All (EB & WB)	110-120	N 35° 11' 39" W 101° 04' 26

Figure B-1. Example Permanent WIM Stations.

#	Site ID#	District (County)	Climatic Region	Hwy	Lane Direction	Mile Marker	GPS Coordinates
1	TS001	LRD (Webb)	Dry-warm	US 83	NB (Outside)	678-680	N 28° 02' 37.4", W 099° 32' 59.8"
2	TS002	BRY (Robertson)	Wet-Warm	SH7	All (EB & WB)	618-616	N 31° 15' 27.1" W 96° 21' 09.5"
3	TS003	BRY(Leon)	Wet-Warm	SH7	WB-L1	658-660	N 31° 18', W 95° 35'
4	TS007	FTW (Wise)	Wet-Cold	SH 114	EB-L1	582-584	N 33°02; W 97°25'
5	TS004	LRD (Dimmit)	Dry-Warm	FM 468	EB-L1	432-434	N 28°33'; W 99°30'
6	TS005	CRP (Live Oak)	Moderate	US 281	NB-L1 & SB-L1	620-622	N 28°27'59.0", W 98°10'50.7"
7	TS006	BWD (Comanche)	Dry-Warm	SH 6	NB-L1	386-384	N 32°13; W 98°57'W
8	TS008	ODA (Midland)	Dry-Warm	FM 1787	All (EB & WB)	280	N 31°41'; W 102°07'
9	TS009	LRD (Webb)	Dry-Warm	US 83	NB (Outside)	696-698	N 27° 46' 46.2", W 099° 27' 0.2"

Figure B-2. Example Portable WIM Sites.

#	Site ID#	District (County)	Climatic Region	Hwy	Lane Direction	Mile Marker	GPS Coordinates
1	TTI00001	ATL (Panola)	Wet-Cold	US 59	SB (Outside)	308-310	N 32° 12' 05.3" W 94° 20' 35.5"
2	TTI00051	AUS (Bastrop)	Moderate	SH 304	SB	450-452	N 30° 06' 06.8" W 97° 21' 08.5"
3	TTI00024	YKM(Lavaca)	Wet-Warm	SH 95	SB	522-524	N 29° 22' 34.6" W 97° 09' 52.0"
4	TTI00002	FTW (Wise)	Wet-Cold	SH 114	EB (Outside)	582-584	N 33° 02' 12.1" W 97° 25' 34.5"
5	TTI00005	LRD (Maverick)	Dry-Warm	Loop 480	SB & NB (Outside)	570-567	N 28° 40' 58.9" W 100° 30' 10.5"
6	TTI00016	HOU(Harris)	Wet-Warm	FM 2100	NB & SB	456-454	N 29° 55' 32.6" W 95° 04' 18.2"
7	TTI00007	PAR(Lamar)	Wet-Cold	US 271	NB & SB	187-188	N 33° 51' 06.50" W 95° 30' 33.20"
8	TTI00019	SAT(Comal)	Dry-Warm	IH 35	SB (Outside)	190-189	N 29° 42' 34.8" W 98° 05' 23.8"
9	TTI00009	WAC(Bell)	Moderate	IH 35 (Frontage)	NB & SB	269-268	N 30° 58' 25.90" W 97° 30' 55.2"

Figure B-3. Example PTT Sites.

Serial#	ID#	Station#	StationEquipment Type	GPS Location	Ref_MileMarker	GoogleMap Link	District	County	HWY	LaneDirection	LaneDesignation	fLanesInOneDire
TVS_0000029	T-WIMs_TS007	TS007	Portable WIM (TRS-3)	N 33° 02'12.0", W 97° 25'28.7"	582-584	https://goo.gl/HqcMDv	Fort Worth	Wise	SH 114	EB	Outside (L1)	
TVS_0000001	T-WIMs_TS001	TS001	Portable WIM (TRS)	N 28° 02' 37.4", W 099° 32' 59.8"	678-680	https://goo.gl/udr6tl	Laredo	Webb	US 83	NB	Outside	
TVS_0000002	T-WIMs_TS001	TS001	Pneumatic Traffic Tube Counters (Apollo)	N 28° 02' 37.4", W 099° 32' 59.8"	678-680	https://goo.gl/udr6tl	Laredo	Webb	US 83	NB	Outside	
TVS_0000003	P-WIM_LW531	W531	Permanent WIM	N 28° 12' 52" W 99° 18' 21"	51-52	https://goo.gl/HFU3zL	Laredo	La Salle	IH 35	NB	Outside (L1)	2.00
TVS_0000004	P-WIM_LW531	W531	Permanent WIM	N 28° 12' 52" W 99° 18' 21"	51-52	https://goo.gl/HFU3zL	Laredo	La Salle	IH 35	NB	Inside (L2)	2.00
TVS_0000005	P-WIM_LW531	W531	Permanent WIM	N 28° 12' 52" W 99° 18' 21"	51-52	https://goo.gl/HFU3zL	Laredo	La Salle	IH 35	SB	Outside (L1)	2.00
TVS_0000006	P-WIM_LW531	W531	Permanent WIM	N 28° 12' 52" W 99° 18' 21"	51-52	https://goo.gl/HFU3zL	Laredo	La Salle	IH 35	SB	Inside (L2)	2.00
TVS_0000007	T-WIMs_TS002	TS002	Portable WIM (ECM)	N 31° 15' 27.1" W 96° 21' 09.5"	618-616	https://goo.gl/bj2xjo	Bryan	Robertson	SH 7	WB	Outside	
TVS_0000008	T-WIMs_TS002	TS002	Portable WIM (ECM)	N 31° 15' 27.1" W 96° 21' 09.5"	618-616	https://goo.gl/bj2xjo	Bryan	Robertson	SH 7	EB	Outside	
TVS_0000009	T-WIMs_TS002	TS002	Pneumatic Traffic Tube Counters (Apollo)	N 31° 15' 27.1" W 96° 21' 09.5"	618-616	https://goo.gl/bj2xjo	Bryan	Robertson	SH 7	WB	Outside	
TVS_0000010	T-WIMs_TS002	TS002	Pneumatic Traffic Tube Counters (Apollo)	N 31° 15' 27.1" W 96° 21' 09.5"	618-616	https://goo.gl/bj2xjo	Bryan	Robertson	SH 7	EB	Outside	
TVS_0000011	T-WIMs_TS003	TS003	Portable WIM (TRS-4)	N 31° 18', W 95° 35'	660-658	https://goo.gl/csEjx0	Bryan	Leon	SH 7	WB	Outside	
TVS_0000012	P-WIM_LW523	W523	Permanent WIM	N 26° 41' 09" W 98° 06' 53"	750-748	https://goo.gl/c5GCVs	Pharr	Hidalgo	US 281	NB	Outside (L1)	
TVS_0000013	P-WIM_LW523	W523	Permanent WIM	N 26° 41' 09" W 98° 06' 53"	750-748	https://goo.gl/c5GCVs	Pharr	Hidalgo	US 281	NB	Inside (L2)	
TVS_0000014	P-WIM_LW523	W523	Permanent WIM	N 26° 41' 09" W 98° 06' 53"	750-748	https://goo.gl/c5GCVs	Pharr	Hidalgo	US 281	SB	Outside (L1)	
TVS_0000015	P-WIM_LW523	W523	Permanent WIM	N 26° 41' 09" W 98° 06' 53"	750-748	https://goo.gl/c5GCVs	Pharr	Hidalgo	US 281	SB	Inside (L2)	
TVS_0000016	P-WIM_LW541	W541	Permanent WIM	N 33° 13' 32" W 94° 05' 56"	232-230	https://goo.gl/CoU93n	Atlanta	Cass	FM 3129	NB	Outside (L1)	
TVS_0000017	P-WIM_LW541	W541	Permanent WIM	N 33° 13' 32" W 94° 05' 56"	232-230	https://goo.gl/CoU93n	Atlanta	Cass	FM 3129	SB	Outside (L1)	
TVS_0000018	T-WIMs_TS003	TS003	Portable WIM (TRS-4)	N 31° 18', W 95° 35'	660-658	https://goo.gl/csEjx0	Bryan	Leon	SH 7	WB	Outside(L1)	
TVS_0000019	T-WIMs_TS004	TS004	Portable WIM (TRS-3)	N 28°33', W 99°30'	432-434	https://goo.gl/IKbFN9	Laredo	Dimmit	FM 468	EB	Outside(L1)	
TVS_0000020	T-WIMs_TS005	TS005	Portable WIM (TRS-2)	N 28°27'59.0", W 98°10'50.7"	620-622	https://goo.gl/18BcvR	Corpus Christi	Live Oak	US 281	NB	Outside(L1)	
TVS_0000021	T-WIMs_TS005	TS005	Portable WIM (TRS-2)	N 28°27'59.0", W 98°10'50.7"	620-622	https://goo.gl/18BcvR	Corpus Christi	Live Oak	US 281	SB	Outside(L2)	
TVS_0000022	T-WIMs_TS006	TS006	Portable WIM (TRS-1)	N 32° 13', W -98° 57'	386-384	https://goo.gl/3UIiaP	Brownwoo d	Comanche	SH 6	NB	Outside(L1)	
TVS_0000023	T-WIMs_TS008	TS008	Portable WIM (TRS-1)	N 31° 41'16.4", W 102° 07'15.3"	280	https://goo.gl/7qY2es	Odessa	Midland	FM 1787	SB	Outside(L1)	
TVS_0000024	T-WIMs_TS008	TS008	Portable WIM (TRS-1)	N 31° 41'16.4", W 102° 07'15.3"	280	https://goo.gl/7qY2es	Odessa	Midland	FM 1787	SB	Outside(L1)	
TVS_0000025	P-WIM_LW527	W527	Permanent WIM	N 33° 02' 11", W 97° 25' 56"	594-596	https://goo.gl/5UcHT7	Fort Worth	Wise	SH 114	EB	Outside (L1)	
TVS_0000026	P-WIM_LW527	W527	Permanent WIM	N 33° 02' 11", W 97° 25' 56"	594-596	https://goo.gl/5UcHT7	Fort Worth	Wise	SH 114	EB	Inside (L2)	
TVS_0000027	P-WIM_LW527	W527	Permanent WIM	N 33° 02' 11" ,W 97° 25' 56"	594-596	https://goo.gl/5UcHT7	Fort Worth	Wise	SH 114	WB	Outside (L1)	

Figure B-4. Example WIM Location Details in the T-DSS.

