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Effects of Alternative Traffic Input Levels on Interstate Pavement Performance in New Mexico

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EFFECTS OF ALTERNATIVE TRAFFIC INPUT LEVELS ON INTERSTATE PAVEMENT PERFORMANCE IN NEW MEXICO

by

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THESIS

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DEDICATIONS

To my parents

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ABSTRACT

Traffic is one of the key inputs in pavement design. The pavement Mechanistic-Empirical (ME) design allows three different types of input level of traffic data based on the availability of the data. They are: site specific data (Level 1), regional data (Level 2), and the national data (Level 3). Level 1 inputs (e.g., load magnitude, configuration, and frequency) are generated from Weigh-in-Motion (WIM) station installed in each site. However, it is not always practically possible to install WIM station due to high cost of WIMs. Therefore, often time the designers have to rely on the Level 2 or Level 3 traffic data. But it is not known yet how good the national data or the regional data compared to New Mexico's site specific data in predicting interstate pavement performances. To this end, this study examines the effects of different levels of traffic inputs on predicted pavement distresses in New Mexico. Two major interstate highways were considered in this study: Interstate-40 (I-40) and Interstate-25 (I-25). Site-specific inputs were developed using installed WIM stations at the pavement sites. WIM data was analyzed using an advanced and updated software developed by the UNM researchers. Traffic data were simulated through the ME design software for predicting pavement performances. Results show that axle load spectra (ALS) and lane distribution have a great influence on predicted interstate pavement performance. Vehicle class distribution (VCD), directional distribution, and standard deviation of lateral wander have a moderate impact on pavement performance. Monthly adjustment factor, axles per vehicle, axle spacing, and operational speed have very little effect on the predicted pavement performance. On the other hand, predicted pavement performance is insensitive to hourly distribution and wheelbase distribution. Hence, regional traffic data were developed from ten site specific data using both arithmetic average and clustering methods. Since, ALS and VCD are two inputs which affect the predicted distresses significantly, these two values were considered for this case. Finally, using the regional inputs, the national inputs, and the site-specific inputs of VCD and ALS, pavement ME predicted performances were determined. Results show that predicted performance by the cluster data are much closer to those by the site-specific data. Performance generated by the ME default values are significantly different from those generated by the site-specific or cluster values. When comparing performance by the ME design default to those by the statewide average data, the ME design default VCD produces less error than the ALS. Therefore, this study recommends using clustered data or site-specific WIM data instead of ME default or statewide average value. In addition, a guideline was successfully established to select appropriate axle load spectra inputs based on vehicle class data.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Problem Statement

The newly developed pavement Mechanistic-Empirical (ME) design procedure is a more appropriate procedure for analysis and design of pavement structures than the old AASHTO 1993 method. Because, the ME design considers detailed information about traffic, climate, and material properties whereas AASHTO 1993 method was based on just Equivalent Single Axle Load (ESAL) without any climatic consideration (AASHTO 1993). Furthermore, the previous method was purely empirical whereas the ME design uses mechanistic principles for determining the stresses and strains in the pavement structure (asphalt concrete, granular bases, and subgrade). Then, some empirically-based models are used for predicting distresses such as permanent deformation, cracking, or roughness and performance during the pavement design life. The ME design needs four types of traffic inputs for analysis and design of a pavement section. These inputs are traffic, climate, materials properties, and section properties. Among these inputs, traffic is one of the primary parameter in pavement design as it represents the magnitude and frequency of the loading that is applied to a pavement. Therefore, the ME design needs four different categories of traffic inputs. They are: base year traffic volume, traffic adjustment factors, axle load spectra, and axle configurations. In an ideal case, these traffic inputs should be generated from the Weigh-in-Motion (WIM) station or traffic counter devices. However, WIM stations are not available at all interstation locations. In addition, there are situations where existing WIM data quality is questionable and/or obtaining these information is not always practical. For these reasons, pavement ME design procedure recommends to generate a regional traffic library for each state for those site where site specific data is not available. Two different approach are commonly followed to generate the regional data. One is the simple arithmetic average method and the other is the cluster method. In addition, the ME design has some default values based on national average data for whose sites where both the site specific and the regional data are not available. At this point, there is no attempt done to develop the regional data for New Mexico. Though, there are 10 WIM stations raw data available for New Mexico. The main reason is the difficulties associated with dealing with the raw WIM. The raw WIM data are too large to be handled manually or by simple spreadsheet. In addition, there is no efficient and user-friendly software available in the literature, which can effectively handle the WIM data. Thus, generating site specific data is challenging and it leads to use default data especially (axle load spectra) in most of the cases especially for pavement design and analysis. Therefore, it became necessary to see that how goodness is the ME default data compare to the site specific data in respect to predicting pavement performance. If the ME default data fails to reflect the site specific condition, then, it also important to see that how goodness is the regional data for New Mexico.

1.2 Hypothesis

1.2.1 Hypothesis 1

The ME pavement design procedure needs eleven traffic inputs to predict the distresses of a pavement section. It is recommended to use site specific values of these inputs. However, it is common practice to use software default values in order to avoid complexity. The ME default data may give error result in predicting pavement performance compare to that using the site specific data in New Mexico.

1.2.2 Hypothesis 2

If the ME default data is not good enough, it is recommended to develop a regional traffic data for each state in order to cover those pavements where there is no WIM station installed. There are two common practices recommended to be followed. One is the simple arithmetic average and another one is cluster analysis. Cluster generated traffic data may give less error prediction than the arithmetic average data.

1.2.3 Hypothesis 3

If cluster methodology gives less error prediction, there is a problem to select the appropriate ALS cluster when WIM stations are not available. However, there may be a relationship among clustered VCDs and clustered ALSs which can give a guideline to select appropriate cluster combination.

1.3 Objectives

Objectives under Hypothesis One:

- Develop the site specific traffic inputs using raw WIM data.
- Predict the pavement response using both site specific and the ME design default data.
- Compare the predicted performance for two different input levels.
- Categorize the eleven traffic inputs on based on their influence levels in pavement response.

Objectives under Hypothesis Two:

- Develop the regional traffic data using both arithmetic average method and cluster analysis.

- Predict the pavement response using the site specific, the regional data (both arithmetic average and cluster generated), and the ME design default data.
- Find out which regional data gives less error in predicting pavement performance.

Objectives under Hypothesis Three:

- Develop an interaction diagram between VCD and ALS clusters.
- Propose a guideline to select appropriate ALS cluster input based on the interaction diagram.
- Investigate the possible error due to selection of wrong combinations of VCD and ALS clusters.

1.4 Outline

This thesis will include 5 chapters:

- Chapter 1 – Introduction
- Chapter 2 – Literature Review
- Chapter 3 – Data Collection and Processing
- Chapter 4 – Effects of Alternative Traffic Data on Predicted Pavement Performance
- Chapter 5 – Conclusions and Recommendations

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents a summary of traffic data require by the ME design and its effect on pavement performance related by previously conducted and on-going research.