APPENDIX C. EXAMPLE TRAFFIC DATA ANALYSIS RESULTS

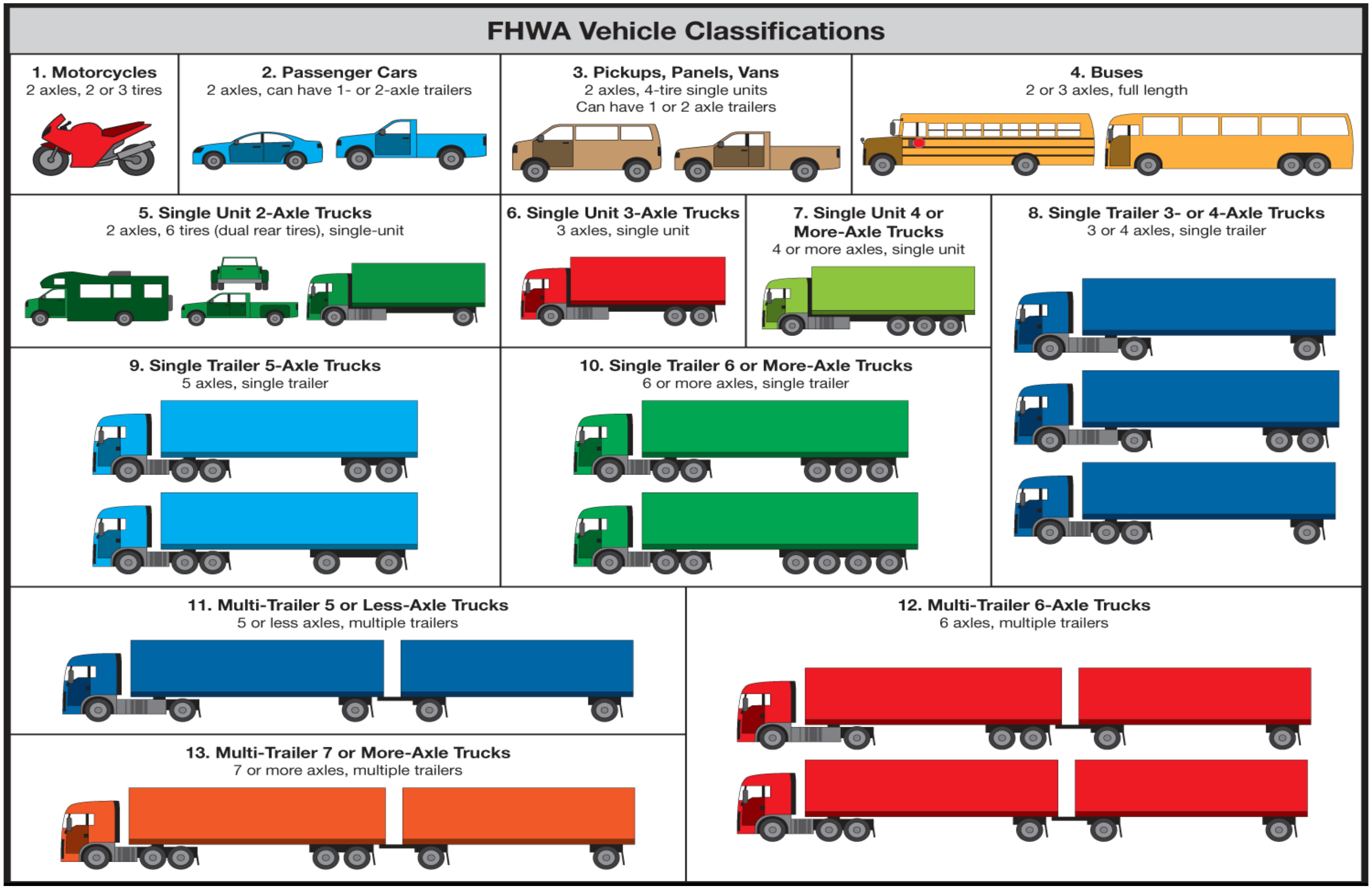


Figure C-1. FHWA Vehicle Classification System.

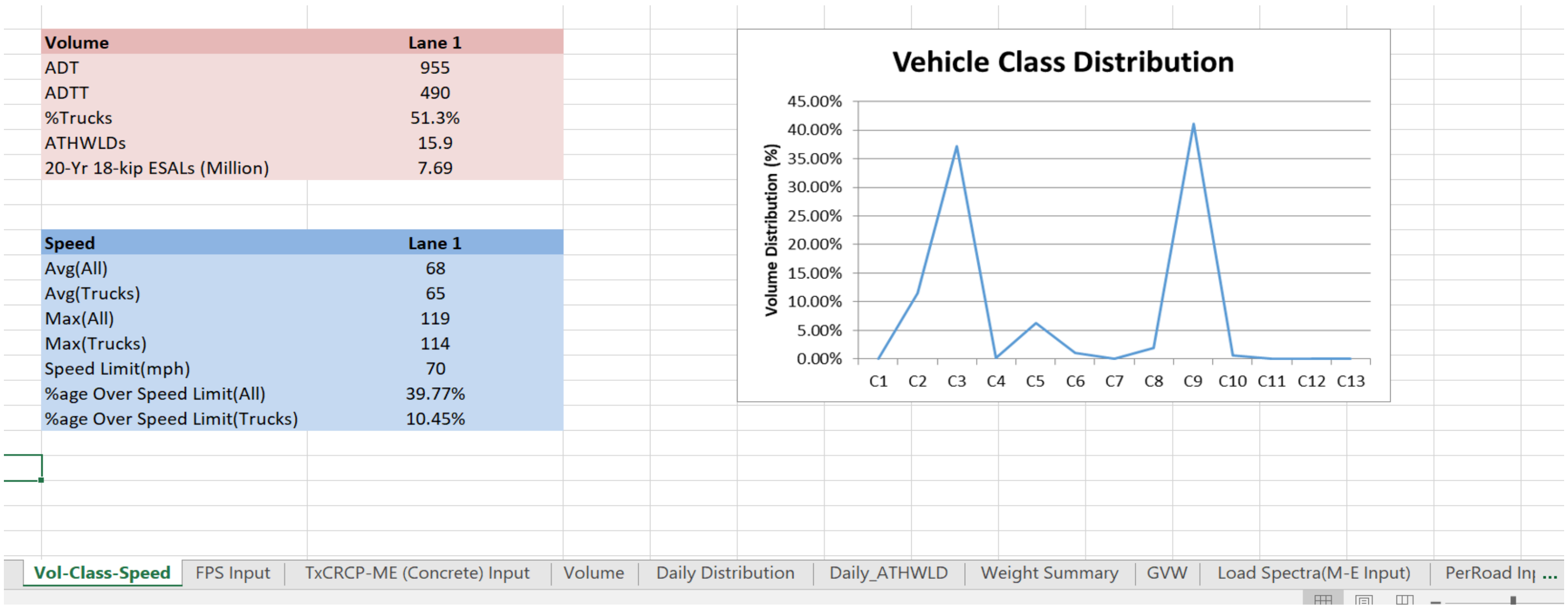


Figure C-2. Example Output from Portable WIM Macro Analysis.

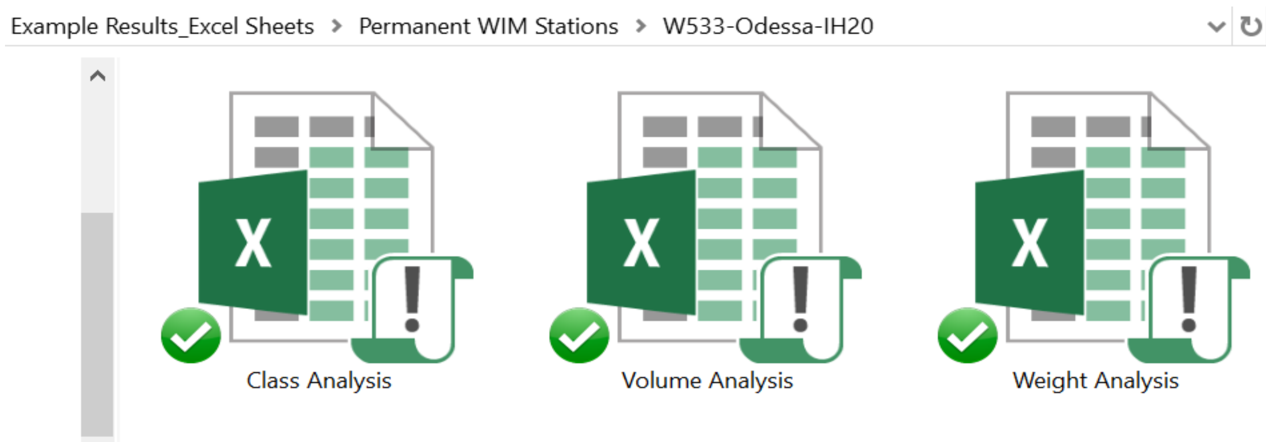


Figure C-3. Example Output Results (MS Excel Files) from Permanent WIM Macro Analysis.