2.2 Traffic Data

Traffic is one of the primary inputs in pavement design as it represents the magnitude and frequency of the loading that is applied to a pavement. However, in past only volumetric data was used to determine pavement life. Later Equivalent Single-Axle Load (ESAL) method was used to determine the pavement life (AASHTO 1993). This approach is based on converting the pavement damage caused by an axle with a specific weight and configuration into an equivalent damage from a standard 18-kip (80-kN) single-axle load. Then, pavement life is accounted for by the ESALs that have accumulated during its life. However, this empirical method cannot give reliable result due to rapid growth of traffic, change of vehicle characteristics, and absence of weather consideration. Therefore, a new Mechanistic-Empirical (ME) pavement design procedure is widely accepted as this method provides the capability to handle different axle con-figuration and other factors (AASHTO 2008). This method requires volumetric as well as weight data to calculate the pavement distresses. This method needs more detailed information regarding axle configurations to calculate the stress and strain beneath a wheel using mechanistic approach. Then, using some empirical models it predicts the different pavement distresses.

2.3 Traffic Inputs for ME Design

The ME design software requires four different categories of traffic inputs; which are given below:

2.3.1 Base Year Traffic Information

Annual Average Daily Truck Traffic (AADTT)

Annual average daily truck traffic (AADTT) (two) indicates number of trucks run over the pavement. AADTT is needed for opening year condition and this value are being used as the base for future growth projection.

Operational Speed

Operational speed refers the running speed of the traffic. It is important when traffic speed is lower.

Traffic Growth Rate

As traffic volume increases year to year, traffic growth factor is very important to forecast the future traffic. Long term data is necessary to generate the traffic growth rate.

2.3.2 Traffic Volume Adjustment Factors

Direction Distribution

Directional distribution is the percentage of truck traffic in the design direction. Unless a roadway has an unbalanced travel for trucks, it should be assumed as 50%.

Lane Distribution

Lane distribution indicates the percentage of truck traffic for the design lane. If there are more than one lane in each travel direction the driving lane is typically the outside lane and other lanes are referred as passing lane. Usually, driving should have more truck than passing lane.

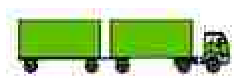
Monthly Adjustment Factor (MAF)

The monthly adjustment factor (MAF) reflects truck travel patterns throughout the year. Moreover, MAFs for different types of vehicles may be different. There are 10 truck types that result 10 potential different temporal patterns over a 12 month period. Mathematically, the monthly adjustment factor for a given vehicle class and a given month is obtained by dividing the average Monthly Average Daily Truck Traffic (MADTT) for the month by the summation of all the 12 month MADTTs and then, multiplied by 12. If there is no monthly variation existed for a vehicle class then MAF will be 1 for every month for that vehicle class.

Vehicle Class Distribution (VCD)

The Federal Highway Administration (FHWA) classifies vehicles into 13 distinct classes based on the number of axles and number of trailers (TMG 2013). FHWA vehicle class distribution are summarized in Table 2.1. Vehicle class distribution (VCD) refers to the percentage of each type of vehicle thought the year. However, the ME design does not consider the light weight vehicles such as the motorcycle, and passenger car. Therefore, in the ME design VCD refers as distribution of different types of trucks (Class 4 to Class 13). This is one of the most demanding data sets for pavement design.

Table 2.1 FHWA Vehicle Classification (TMG 2013)

Class	Descriptions	Figures
1	Motorcycles	
2	Passenger Cars	 
3	Other two-axle, four-tire single unit vehicles	
4	Buses	 
5	Two-axle, six-tire single unit trucks	
6	Three-axle single unit trucks	
7	Four, or more axle single unit trucks	
8	Four or fewer axle single-trailer trucks.	
9	Five-axle single-trailer trucks.	 
10	Six or more axle single-trailer trucks	
11	Five or fewer axle multi-trailer trucks.	
12	Six-axle multi-trailer trucks	
13	Seven or more axle multi-trailer trucks	

Hourly Distribution

Hourly distribution refers to the distribution of AADTT among a 24 hour period starting at midnight. This distribution is the annual average. Since temperature varies with the day hours, therefore, hourly distribution is an important inputs for pavement analysis.

2.3.3 Axle Load Spectra

Axle Load Spectra (ALS)

Depending on axle configuration, there are four types of axles are available: single, tandem, tridem and quad (TMG 2013). Axle load spectra (ALS) captures the information in terms of distributions of vehicles based on axle weight under a given vehicle class and axle configuration for a given month. This is one of the most demanding data sets for pavement design. Detailed information of ALS is given below:

- Single axle: There are 39 axle weight groups for single axle configuration vehicles. The axle weight group ranges from 1360 kg to 18600 kg with an increments of 453.68 kg.
- Tandem axle: For tandem axle vehicles, the axle weight group starts from 2720 kg to 37200 kg with increments of 907.36 kg.
- Tridem axle: For tridem axle vehicles, the axle weight group starts from 5440 kg to 46260 kg with increments of 1361.05 kg.
- Quad axle: Similar to tridem for quad axle vehicles, the axle weight group starts from 5440 kg to 46260 kg with increments of 1361.05 kg.

2.3.4 Axle Configuration

Number of axles per truck

The number of axles per truck refers the possible distribution of different axle configurations for each type of trucks. For example, there are two types of Class 4 vehicles are available. One has two single axles and another one has one single and one tandem axles. Number of single axles per truck refers the total number of single axles from the total number of Class 4 vehicles divided by the total number of Class 4 vehicles. Number of tandem axles per truck refers the total number of tandem axles from the total number of Class 4 vehicles divided by the total number of Class 4 vehicles.

Axle Spacing

Axle spacing data is only applicable to tandem, tridem, and quad vehicles. It is the average distance between two or more consecutive axles. Axle spacing is used to calculate the stress-strain under an axle of specific load. Axle spacing is also important to determine the axle type.

Lateral Wander distribution

Mean wheel location refers as the annual average distance of outer wheel from edge line. Wander distribution indicates as the standard deviation of the wheel position.

Wheelbase Distribution

The distance between the steering and the first device axle of a tractor or a heavy single unit. The ME design software categorize the vehicles into three groups based on their wheelbase distance.

2.4 Hierarchical Input Levels

In an ideal case, all traffic inputs should be generated from the Weigh-in-Motion (WIM) station or traffic counter devices for both new pavement and rehabilitation design procedure. However, obtaining this information is not always practical. In addition, there are situations where existing WIM data quality is questionable and/or WIM stations are not available at all interstation locations. Therefore, the Traffic Monitoring Guide (TMG 2001) recommends to develop a traffic library for each state. Moreover, pavement ME design software has come up with some default values (Level 3 input) if no data is available. the ME design defines all the input levels in three different categories, as described below (AASHTO 2008):

- Level 1 - This level defines a very good knowledge of traffic data for a specific site. This level is also called the “site-specific” level.
- Level 2 - This level defines a weak knowledge of traffic data for a specific site. This is known as the “regional” data. Level 2 data can be generated in two ways: by the mean value of the statewide data, and by clustering a regional traffic data.
- Level 3 - The ME design has default value those are the national average value developed using the Long Term Pavement Performance (LTPP) data all over the country. Nationally measured data is used as Level 3 data. This level is also called the “ME default” data. This data will be used when there is a very poor knowledge of traffic data for the site.

Selection of these input levels depends on the availability of data and importance of the pavement structure under investigation. For example, interstate pavement design should use site specific or Level 1 (highest accuracy level). Similarly secondary roads can use

Level 2 or Level 3. This study investigates the effects of input levels on predicted pavement performance.

2.5 Cluster Methodology

The term "cluster analysis" is a set of different algorithms and methods for grouping objects of similar kind into respective categories. In both research and industrial purpose, identifying groups of individuals or objects that are similar to each other but different from individuals in other groups can be intellectually satisfying, profitable, or sometimes both. Thus, cluster analysis is an efficient data analysis tool which aims at sorting different objects into groups in a way that the degree of association between two objects is maximal if they belong to the same group and minimal otherwise. Given the above, cluster analysis can be used to discover structures in data without providing an explanation/interpretation.

2.5.1 Cluster Analysis Classification

There are methods of cluster analysis are widely used. They are listed below:

Hierarchical cluster

Hierarchical clustering makes group data over a variety of scales by creating a cluster tree (known as Dendrogram). There are mainly three steps to do the agglomerative hierarchical cluster analysis on a data set. Firstly, this method calculates the distance of each object (known as Euclidean distance) in the data set where smaller distance represents the most similar, whereas, greater distance represents the most distinct. Secondly, it groups the most similar two objects into a pair (binary cluster). As objects are paired into binary clusters, the newly formed clusters are grouped into larger clusters until a hierarchical tree is formed. Finally, it creates a partition between the most distinct groups.

Non-hierarchical or K-means cluster

Non-hierarchical or K-means cluster analysis tends to be used when large data sets are involved. It is sometimes preferred because it allows subjects to move from one cluster to another. This method can cluster the data into user defined number of clusters.

2.5.2 Determination Optimum Number of Cluster

Determination of optimum number of cluster is the most challenge in cluster analysis. In hierarchical cluster, the dendrogram illustrates which clusters have been joined at each stage of the analysis and the distance between clusters at the time of joining. If there is a large jump in the distance between clusters from one stage to another then this suggests that at one stage clusters that are relatively close together were joined whereas, at the following stage, the clusters that were joined were relatively far apart. This implies that the optimum number of clusters may be the number present just before that large jump in distance. On the other hand, K-means is an iterative algorithms that finds the optimum number of clusters in data set by observing accuracy (the sum of squared error, SSE) and parsimony (the total number of clusters used) (Race 2014). The SSE and the number of clusters used have an inverse relationship. As the number of clusters increases, the clustering results get more accurate (SSE decreases). If the relationship is plotted in a plain graph it can be observed that initially SSE decreases at a higher rate with increase of number of cluster, at a certain point the decreasing rate drops drastically and there will be a determining “elbow” in the curve/line. This point indicates the optimum number of clusters present in the data. This method is known as elbow criterion.

2.6 Past Studies

To this day, several studies have been conducted to see the effects of input levels on predicted pavement performance. Timm et al. (2006) developed the statewide average axle load spectra for Alabama. They found that the developed load spectra does not affect the pavement thickness as much as it is affected by the statewide average load spectra. But they did not show the effects of other site-specific inputs on pavement performance. Tran and Hall (2007a, 2007b) developed the statewide average traffic volume adjustment factors and axle load spectra for Arkansas. They found that the statewide average vehicle classification and axle load spectra have significant effects on pavement performance compare to those by the ME default value. However, they did not study the effect of monthly and hourly distribution, number of axle per truck, axle spacing, wheelbase distribution, etc. Swan et al. (2008) developed regional traffic inputs for Ontario. They also found that pavement performance determined by regional vehicle classification and axle load spectra vary significantly from those determined by the ME default values. Smith and Diefenderfer (2010) developed the statewide average vehicle classification and axle load spectra for Virginia. They suggested to use the statewide average axle load spectra over the ME default spectra. They also suggested to use the ME default vehicle classification rather than the statewide average. However, their studies did not show how good the statewide average data is compared to the site-specific value. Romanoschi et al. (2011) observed considerable differences between the site-specific and the ME default vehicle classification and axle load spectra in New York. They showed the importance of the direct measurement of the vehicle classification and axle load distribution. However, they did not show a difference in results using all three input levels of axle load spectra.

Instead of statewide average, few researchers studied traffic data using the cluster analysis as proposed by the Traffic Monitoring Guide (TMG 2001). Papagiannakis et al. (2006) proposed to use the cluster analysis method to group traffic monitoring sites on the basis of similarities in tandem axle load spectra of Class 9 vehicles. Sayyady et al. (2010) developed traffic inputs for North Carolina using the cluster analysis. Wang et al. (2009) developed truck groups of similar traffic characteristics on the basis of the ME required traffic attributes for Arkansas. Ishak et al. (2010) developed the axle load spectra for Louisiana using the cluster analysis. They found that the developed regional data differ significantly from the ME default value. However, these studies did not show the effects of the cluster generated traffic data on pavement performances.

Lu et al. (2009) calculated traffic data using regression and cluster analysis. They showed that the cluster analysis data were more satisfactory than the regression analysis data. Traffic library for Michigan was developed using cluster methodology (Haider et al. 2011, Buch et al. 2009). These studies found that defaults traffic inputs don't accurately reflect the local traffic conditions in the state of Michigan. Darter et al. (2013) developed the statewide traffic inputs for Arizona using the cluster analysis. However, their studies are different from the study presented herein, because they did not compare the effects of all three input levels on pavement performances. Abbas et al. (2014a, 2014b) used the cluster analysis to develop the regional data for Ohio State. They compared all three input levels for axle load spectra and found that the ME default value underestimates the design life compared to that by the site-specific value. They also observed that the cluster generated value matches better with the site-specific value compared to the statewide average value. For VCD, they found that the functional classification, the ME design default values, and cluster analysis methods may significantly underestimate or overestimate the predicted pavement service life. Recent studies by the researchers showed that the measured traffic data in New Mexico differs significantly from the ME default data (Tarefder and Islam 2015). It also revealed that vehicle class distribution and axle load spectra vary significantly from site to site. However, those studies did not show the effects of site-specific parameter on predicted distresses in pavement.