FPS Parameter	NB-L1 (Outside)	NB-L2 (Inside)	SB-L1 (Outside)	SB-L2 (Inside)	Comment
ADT-Beginning	6,113	2,699	6,213	2,656	ADT at the beginning of the design period
ADT-END 20 Year	23,001	10,155	23,377	9,994	ADT at the end of the design period (20 yrs)
18 kip ESALs 20 Years (millions)	39.08	5.49	40.11	5.76	@ 6.85% Gr
Avg. vehicle speed (mph)	~65	~65	~65	~65	Approach speed assumed to be equal to operational speed
% Trucks in ADT	47%	13%	51%	14%	
ATHWLD (kips)	14.3	11.8	12.3	12.7	
%Tandem axles	55.5%	51.1%	57.9%	54.9%	

Figure C-4. FPS Traffic Input Data (Station W531, IH 35).

Station	Hwy	District	Year	Direction	Lane	20-yr 18-kip ESALs (million)	30-yr 18-kip ESALs (million)	30-yr 18-kip ESALs (millions) by Slab Thickness				
								8"	9"	10"	11'	12"
W531	IH 35	Laredo	2015	NB	L1 (Outside)	39.1	70.2	93.5	94.4	95.1	95.4	95.6
				NB	L2 (Inside)	5.5	9.2	11.0	11.2	11.3	11.3	11.4
				SB	L1 (Outside)	40.1	78.0	-	-	-	-	-
				SB	L2 (Inside)	5.8	9.2	-	-	-	-	-

Figure C-5. Concrete Traffic Input Data (Station W531, IH 35).

Highway	ADT		Base Year				ATHWLD	% Tandem ATHWLD	18-kip ESALs 30-Yrs (1 Dir) (millions)	
	Begin	30 years	Dir Dist. %	K-factor	% Trucks				Slab	EASLs
					ADT	DHV				
IH 35 (SB) Lanes = 3	22841	55440	46-54	5.8	20.2	40.8	14.9	47.8	8”	141.6
									9”	143.0
									10”	144.1
									11”	144.8
									12”	145.1

Figure C-6. Concrete Traffic Input Data (IH 35, Austin).

Table C-1. Example Permanent WIM Traffic Data Analysis.

Station	Hwy	District	Data Period	Dir & Lane	ADT	ADTT	%Truck in ADT	Traffic Growth	ADT-End 20 yr	20-yr 18-kip ESALs (million)	ATHWLD	%age Tandem
W4142	US 96	Beaumont	2016	EB-L1	2526	595	24%	4.9%	6515	5.2	11.4	38.1%
				EB-L2	1302	101	8%	4.9%	3356	0.7	10.3	28.2%
				WB-L1	2485	465	19%	4.9%	6407	4.8	11.3	40.6%
				WB-L2	1280	58	5%	4.9%	3301	0.4	10.6	40.1%
W506	US 287	Wichita Falls	2016	NB-L1	6531	2378	36%	5.6%	19357	27.7	11.9	43.9%
				NB-L2	3364	422	13%	5.6%	9971	3.7	12.4	29.3%
				SB-L1	6551	2270	35%	5.6%	19417	29.9	12.8	41.7%
				SB-L2	3374	339	10%	5.6%	10000	2.3	12.2	27.0%
W518	IH 10	San Antonio	2016	EB-L1	3956	1761	45%	4.4%	9266	14.8	15.2	48.3%
				EB-L2	2038	141	7%	4.4%	4773	0.8	15.8	37.1%
				WB-L1	3907	1741	45%	4.4%	9151	19.1	15.2	45.5%
				WB-L2	2013	163	8%	4.4%	4715	0.8	15.5	30.9%
W522	US 281	Pharr	2016	SB-L1	5508	1501	27%	8.1%	26005	17.8	15.1	57.1%
W523	US 281	Pharr	2015	NB-L1	5238	2089	40%	5.7%	15963	21.1	15.5	49.0%
				NB-L2	2124	307	14%	5.7%	6473	1.8	13.0	34.0%
				SB-L1	5015	1968	39%	5.7%	15284	19.2	14.4	48.0%
				SB-L2	2150	355	17%	5.7%	6552	1.7	12.9	35.0%
W523	US 281	Pharr	2016	NB-L1	5244	1971	38%	5.7%	15714	23.9	16.0	49.4%
				NB-L2	2702	266	10%	5.7%	6372	2.1	16.0	34.6%
				SB-L1	5127	1886	37%	5.7%	15045	19.9	15.6	47.8%
				SB-L2	2641	320	12%	5.7%	6450	2.5	16.2	35.3%
W524	IH 10	El Paso	2015	EB-L1	8539	3515	41%	4.6%	21112	34.5	12.1	49.0%
				EB-L2	4845	778	16%	4.6%	11979	6.1	10.8	42.0%
				WB-L1	6411	2517	39%	4.6%	15851	24.7	11.6	49.0%
				WB-L2	4650	713	15%	4.6%	11497	5.9	17.9	34.0%
W526	IH 20	Atlanta	2016	EB-L1	9622	2443	25%	3.0%	17378	15.0	12.9	43.0%
				EB-L2	4957	921	19%	3.0%	8953	1.9	11.1	43.0%
				WB-L1	10791	3819	35%	3.0%	19490	21.1	13.6	47.0%
				WB-L2	5559	1190	21%	3.0%	10040	4.6	12.3	32.0%
W527	SH 114	FTW	2015	EB-L1	4802	1572	33%	8.3%	23571	39.4	17.0	43.0%
				EB-L2	3236	509	16%	8.3%	15884.5	8.8	17.5	26.0%
				WB-L1	4378	1718	39%	8.3%	21490.21	37.3	11.6	43.0%
				WB-L2	2844	429	15%	8.3%	13960.29	6.9	8.4	26.0%
W527	SH 114	FTW	2016	EB-L1	6099	1768	29%	8.7%	32143	42.1	18.1	42.6%
				EB-L2	3142	567	18%	8.7%	16558	7.1	16.9	25.5%

Table C-1. Example Permanent WIM Traffic Data Analysis (Continued).

Station	Hwy	District	Data Period	Dir & Lane	ADT	ADTT	%Truck in ADT	Traffic Growth	ADT-End 20 yr	20-yr 18-kip ESALs (million)	ATHWLD	%age Tandem
W528	US 287	Wichita Falls	2016	NB-L1	3699	1914	52%	4.2%	8383	22.2	17.3	44.0%
				NB-L2	1906	234	12%	4.2%	4319	1.8	17.0	35.0%
				SB-L1	3594	1687	47%	4.2%	8145	17.0	15.0	44.0%
				SB-L2	1851	206	11%	4.2%	4195	1.3	16.7	32.0%
W529	US 287	Wichita Falls	2016	NB-L1	7584	2572	34%	4.6%	18466	23.2	12.2	43.0%
				NB-L2	3907	499	13%	4.6%	9513	2.6	11.9	29.0%
				SB-L1	7415	2785	38%	4.6%	18055	22.4	12.5	38.0%
				SB-L2	3820	498	13%	4.6%	9301	2.1	11.8	23.0%
W530	US 82	Wichita Falls	2016	EB-L1	1378	558	40%	4.3%	3180	3.5	15.3	37.5%
				EB-L2	710	38	5%	4.3%	2215	0.1	15.5	24.6%
				WB-L1	1429	596	42%	4.3%	3297	4.3	15.7	34.7%
				WB-L2	736	40	5%	4.3%	2298	0.1	15.3	22.0%
W531	IH 35	Laredo	2015	NB-L1	6113	2880	47%	6.9%	23001	39.1	14.3	57.0%
				NB-L2	2699	348	13%	6.9%	10155	5.5	11.8	57.0%
				SB-L1	6213	3159	51%	6.9%	23377	40.1	12.3	59.0%
				SB-L2	2656	366	14%	6.9%	9994	5.8	12.7	58.0%
W531	IH 35	Laredo	2016	NB-L1	6182	3052	44%	6.7%	22716	56.6	16.6	57.0%
				NB-L2	3185	337	11%	6.7%	11702	6.5	17.8	56.9%
				SB-L1	6263	3258	52%	6.7%	23013	42.2	15.0	58.7%
				SB-L2	3226	388	12%	6.7%	11855	3.7	16.2	57.7%
W532	SH 130	Austin	2016	NB-L1	6733	1747	26%	13.7%	87476	39.0	11.9	40.0%
				NB-L2	3468	368	11%	13.7%	45057	3.4	11.1	19.0%
				SB-L1	6730	1794	27%	13.7%	87437	79.7	12.6	40.0%
				SB-L2	3467	314	9%	13.7%	45044	4.7	11.5	21.0%
W533	IH 20	Odessa	2016	EB-L1	11993	5686	47%	3.0%	21661	19.2	13.7	35.0%
				EB-L2	6178	2147	33%	3.0%	11158	5.9	13.9	22.0%
				WB-L1	11301	4776	42%	3.0%	20411	16.1	13.6	35.0%
				WB-L2	5822	2213	38%	3.0%	10515	7.2	13.8	23.0%
W534	IH 69	Corpus Christi	2015	NB-L1	5410	1977	37%	4.1%	11956	27.1	16.5	44.0%
				NB-L2	2744	581	21%	4.1%	6064	4.7	13.6	29.0%
				SB-L1	5344	2072	39%	4.1%	11810	25.7	15.9	42.0%
				SB-L2	2728	423	16%	4.1%	6029	4.4	12.7	27.0%
W534	IH 69	Corpus Christi	2016	NB-L1	5823	2074	36%	4.3%	13437	30.7	18.0	45.8%
				NB-L2	2999	682	23%	4.3%	6922	3.6	16.2	21.6%
				SB-L1	5604	2080	37%	4.3%	12933	29.4	18.5	44.6%
				SB-L2	2887	455	16%	4.3%	6663	3.5	18.3	28.1%

Table C-1. Example Permanent WIM Traffic Data Analysis (Continued).