2.7 Remarks

This chapter has discussed the previous and ongoing research on traffic data and its effect on pavement performance for different states. It reveals that the site-specific data (Level 1) as well as the regional data (Level 2) differs from the ME default data (Level 3). In order to implement new ME pavement design system, it is extremely needed to develop a traffic library for New Mexico using site WIM station data. A regional (Level 2) data should be developed to use for those place where site specific data is not present. Between two methods of generating Level 2 traffic data (average or clustered), which one will be better to use for New Mexico is not known. Furthermore, most of the previous studies did not show how the regional data compares to site-specific data specifically in terms of pavement performance. To this end, this current study determines the effects of different input levels (Level 1, Level 2 by arithmetic average, Level 2 by cluster analysis, and Level 3) on the pavement performance.

CHAPTER 3

DATA COLLECTION AND PROCESSING

3.1 WIM Data

WIM station classifies each vehicle according to the FHWA classification and stores the number of each type of vehicle in each lane for a specific period of time. It also stores the weight of each axle of a vehicle and spacing between the axles. Raw data is stored into two special file formats. Volumetric data is stored in a class file which has an extension of *.CLA (C-card) and axle load data is stored in a weight file with an extension of *.WGT (W-card). In class files, each row contains the total information of volumetric data for 15 minutes. Where, in weight file, each vehicle information is stored in separated row. Detailed description of rows in class and weigh file are given in Table 3.1 and Table 3.2 respectively. State codes for different states are listed in Table 3.3. Lane codes and directional codes are listed in Table 3.4 and Table 3.5 respectively.

Table 3.1 Description of a row in class file

Field	Position	Size	Description
1	1	1	Record Type
2	2	2	State Code
3	4	6	Station ID
4	10	1	Direction of Travel Code
5	11	1	Lane of Travel
6	12	2	Year of Data
7	14	2	Month of Data

Table 3.1 (cont.) Description of a row in class file

Field	Position	Size	Description
8	16	2	Day of Data
9	18	2	Hour of Data
10	20	5	Total Volume
11	25	5	Class 1 Count
12	30	5	Class 2 Count
13	35	5	Class 3 Count
14	40	5	Class 4 Count
15	45	5	Class 5 Count
16	50	5	Class 6 Count
17	55	5	Class 7 Count
18	60	5	Class 8 Count
19	65	5	Class 9 Count
20	70	5	Class 10 Count
21	75	5	Class 11 Count
22	80	5	Class 12 Count
23	85	5	Class 13 Count
24	90	5	Class 14 Count
25	95	5	Class 15 Count

Table 3.2 Description of a row in weight file

Field	Position	Size	Description
1	1	1	Record Type
2	2	2	State Code
3	4	6	Station ID
4	10	1	Direction of Travel Code
5	11	1	Lane of Travel
6	12	2	Year of Data
7	14	2	Month of Data
8	16	2	Day of Data
9	18	2	Hour of Data
10	20	2	Vehicle Class
11	22	7	Total Weight of Vehicle
12	29	2	Number of Axles
13	31	3	Axle Weight 1
14	34	3	Axles 1-2 Spacing
15	37	3	Axle Weight 2
16	40	3	Axles 2-3 Spacing
17	43	3	Axle Weight 3
18	46	3	Axles 3-4 Spacing
19	49	3	Axle Weight 4
20	52	3	Axles 4-5 Spacing
21	55	3	Axle Weight 5

Table 3.2 (cont.) Description of a row in weight file

Field	Position	Size	Description
22	58	3	Axles 5-6 Spacing
23	61	3	Axle Weight 6
24	64	3	Axles 6-7 Spacing
25	67	3	Axle Weight 7
26	70	3	Axles 7-8 Spacing
27	73	3	Axle Weight 8
28	76	3	Axles 8-9 Spacing
29	79	3	Axle Weight 9
30	82	3	Axles 9-10 Spacing
31	85	3	Axle Weight 10
32	88	3	Axles 10-11 Spacing
33	91	3	Axle Weight 11
34	94	3	Axles 11-12 Spacing
35	97	3	Axle Weight 12
36	100	3	Axles 12-13 Spacing
37	103	3	Axle Weight 13

These raw data are too large to be handled manually or by simple spreadsheet. For this reason, a software called TrafLoad was developed to abstract the raw WIM data. However, WIM data are sometimes questionable due to sensor error or other technical reasons. This erroneous WIM data gives error in distress prediction (Haider et al. 2010, Tarefder and

Rodriguez-Ruiz 2013). Past studies show that use of TrafLoad is not reliable because it only performs rudimentary checks for valid site IDs and lanes and direction values, and does not provide a sophisticated QC procedure (Wilkinson 2005). Thus, several studies were conducted to introduce more sophisticated QC procedures in order to find out the error (Ramachandran et al. 2011, Mia et al. 2013). These procedures were developed based on monitoring axle spacing, peak patterns of tandem axles and percentages of gross vehicle weight. These procedures can indicate whether WIM data is erroneous or not. However, these studies didn't describe how to handle the erroneous data. In addition, there is no efficient and user-friendly software available in the literature, which can effectively handle the WIM data.

Table 3.3 State codes according to TMG (2013)

State	Code	State	Code	State	Code
Alabama	1	Georgia	13	Maryland	24
Alaska	2	Hawaii	15	Massachusetts	25
Arizona	4	Idaho	16	Michigan	26
Arkansas	5	Illinois	17	Minnesota	27
California	6	Indiana	18	Mississippi	28
Colorado	8	Iowa	19	Missouri	29
Connecticut	9	Kansas	20	Montana	30
Delaware	10	Kentucky	21	Nebraska	31
D.C.	11	Louisiana	22	Nevada	32
Florida	12	Maine	23	New Hampshire	33

Table 3.3 (cont.) State codes according to TMG (2013)

State	Code	State	Code	State	Code
New Jersey	34	Rhode Island	44	West Virginia	54
New Mexico	35	South Carolina	45	Wisconsin	55
New York	36	South Dakota	46	Wyoming	56
North Carolina	37	Tennessee	47	Puerto Rico	72
North Dakota	38	Texas	48	American Samoa	60
Ohio	39	Utah	49	Guam	66
Oklahoma	40	Vermont	50	Northern Mariana Islands	69
Oregon	41	Virginia	51	Puerto Rico	72
Pennsylvania	42	Washington	53	Virgin Islands of the U.S.	78

Table 3.4 Lane codes according to TMG (2013)

Code	Lane Code
0	Data with lanes combined
1	Outside (rightmost) lane
2-9	Other lanes

Table 3.5 Directional codes according to TMG (2013)

Code	Directional Code
1	North
2	Northeast
3	East
4	Southeast
5	South
6	Southwest
7	West
8	Northwest
9	North-South or Northeast-Southwest combined (volume stations only)
0	East-West or Southeast-Northwest combined (volume stations only)

3.2 Weigh-in-Motion Data Analysis Software (WIMDAS)

3.2.1 Description

The raw WIM files are text files, which cannot be used in the ME design software without further processing. In addition, these files are too large to process with simple spreadsheets. Therefore, it is badly needed to develop a data processing software to process the raw data. WIMDAS is a highly efficient software written in C-sharp (C#) language, which can perform QC as well as generate the ME design inputs. The WIMDAS uses data collected from WIM stations as inputs. After analyzing the raw data, the software gives the outputs that can be directly used in ME design software. The main interface of WIMDAS is shown in Figure 3.1. It has three modules, which are mentioned below:

- Traffic Distribution (First Module): The first module deals with the traffic classification and distribution. It analyzes the class file and calculates total vehicle, Annual Average Daily Truck Traffic (AADTT), directional distribution, hourly distribution, monthly distribution, average axle per truck and so on.

- Weight Distribution (Second Module): The second module analyzes the weight distribution of the vehicle.
- Axle Load Spectra (Third Module): The third module generates the axle load spectra, axle per truck, axle spacing, and wheelbase distribution.

Figure 3.1 Startup screen of WIM Data Analysis Software (WIMDAS)

3.2.2 Working Methodology

WIM data are stored in text file. Therefore, WIMDAS is developed such a way that it can read the raw text messages and extract the key information using some complicated mathematical formulas. It also can detect the errors in the WIM raw data. Moreover, WIMDAS can eliminate the error data for simplification. In addition, it can also replace the error data by averaging adjacent rows. Thus, it minimize the chance to reduce total volume of traffic/load. Finally, it can able to generate outputs for in text and xml format.

These format can be directly imported by the ME design software. The working methodology of WIMDAS is shown in Figure 3.2.

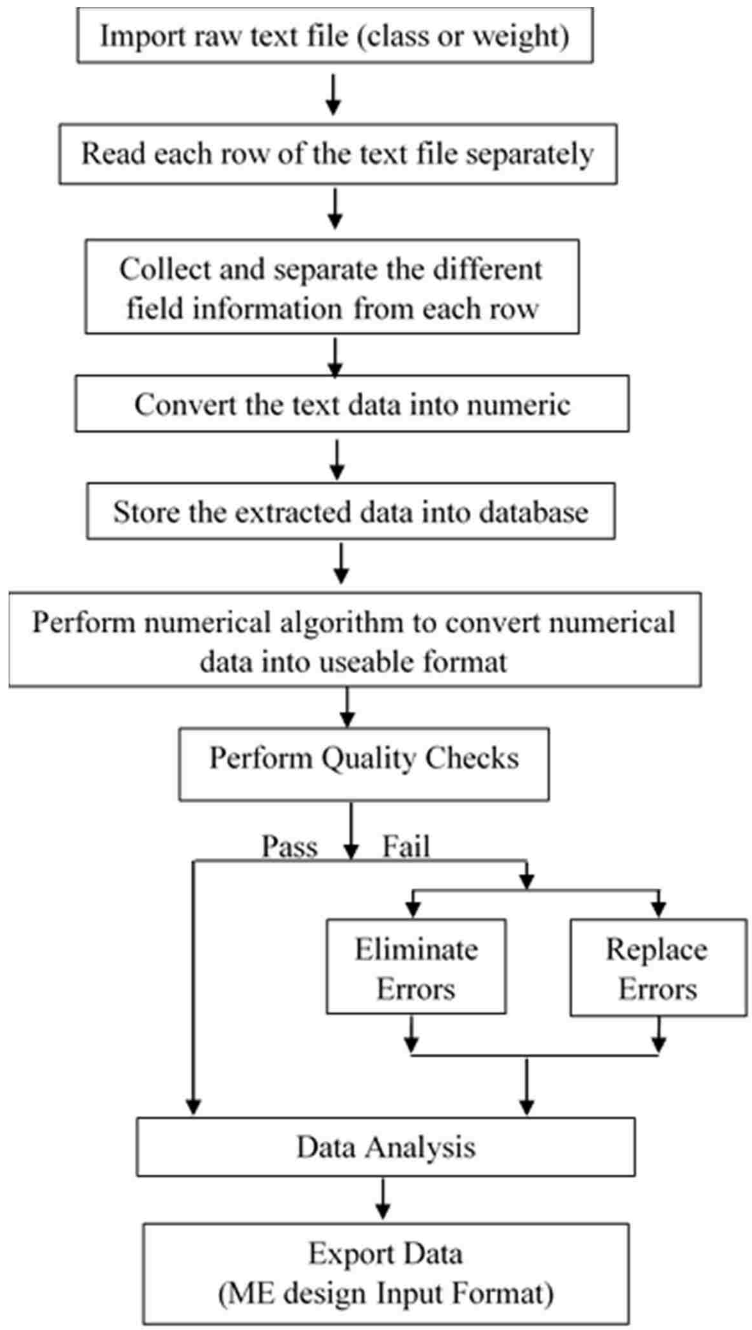


Figure 3.2 Working methodology of WIM Data Analysis Software (WIMDAS)

3.2.3 Quality Checks

WIM data are sometimes questionable due to sensor error or other technical reasons. In addition, past studies revealed that predicted pavement life is highly sensible to the quality of WIM data. Thus researchers recommend to perform quality checks in order to get good result. There are 14 quality checks for class data and 15 quality checks for weight data. Table 3.6 lists the quality checks for class data used in this software. Table 3.7 lists the quality checks for weight data used in this software.

3.3 Data Collection and Processing

3.3.1 Data Collection

A total of ten WIM stations data were used in this study. WIM data were collected in cooperation with the New Mexico Department of Transportation (NMDOT). Table 3.8 lists the data sources used for this analysis. It also indicates the station codes and year of data used for this analysis. Figure 3.2 shows the site locations and the routes where the selected WIM stations are installed. Seven of them are located in three Interstate (I) routes (I-10, I-25 and I-40) and the rest of them are in United States (US) major highways (US-62, US-550).

Table 3.6 Quality checks for class data

Check No.	Description of quality control checks
1	The record type is correct or not, e. g. *.CLA for class file.
2	The state code is correct or not, e.g. state code for New Mexico is 35.
3	The WIM site ID is unique and correct or not.
4	The direction pair is correct or not, e.g. direction pair (1, 5) indicates north-south direction
5	The lane number is correct or not, e.g. lane number should be from 1 to number of lanes at that section.
6	The year is correct or not.
7	The month is correct or not, e.g. month should be 1 to 12.
8	The day is correct or not, e.g. day should be 1 to 31.
9	The time is correct or not, e.g. hour should be 0 to 23.
10	The total hourly volume per lane does not exceed the maximum limit.
11	The total volume at noon should be greater than total volume at midnight.
12	The total volume should not be constant for four consecutive hours.
13	The percentage of motorcycles should be less than 5%.
14	The percentage of unclassified vehicles should be less than 5%.