Station	Hwy	District	Data Period	Dir & Lane	ADT	ADTT	%Truck in ADT	Traffic Growth	ADT-End 20 yr	20-yr 18-kip ESALs (million)	ATHWLD	%age Tandem
W535	US 59	Corpus Christi	2016	NB-L1	2047	352	17%	3.0%	3698	3.2	18.1	48.6%
				NB-L2	1055	87	8%	3.0%	1904	0.6	16.8	45.9%
				SB-L1	2029	408	20%	3.0%	3017	1.5	17.5	47.7%
				SB-L2	1045	57	6%	3.0%	1888	0.3	16.4	42.2%
W536	SH 45 /SH 130	Austin	2016	NB-L1	8695	2271	26%	16.9%	197497	102.1	15.9	37.1%
				NB-L2	4479	683	15%	16.9%	101735	90.9	12.0	14.1%
				SB-L1	8863	2223	25%	16.9%	200495	119.5	16.0	37.5%
				SB-L2	4566	387	8%	16.9%	103711	58.5	12.7	19.5%
W537	US 84	Lubbock	2016	EB-L1	5687	1373	24%	4.8%	14525	10.4	16.6	38.2%
				EB-L2	3199	353	11%	4.8%	8170	11.1	14.7	20.2%
				WB-L1	5723	1571	27%	4.8%	14619	14.4	16.7	37.8%
				WB-L2	3219	332	10%	4.8%	8223	1.0	14.4	15.7%
W538	US 181	Corpus Christi	2016	NB-L1	2408	113	5%	0.7%	2769	1.0	19.3	48.3%
				NB-L2	1241	16	1%	0.7%	1426	0.1	15.1	35.9%
				SB-L1	2404	114	5%	0.7%	2764	1.2	19.4	45.8%
				SB-L2	1238	6	1%	0.7%	1424	0.0	13.7	32.6%
W541	FM 3129	Atlanta	2015	NB-L1	617	192	31%	3.0%	1115	3.3	11.9	54.3%
				SB-L1	504	166	33%	3.0%	910	0.4	12.8	41.1%
W545	IH 27 / US 87	Lubbock	2016	NB-L1	4671	1107	24%	3.0%	8436	6.3	16.3	42.6%
				NB-L2	2406	124	5%	3.0%	4346	0.3	13.0	21.2%
				SB-L1	4723	1186	25%	3.0%	8528	9.0	16.7	40.1%
				SB-L2	2433	123	5%	3.0%	4392	0.4	13.2	24.3%
W546	SH 121	Paris	2016	NB-L1	3829	460	12%	7.4%	15908	2.2	11.5	38.9%
				SB-L1	3835	460	12%	7.4%	15933	10.6	11.7	43.9%
W547	IH 40	Amarillo	2015	EB-L1	4774	2763	58%	4.6%	11759	49.7	16.6	35.0%
				EB-L2	1140	319	28%	4.6%	2808	5.5	14.3	22.0%
				WB-L1	4722	2762	58%	4.6%	11754	43.4	17.1	35.0%
				WB-L2	1340	283	21%	4.6%	3301	7.1	14.4	23.0%
W548	SH 31	Waco	2016	NB-L1	2691	395	15%	3.2%	5010	2.4	16.4	
				NB-L2	1386	64	5%	3.2%	2581	0.2	15.2	
				SB-L1	2748	421	15%	3.2%	5116	3.0	17.1	
				SB-L2	1416	75	5%	3.2%	2635	0.2	15.2	
W549	US 380	Fort Worth	2016	EB-L1	3972	1087	27%	3.1%	6629	13.8	18.1	50.2%
				EB-L2	2046	112	5%	3.1%	3797	1.2	17.5	51.1%
				WB-L1	4344	1219	28%	3.1%	8062	4.3	14.4	42.9%
				WB-L2	2237	175	8%	3.1%	4152	0.3	11.1	37.4%

Table C-1. Example Permanent WIM Traffic Data Analysis (Continued).

Station	Hwy	District	Data Period	Dir & Lane	ADT	ADTT	%Truck in ADT	Traffic Growth	ADT-End 20 yr	20-yr 18-kip ESALs (million)	ATHWLD	%age Tandem
W550	IH 35	Fort Worth	2016	NB-L1	11622	2885	25%	6.0%	37203	27.7	13.1	46.0%
				NB-L2	5987	455	8%	6.0%	19165	2.6	11.7	36.0%
				SB-L1	11549	2755	24%	6.0%	36969	38.5	11.3	48.0%
				SB-L2	5949	647	11%	6.0%	19043	3.7	12.4	28.0%
W551	US 90	Laredo	2016	EB-L1	2286	255	11%	1.7%	3177	0.4	10.1	41.0%
				WB-L1	2316	289	13%	1.7%	3219	0.9	10.6	40.0%
W552	IH 35 / US 77	Wichita Falls	2016	NB-L1	15651	3347	21%	7.3%	64005	57.7	16.9	46.0%
				NB-L2	8063	803	10%	7.3%	32974	6.7	14.4	36.0%
				SB-L1	15239	3206	21%	7.3%	62320	68.0	17.6	48.0%
				SB-L2	7851	709	9%	7.3%	32107	6.2	13.9	36.0%
W554	SH 6	Bryan	2016	EB-L1	11149	2367	21%	3.3%	21179	25.0	17.4	28.6%
				EB-L2	5743	457	8%	3.3%	10910	1.5	14.6	16.0%
				WB-L1	11300	2233	20%	3.3%	21466	31.3	17.0	30.2%
				WB-L2	5821	554	10%	3.3%	11058	1.7	13.5	15.0%

Table C-2. Example Portable WIM Traffic Data Analysis.

Site	Hwy	District	Period	Dir & Lane	ADT	ADTT	%Truck in ADT	Traffic Growth	ADT-End 20 yr	20-yr 18-kip ESALs (million)	ATHWLD	%age Tandem
TS002	SH 7	Bryan	Feb 27-Mar 09, 2017	WB-L1	812	177	21.80%	3%	2933	2.78	13.79	23.60%
TS002	SH 7	Bryan	Mar 04-Apr 07, 2017	WB-L1	951	195	20.5	3%	3435	5.31	15.5	31.90%
TS003	SH 7	Bryan										
TS004	FM 468	Laredo	Feb 01-Feb 28, 2018	EB-L1	889	362	40.70%	3%	3220	10.16	17	58%
TS004	FM 468	Laredo	Oct 10-Mar 22, 2018	EB-L1	860	357	41.40%	3%	3108	10.53	17	59%
TS004	FM 468	Laredo	April 13-April 29, 2017	NB-L1	770	321	41.70%	3%	1391	2.33	12.6	60%
TS004	FM 468	Laredo	Oct 10-Oct 25, 2017	EB-L1	690	326	47.30%	3%	2493	13.5	22.29	61.30%
TS005	US 281	Corpus Christi	Feb 01-Feb 09, 2018	NB-L1	4354	1450	33.30%	3%	7864	46.14	23.49	39.60%
TS005	US 281	Corpus Christi	Feb 01-Feb 09, 2018	SB-L1	4953	1508	30.40%	3%	8946	35.88	12.74	54.70%
TS005	US 281	Corpus Christi	April 13-April 29, 2017	NB-L1	3876	905	23.30%	3%	7000	11.07	13	54.00%
TS005	US 281	Corpus Christi	April 13-April 29, 2017	SB-L1	1515	448	29.60%	3%	2736	3.43	14	55.00%
TS005	US 281	Corpus Christi	April 13-April 29, 2017	NB-L1	1345	1039	77.20%	3%	2429	47.59	13	54.00%
TS005	US 281	Corpus Christi	April 13-April 29, 2017	SB-L1	2774	1218	43.90%	3%	5009	36.38	10	56.00%
TS005	US 281	Corpus Christi	April 13-April 19, 2017	NB-L1	1354	1038	77.00%	3%	2445	79.9	16.7	67.70%
TS005	US 281	Corpus Christi	April 13-April 19, 2017	SB-L2	3801	1231	32.00%	3%	6865	33.1		51.80%
TS006	SH 6	Brown wood	May 17-July 05, 2017	NB-L1	931	206	22.10%	3%	3362	3.76	10.52	46.00%
TS007	SH 114	Fort Worth	July 19-July 25, 2017	EB-L1	2900	1367	47.10%	3%	10476	38.69	25.06	54.12%
TS008	FM 1787	Odessa	Aug 08-Aug 14, 2017	SB-L1	1337	452	33.80%	3%	4831	7.78	16.29	24.30%
TS008	FM 1787	Odessa	Aug 08-Aug 22, 2017	SB-L1	2367	211	17.80%	3%	4257	4.09	14.36	48.97%
TS010	IH 35	Austin	May 07-May 13, 2018	NB-L1	17590	3935	22.4%	3.00%	31769	92.77	9.27	46.86%
TS010	IH 35	Austin	May 07-May 13, 2018	NB-L2	23204	1978	8.5%	3.00%	41909	68.25	5.82	37.83%

Table C-3. Example PTT Traffic Data Analysis.