Table 3.7 Quality checks for weight data

Check No.	Description of quality control checks
1	The record type is correct or not, e. g. *.WGT for weight file
2	The WIM site ID is unique and correct or not.
3	The direction pair is correct or not, e.g. direction pair (1, 5) indicates north-south direction.
4	The lane number is correct or not, e.g. lane number should be from 1 to number of lanes at that section.
5	The year is correct or not.
6	The month is correct or not, e.g. month should be 1 to 12.
7	The day is correct or not, e.g. day should be 1 to 31.
8	The time is correct or not, e.g. hour should be 0 to 23.
9	The vehicle class is correct or not, e.g. if vehicle Class should be 1 to 13.
10	The number of axles should be equal within the range of axles for that vehicle class.
11	The number of axles should be equal to number of axle spaces plus 1.
12	The number of axles should be equal to number of axle weights.
13	The sum of axle weights should be equal to total weight of vehicle.
14	The sum of axle spaces should not be greater than 35 m.
15	The axle weights should be within acceptable range (20 to 19,000 kg).
16	The axle spacing should be within acceptable range (0.6 m to 15 m).

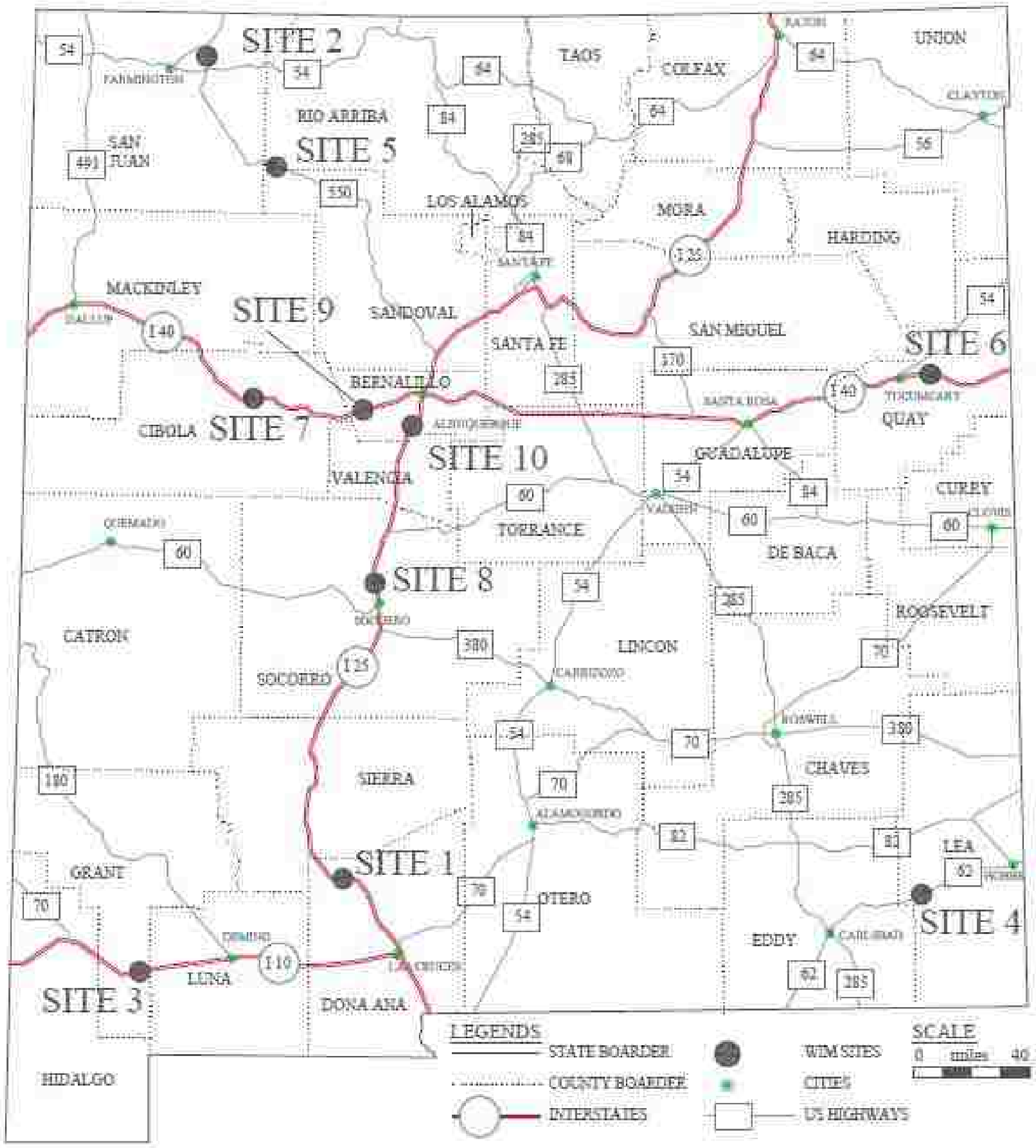


Figure 3.3 Location of WIM stations considered in this study

Table 3.8 WIM stations used in this study

Site	Route Number	Highway Descriptions	Source-Code	Year of data
Site - 1	I-25	Principal Arterial - Interstate	101	2008-2012
Site - 2	US550	Principal Arterial - Other	155	2013-2015
Site - 3	I-10	Principal Arterial - Interstate	501	2008-2012
Site - 4	US-62	Principal Arterial - Other	1112	2004-2005
Site - 5	US-550	Principal Arterial - Other	2007	2011-2012
Site - 6	I-40	Principal Arterial - Interstate	2118	2007-2010
Site - 7	I-40	Principal Arterial - Interstate	3010	2004
Site - 8	I-25	Principal Arterial - Interstate	6035	2001-2004
Site - 9	I-40	Principal Arterial - Interstate	R01	2013-2015
Site - 10	I-25	Principal Arterial - Interstate	R02	2013-2015