Station	Hwy	District	Period	Dir & Lane	ADT	ADTT	%Truck in ADT	Traffic Growth	ADT-End 20 yr	20-yr 18-kip ESALs (million)	Avg Speed (mph)
TxDOT_TTI-00001	US 59	ATLANTA	Nov-16	SB-L1	3701	1086	29.3%	1.7%	5087	13.3	69
TxDOT_TTI-00002	SH 114	FORT WORTH	Dec-14	EB-L1	4230	1015	24.0%	1.8%	5921	12.6	68
TxDOT_TTI-00002	SH 114	FORT WORTH	Dec-14	EB-L2	2178	218	10.0%	1.8%	3051	2.7	68
TxDOT_TTI-00005	Loop 480	LAREDO	Mar-12	SB-L1	336	60	18.0%	5.0%	849	1.1	64
TxDOT_TTI-00007	US 271	PARIS	Oct-11	SB-L1	4531	1241	27.4%	1.8%	6383	15.5	63
TxDOT_TTI-00007	US 271	PARIS	Oct-11	SB-L2	2867	348	12.1%	1.8%	4039	4.3	66
TxDOT_TTI-00009	IH 35 (Frontage Rd)	WACO	May-14	SB-L1	484	53	11.0%	2.0%	705	0.7	57
TxDOT_TTI-00009	IH 35 (Frontage Rd)	WACO	May-14	SB-L2	312	16	5.0%	2.0%	455	0.2	57
TxDOT_TTI-00016	FM 2100	HOUSTON	Sep-14	NB-L1	3954	356	9.0%	2.0%	5760	4.5	49
TxDOT_TTI-00019	IH 35	SAN ANTONIO		SB-L1	60500	9680	16.0%	2.0%	88137	18.7	
TxDOT_TTI-00024	SH 95	YOAKUM	Mar-15	SB-L1	2162	324	15.0%	2.0%	3150	4.1	65
TxDOT_TTI-00036	FM 2100	HOUSTON	Apr-17	SB-L1	3895	390	10.0%	2.0%	5674	5.0	49
TxDOT_TTI-00041	US 83	LAREDO	May-17	WB-L1	9856	890	9.0%	2.0%	14358	11.3	26
TxDOT_TTI-00051	SH 304	AUSTIN	Apr-16	SB-L1	4201	229	5.5%	2.0%	6120	2.9	58
TxDOT_TTI-00055	SPUR 400	LAREDO	May-17	EB-L1	5384	135	2.5%	2.0%	7843	1.7	41
TxDOT_TTI-00066	SH 358	CORPUS CHRISTI	Mar-17	WB-L1	2351	58	2.5%	2.0%	3425	0.7	40
TxDOT_TTI-00077	US 271	PARIS	Oct-11	NB-L1	4579	1062	23.2%	1.8%	6451	16.7	65
TxDOT_TTI-00077	US 271	PARIS	Oct-11	NB-L2	3106	376	12.1%	1.8%	4376	4.7	68
TxDOT_TTI-00078	SPUR 400	LAREDO	May-17	EB-L1	5295	107	2.0%	2.0%	7714	1.4	41
TxDOT_TTI-00080	SH 260	LAREDO	May-17	NB-L1	5766	224	3.9%	2.0%	8400	2.8	40
TxDOT_TTI-00081	US 83	LAREDO	May-17	WB-L1	10158	1069	10.5%	2.0%	14798	13.6	28
TxDOT_TTI-00083	SH 121	PARIS	Apr-17	SB-L1	3982	533	13.4%	1.7%	5434	6.5	73

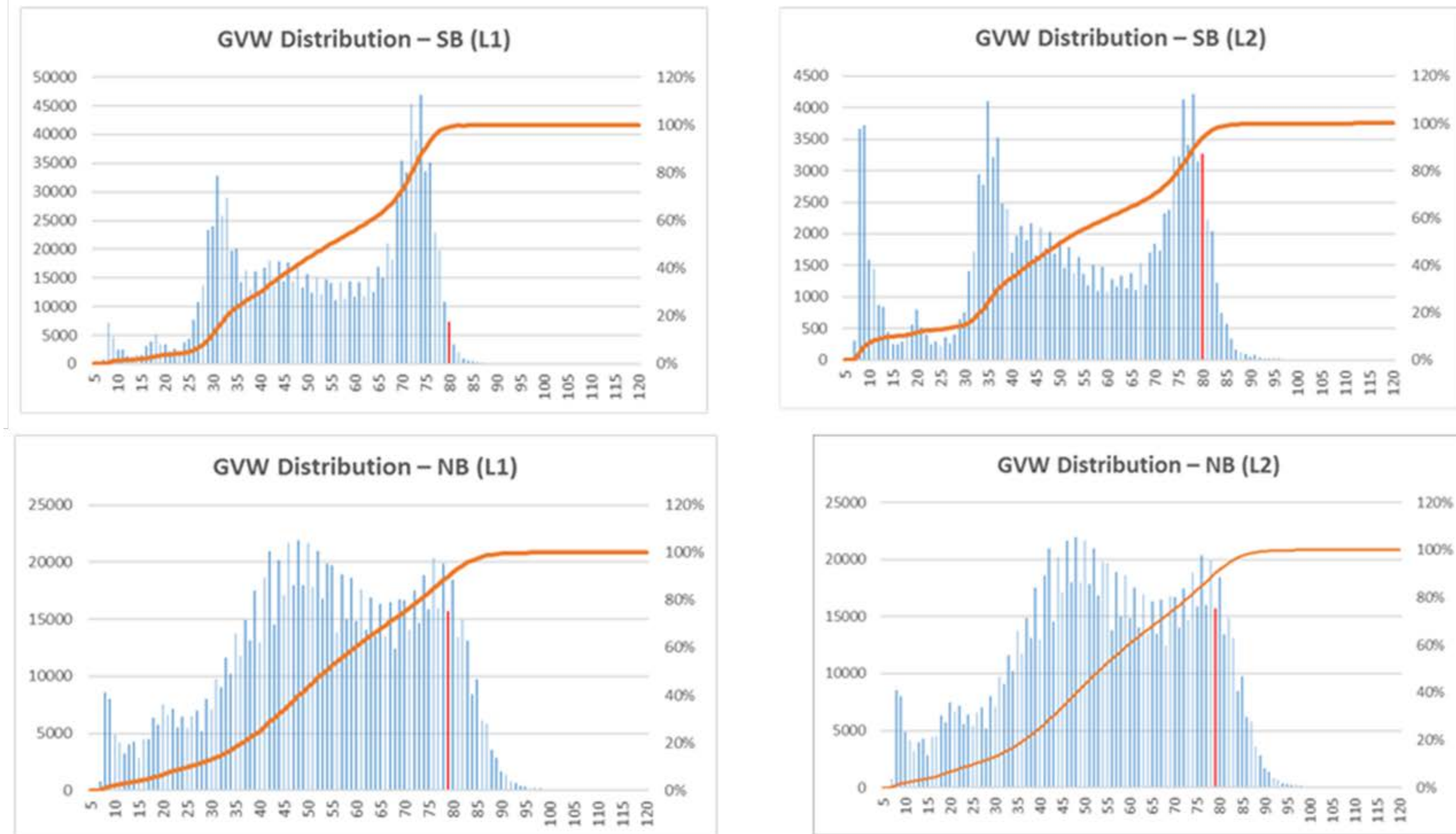


Figure C-7. GVW Distribution (Station W531, IH 35).

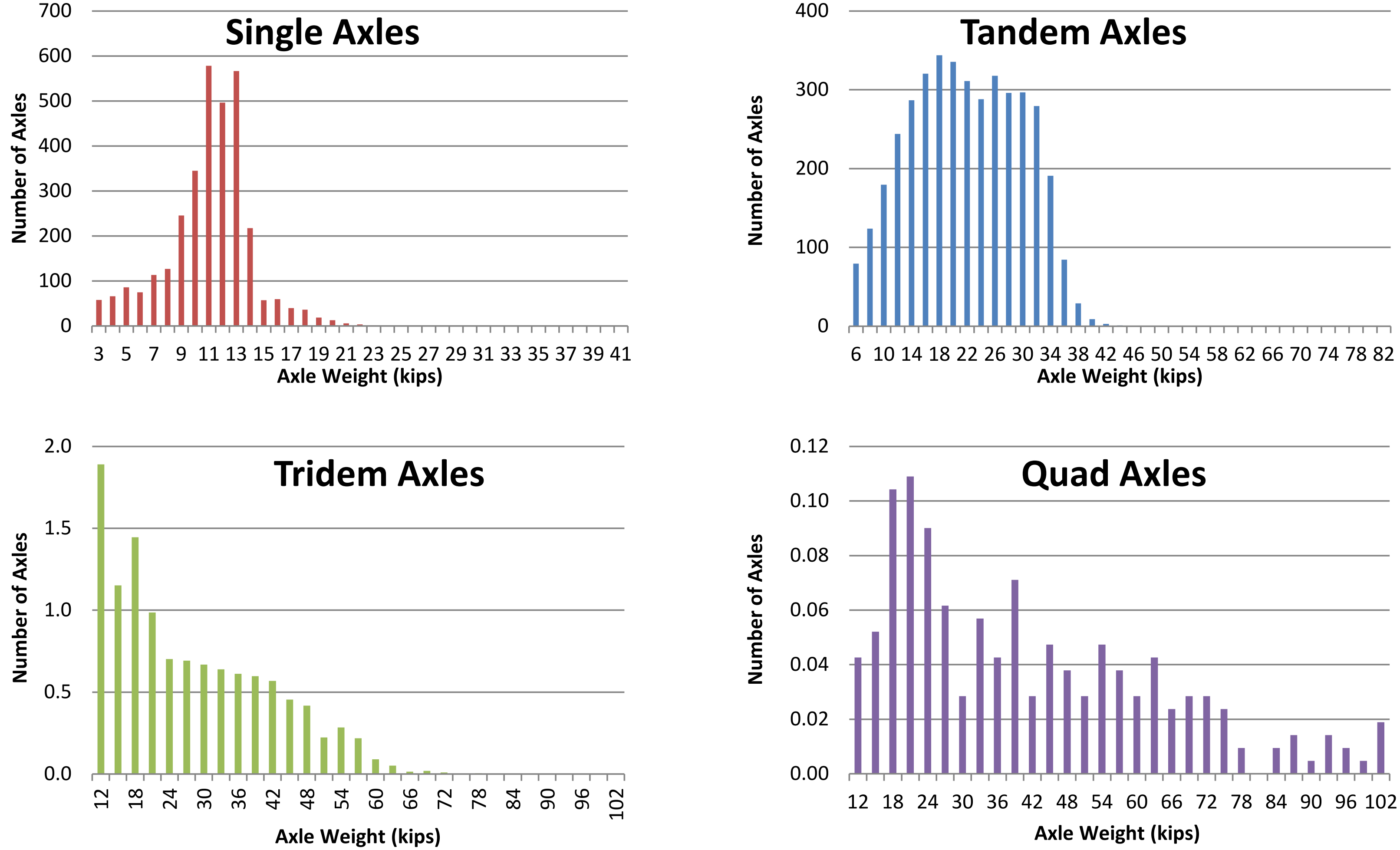


Figure C-8. Axle Weight Distribution (Station W531, IH 35).

Station#	Most Overload Lane	ADTT	Daily OW Trucks (> 80 kips)	%OW
W523 (US 281)	SB outside	1 968	98	5.0%
W524 (IH 10)	EB outside	3 432	77	2.2%
W527 (SH 114)	EB outside	1 670	333	19.9
W531 (IH 35)	NB outside	2 400	144	6.0%
W541 (FM 3129)	NB outside	192	70	36.5%
W547 (IH 40)	WB outside	2 676	159	5.9%
TS010 (IH 35)	SB Middle	4 606	505	11.0%

Station#	%age Number/Count of Overweight Axles			
	Single (20 kips)	Tandem (> 34 kips)	Tridem (> 42 kips)	Quad (> 50 kips)
TS001 (US 83)	2.0%	26.1%	17.0%	16.0%
W541 (FM 3129)	0.5%	41.5%	4.9%	0.0%

Mostly Overloaded Axle	%age Overweight Axle Count	Overweight Record (> 34 kips)
Tandem	8 – 53%	1.3 – 1.8 times (30-80%)

Figure C-9. Truck GVW and Axle Overweight Statistics.

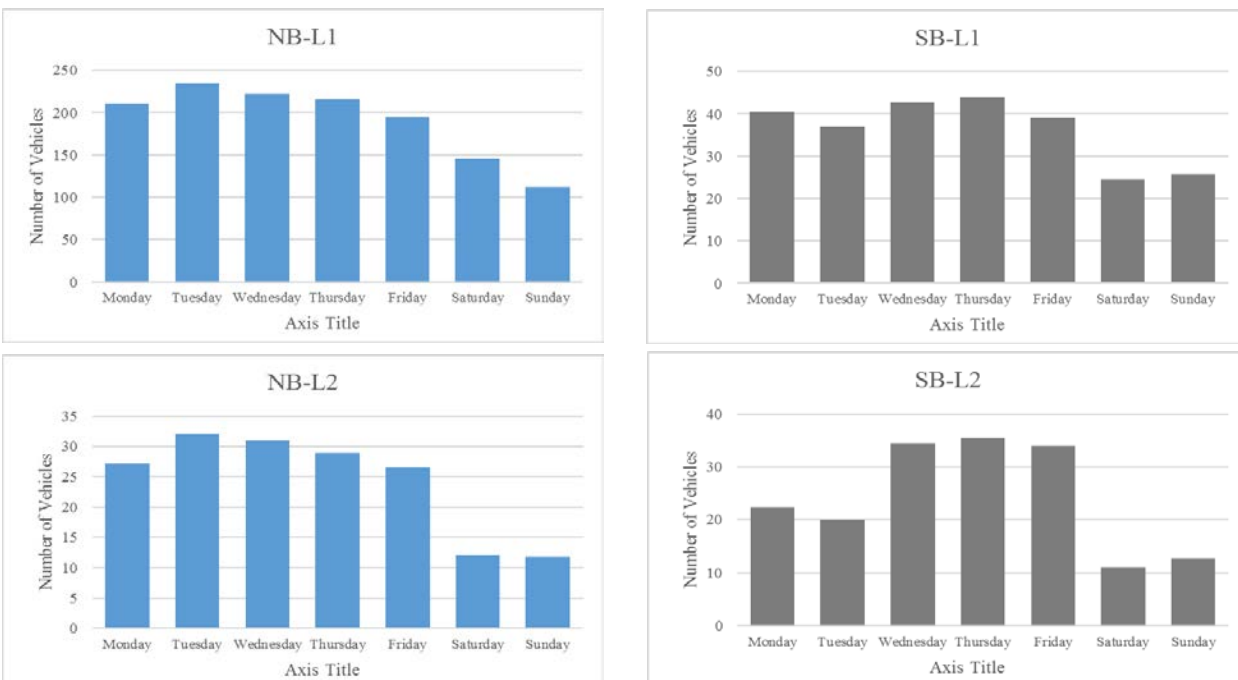


Figure C-10. Daily Truck Overweight Count (Station W531, IH 35).

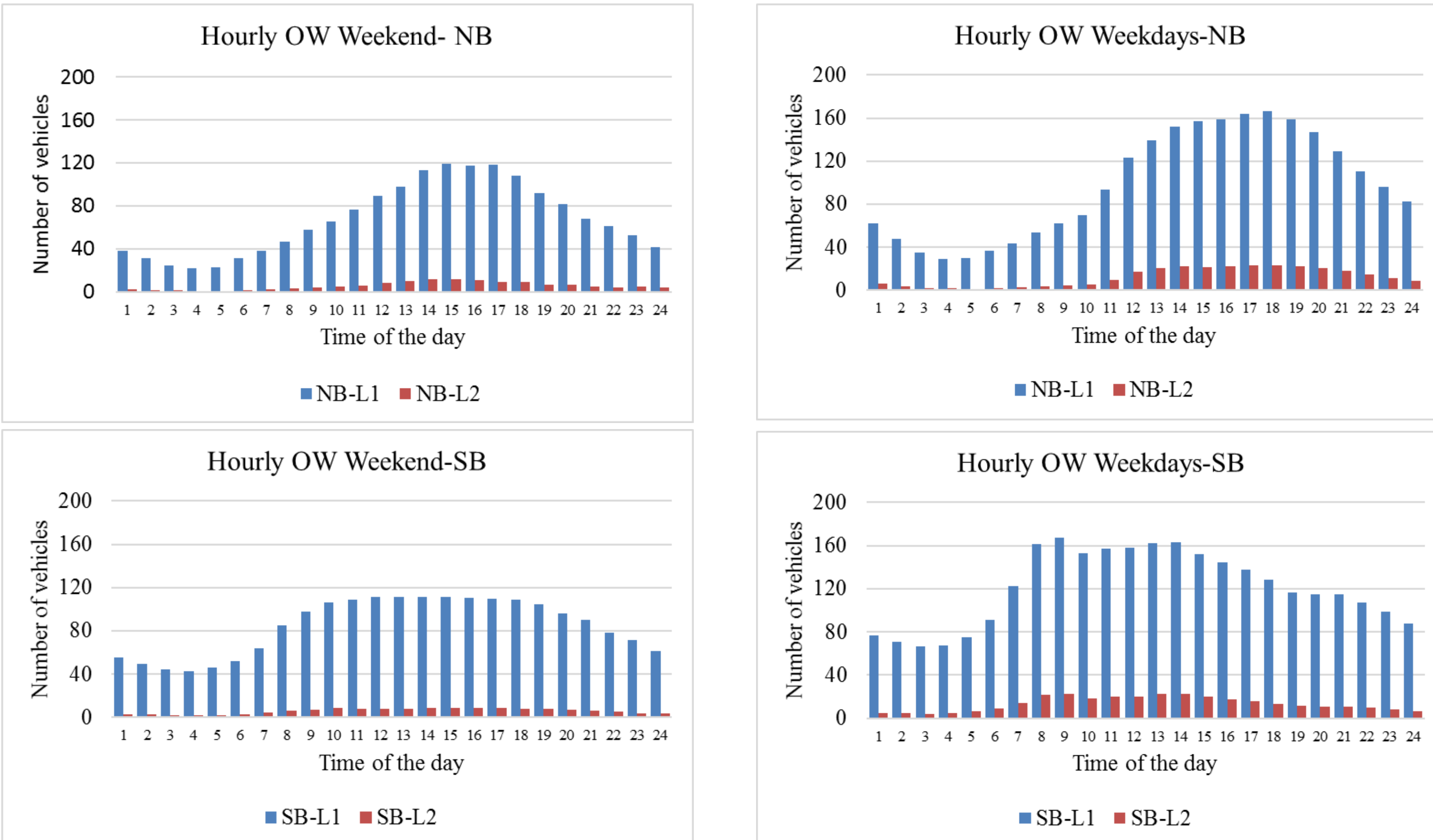
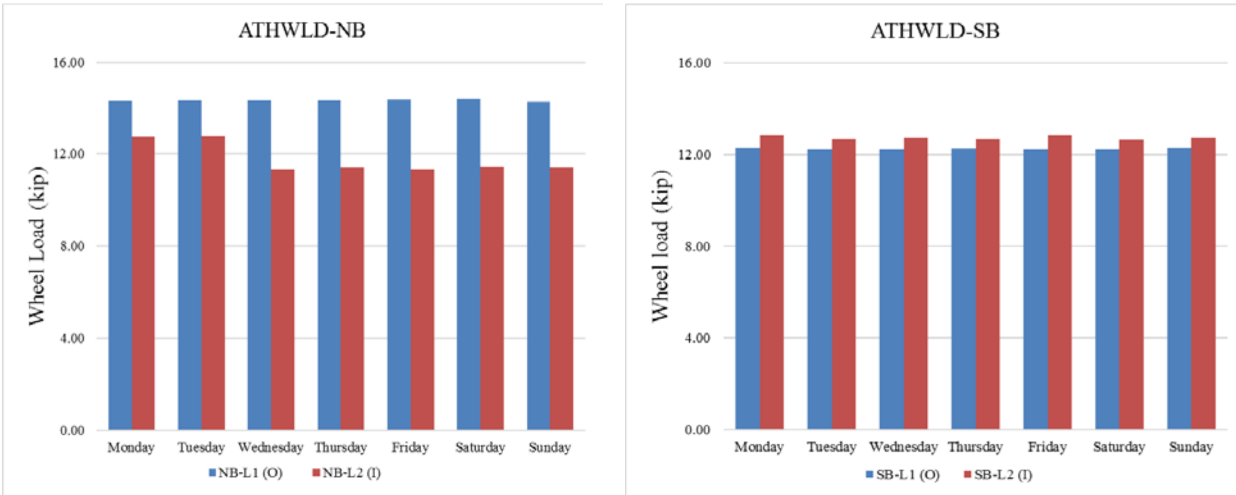


Figure C-11. Overweight Hourly Distribution (Station W531, IH 35).