3.3.2 Data Processing

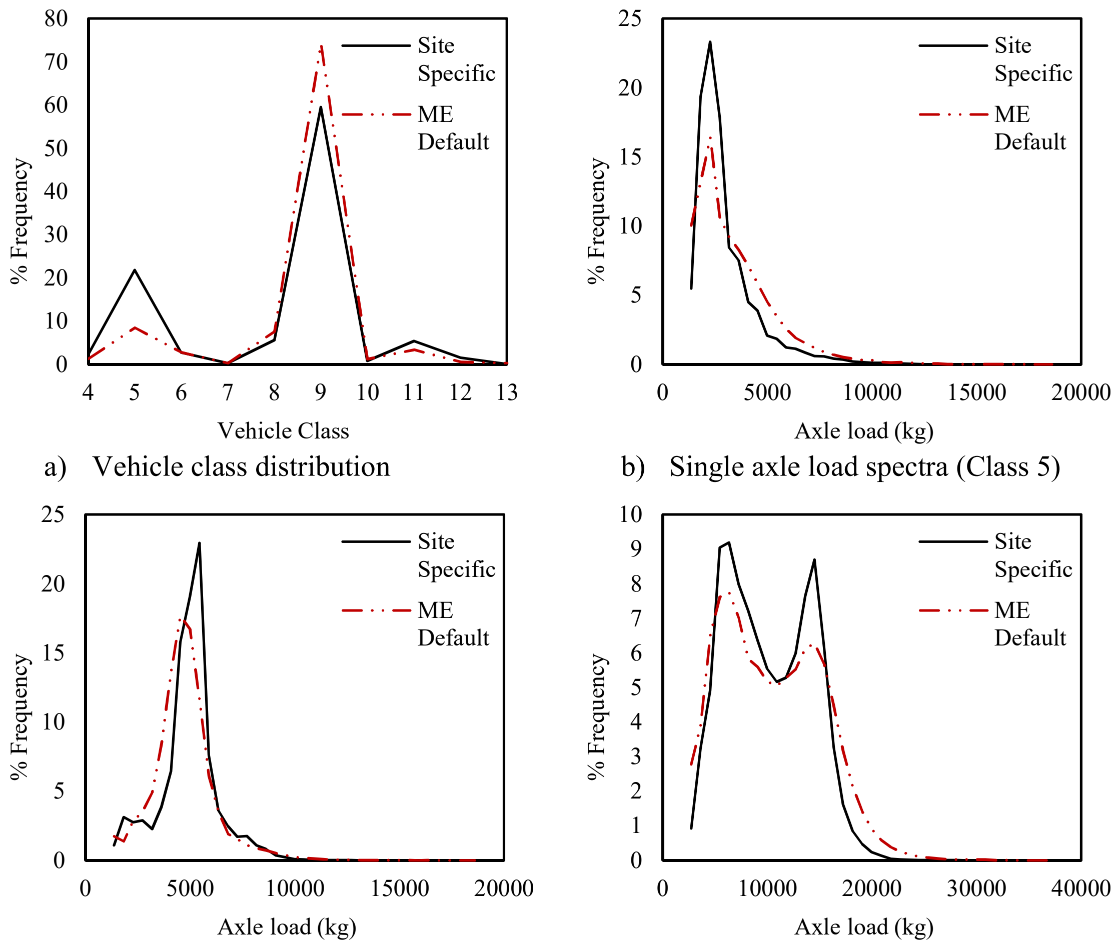
The generated data processing software, WIMDAS was used to generate the site specific data from the raw WIM data. Both class file (*.CLA) and weight file (*.WGT) were used here. ASTM E1572-93 (ASTM 1994) method was used to determine the type of each axle based on their spacing.

3.3.3 Site Specific Traffic Data (Level 1)

Using 10 WIM raw data site specific traffic for the ME design was developed. Site specific values are than compared with the ME design default values.

Site 1: 101

Figure 3.4 compares the site specific traffic inputs with the ME design default value. Figure 3.4(a) shows that the VCD of Site 1 has significantly high percentage of Class 5 vehicle and low percentage of Class 9 vehicle than ME default VCD. Figures 3.4(b) and 3.4(c) show that the single load spectra for both Class 5 and Class 9 are not closed to ME design default. Similarly, tandem axle load spectra for Class 9 vehicle at Site 1 differs from the ME default spectra as shown in Figure 3.4(d).

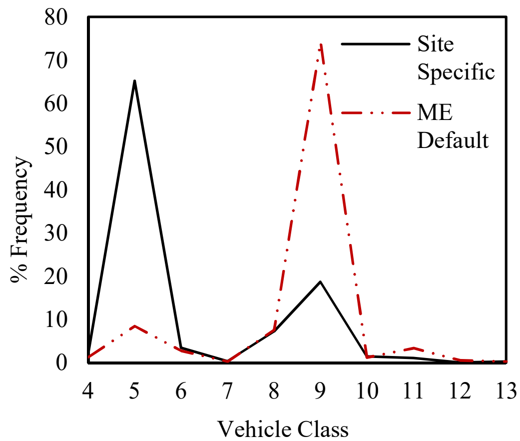


a) Vehicle class distribution
b) Single axle load spectra (Class 5)
c) Single axle load spectra (Class 9)
d) Tandem axle load spectra (Class 9)

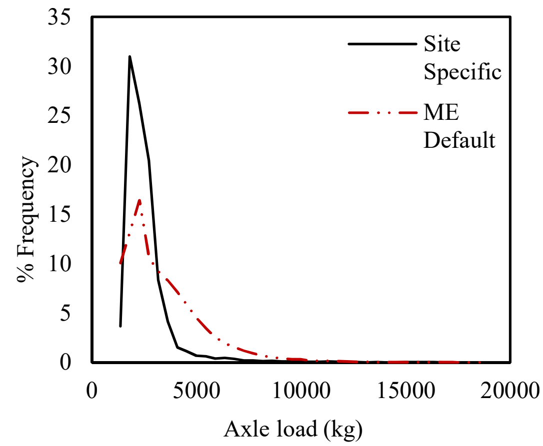
Figure 3.4 Site-specific traffic data at Site-1

Site 2: 155

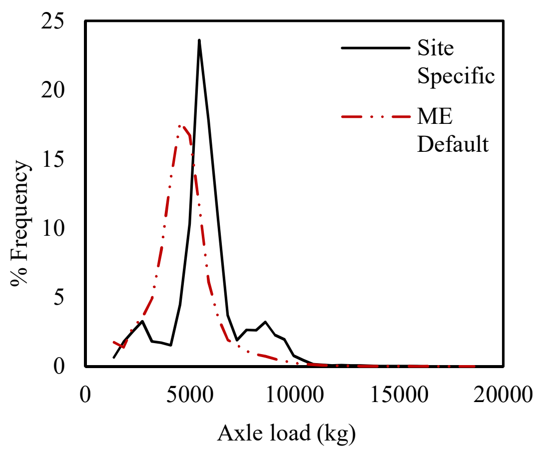
Figure 3.5 compares the site specific traffic inputs at Site 2 with the ME design default value. Figure 3.5(a) shows that the VCD of Site 2 significantly differ from the ME default VCD. It also has significantly higher percentage of Class 5 and lower percentage of Class 9 than the ME design VCD. Similarly, Figures 3.5(b), 3.5(c) and 3.5(d) show that the axle load spectra for Site 2 significantly differ from the ME default ALS.