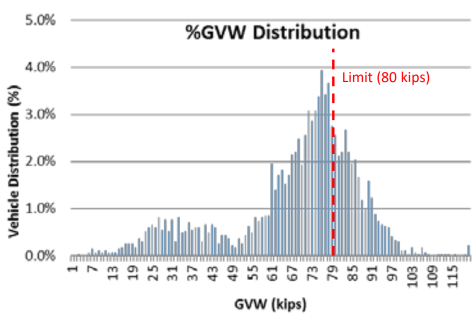


	ATHWLD	% Tandem Axles
NB-L1 (O)	14.34 kips	55.5%
NB-L2 (I)	11.78 kips	51.1%
SB-L1 (O)	12.25 kips	57.9%
SB-L2 (I)	12.74 kips	54.9%

Figure C-12. Daily ATHWLD Distribution (Station W531, IH 35).

Volume	
ADT	1714
ADTT	495
Truck %	28.8%
20-Yr 18-kip ESALs	8.44 million

Parameter	FPS Input
ADT-Beginning	3429
ADT-END 20 Year	6,193
18 kip ESALs 20 Years (million)	8.44
Avg. vehicle speed (mph)	59.7
%Trucks in ADT	28.8%



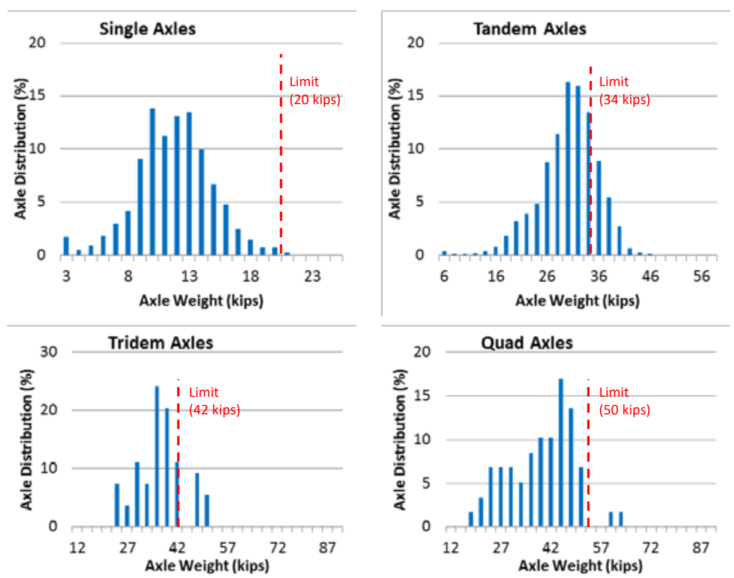


Figure C-13. Portable WIM Data Analysis (US 83 NB, LRD).

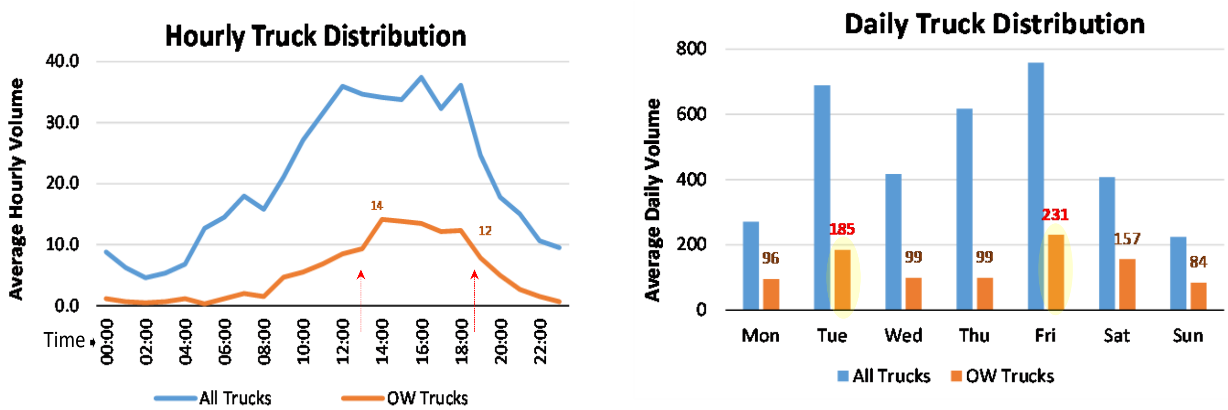


Figure C-14. Portable WIM Data Analysis (US 83 NB, LRD).

US 83	Location 1	Location 2
County	Webb	Dimmit
Nearest RM	698	654
ADT	1 877	2 344
ADTT	610	911
Avg. Truck Speed	59.4 mph	58.7 mph
20-year ESAL	**9.33 million**	**21.21 million**
ATHWLDs	11.39	15.9 kips
Class9 Front Axle Wt. COV	7.5 %	13.4%
Daily GVW overweight	127 (24.8%)	366 (40.2%)
Daily Tandem Axle Overweight	230 (28.4%)	802 (52.5%)

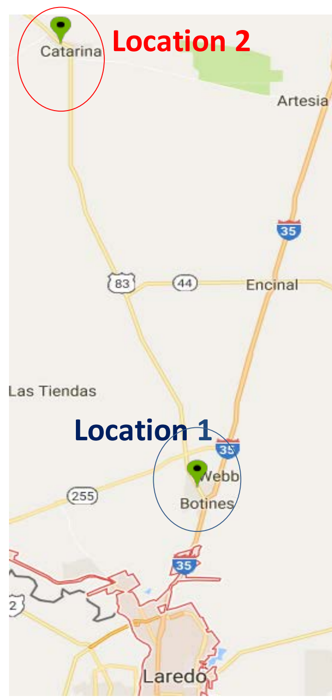
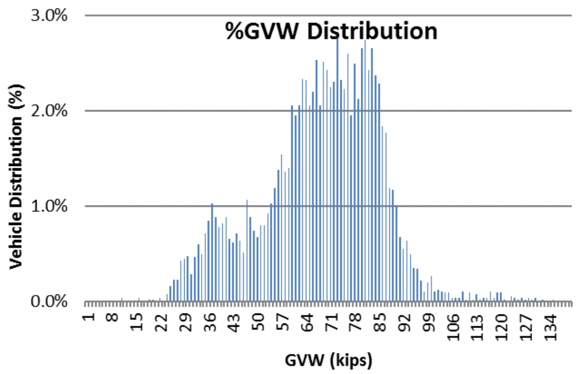
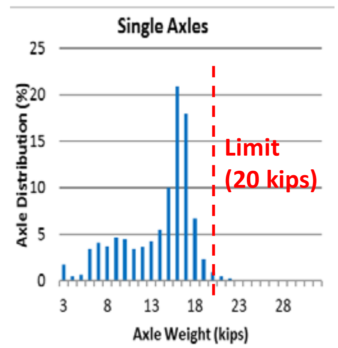
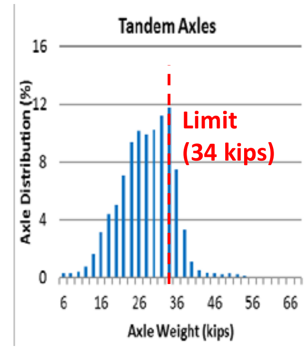


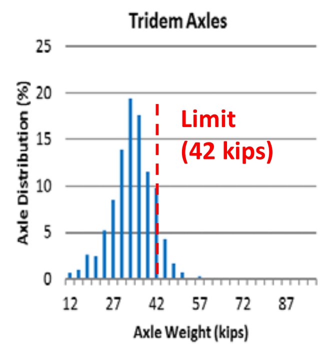
Figure C-15. Portable WIM Data Analysis (US 83 NB, LRD).







Axle Type	Daily Count
Steering Axles	438
Non-steering Single Axles	250
Single Axles	688
Tandem Axles	609
Tridem Axles	63
Quad Axles	3



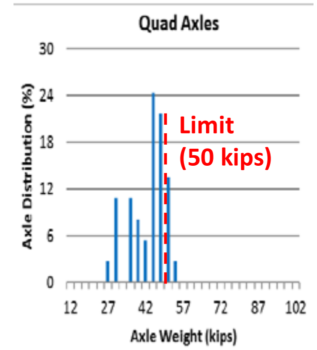
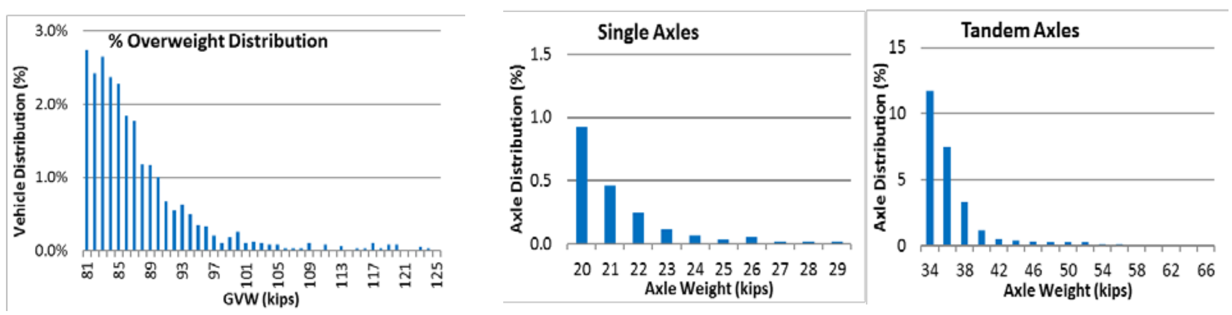


Figure C-16. Portable WIM Data Analysis (US 83 NB, RM 678-680, Webb County, LRD).



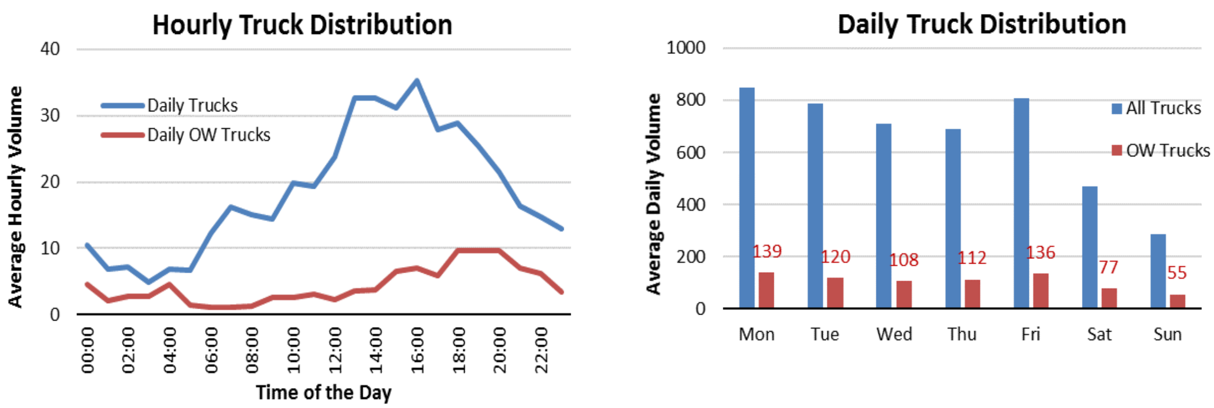
27.6% Overloaded Trucks Daily (GVW ≥ 80 kips)

1.6% Overloaded Trucks Daily (Single Axle Weight ≥20 kips)

28.4% Overloaded Trucks Daily (Tandem Axle Weight ≥34 kips)

Over-Weight summary	Daily Overweight Count (% of Total)	Maximum Overweight Recorded
GVW Overweight (≥ 80 kips)	121 (27.6%)	123 kips (54% Overweight)
Single Axles (≥ 20 kips)	14 (2.0%)	29 kips (45% Overweight)
Tandem Axles (≥ 34 kips)	159 (26.1%)	66 kips (94% Overweight)
Tridem Axles (≥ 42 kips)	11 (17.0%)	57 kips (36% Overweight)
Quad Axles (≥ 50 kips)	0.5 (16.2%)	54 kips (8% Overweight)

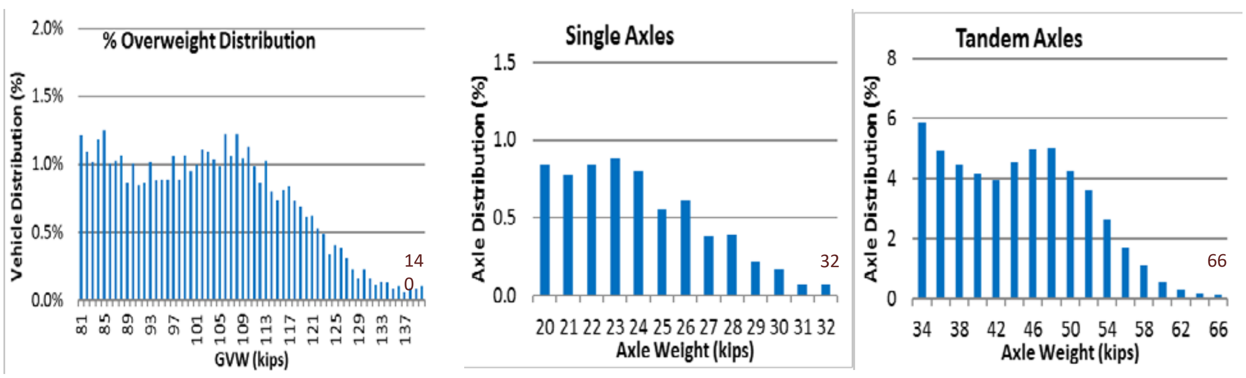
Figure C-17. Portable WIM Data Analysis (US 83 NB, RM 678-680, Webb County, LRD).



⇒ 3:00 PM to 9:00 PM (15:00 – 21:00 hrs) is most critical in terms of overloaded truck operation (GVW ≥ 80 kips), i.e., most overloaded trucks occurred between 3:00 PM & 9:00 PM .

⇒ Monday & Friday has more recorded overweight trucks than the other days of the week – that is most overloaded trucks occurred on Monday & Friday

Figure C-18. Portable WIM Data Analysis (US 83 NB, RM 678-680, Webb County, LRD).



40.2% Overloaded Trucks Daily (GVW ≥ 80 kips)

6.7% Overloaded Trucks Daily (Single Axle Weight ≥20 kips)

52.5% Overloaded Trucks Daily (Tandem Axle Weight ≥34 kips)

Over-Weight summary	Daily Overweight Count (% of Total)	Maximum Overweight Recorded
GVW Overweight (≥ 80 kips)	366 (40.2%)	140 kips (75% Overweight)
Single Axles (≥ 20 kips)	74 (6.7%)	32 kips (78% Overweight)
Tandem Axles (≥ 34 kips)	802 (52.5%)	66 kips (94% Overweight)
Tridem Axles (≥ 42 kips)	14 (60.7%)	93 kips (120% Overweight)
Quad Axles (≥ 50 kips)	4 (65.8%)	102 kips (104% Overweight)

Figure C-19. Portable WIM Data (US 83 NB, RM 654-652, Dimmit County, LRD).

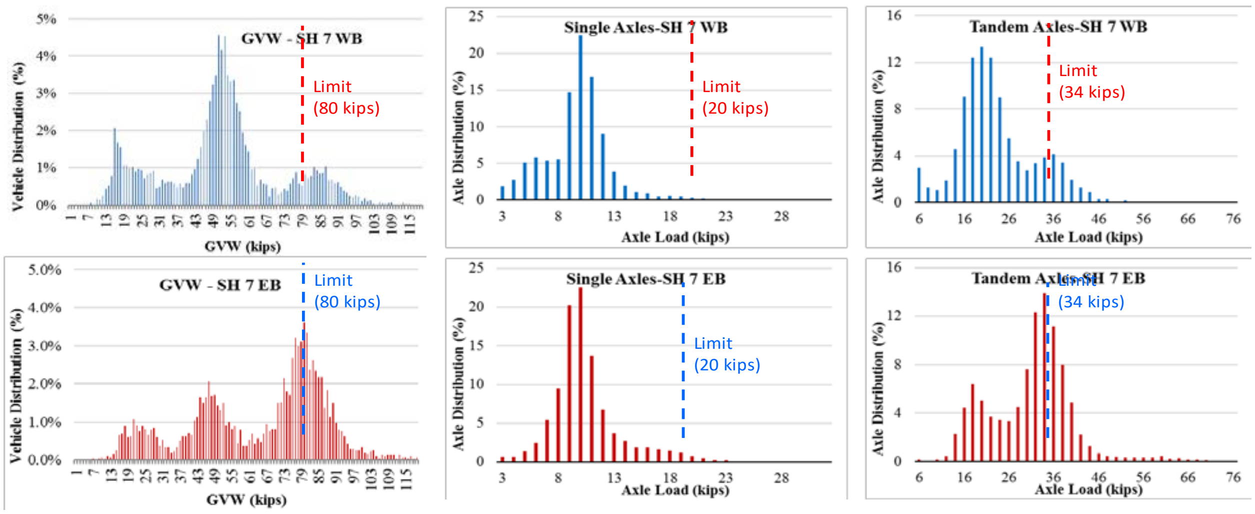


Figure C-20. Portable WIM Data—GVW Distribution (SH 7, WB, BRYN District).

Vehicle Class	Steering Axles	Other Single Axles	Tandem Axles	Tridem Axles	Quad Axles
Class04	1.00	0.19	0.54	-	-
Class05	1.00	1.00	-	-	-
Class06	1.00	-	1.00	-	-
Class07	1.00	-	-	0.48	-
Class08	1.00	1.23	0.77	-	-
Class09	1.00	0.23	1.89	-	-
Class10	1.00	0.00	0.60	1.13	0.20
Class11	1.00	3.90	-	-	-
Class12	1.00	2.65	2.00	1.00	-
Class13	1.00	0.00	0.00	2.00	0.00

Figure C-21. Portable WIM Data—Axles per Truck (IH 35, SB, Austin District).

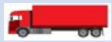
Vehicle Class	Pictorial View	Distribution (%)	Growth Rate (%)	Growth Function
Class04		3.39	3.00	Compound
Class05		6.97	3.00	Compound
Class06		7.81	3.00	Compound
Class07		0.74	3.00	Compound
Class08		4.6	3.00	Compound
Class09		66.23	3.00	Compound
Class10		0.74	3.00	Compound
Class11		2.58	3.00	Compound
Class12		2.23	3.00	Compound
Class13		4.71	3.00	Compound
	Sum of Distribution =	**100.00**		

Figure C-22. Portable WIM Data—VCD (IH 35, SB, Austin District).