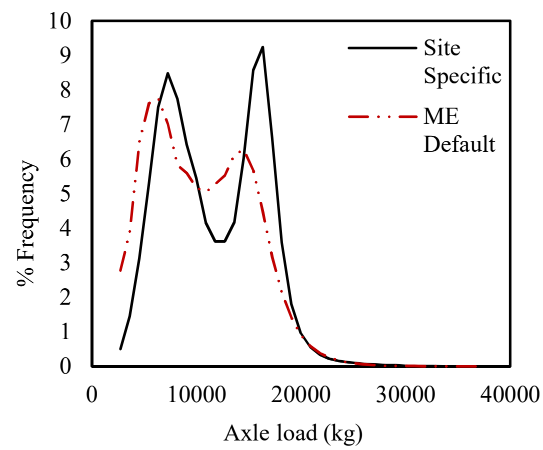
a) Vehicle class distribution



b) Single axle load spectra (Class 5)



c) Single axle load spectra (Class 9)

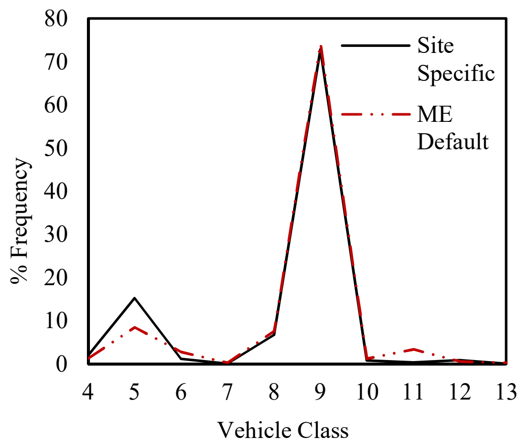


d) Tandem axle load spectra (Class 9)

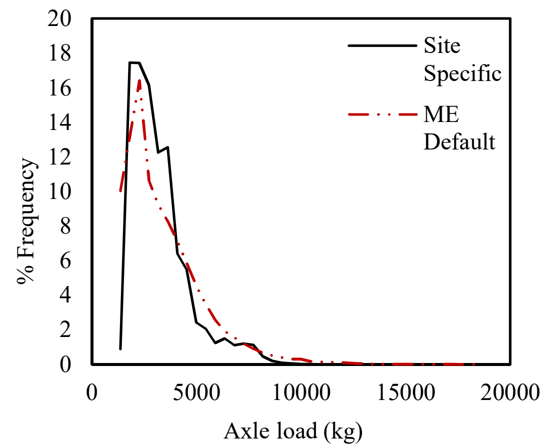
Figure 3.5 Site-specific traffic data at Site-2

Site 3: 501

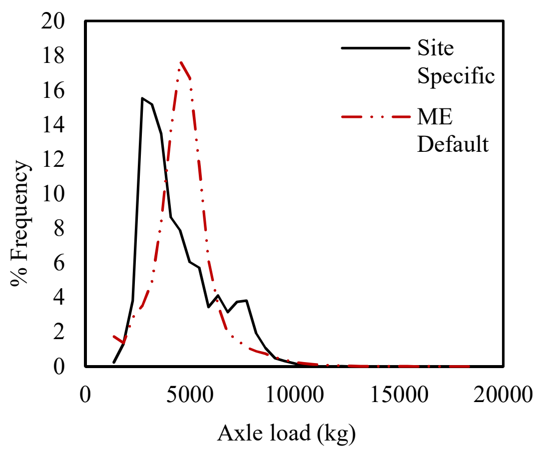
Figure 3.6 compares the site specific traffic inputs at Site 3 with the ME design default value. Figure 3.6(a) shows that the VCD of Site 3 is closed to the ME default VCD. Figures 3.6(b) shows that the single load spectra for both Class 5 is closed to the ME default distribution. However, Figure 3.6(c) shows that site specific single axle load distribution for Class 9 has lower percentage of light vehicles. Site 3 has higher percentage of light tandem axle than other ALSs (Figure 3.6(d)).



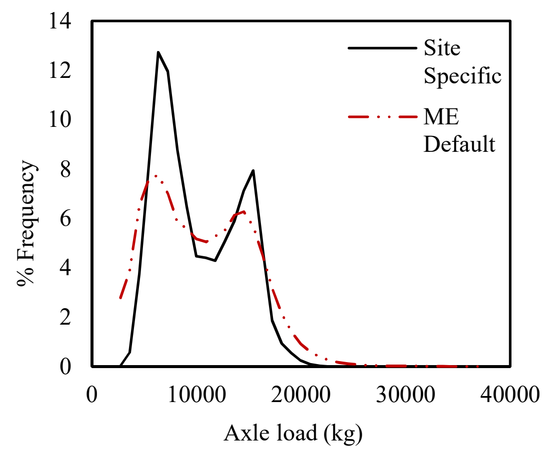
a) Vehicle class distribution



b) Single axle load spectra (Class 5)



c) Single axle load spectra (Class 9)

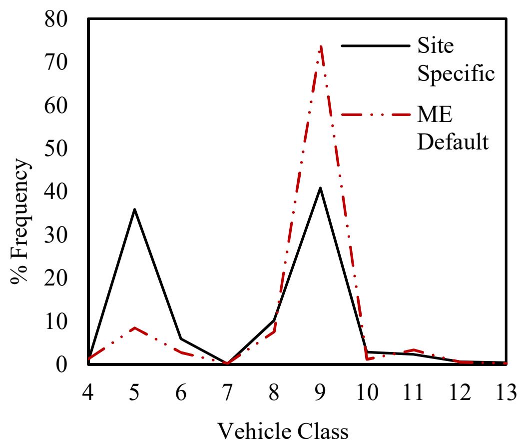


d) Tandem axle load spectra (Class 9)

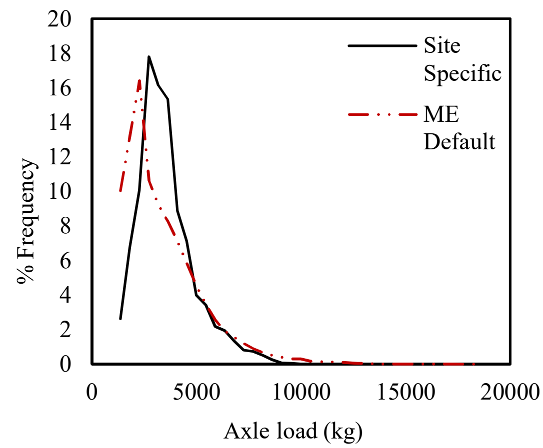
Figure 3.6 Site-specific traffic data at Site-3

Site 4: 1112

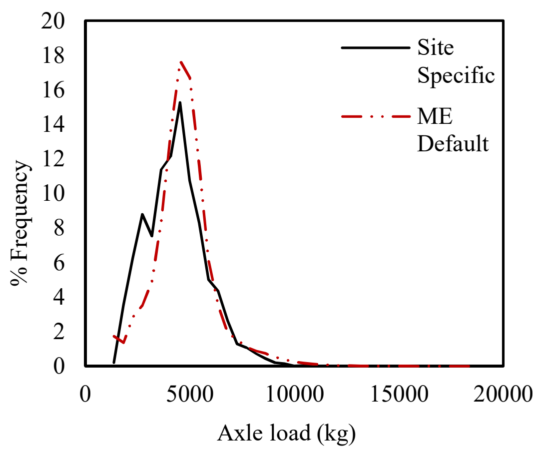
Figure 3.7 compares the site specific traffic inputs at Site 4 with the ME design default value. Figure 3.7(a) shows that the VCD of Site 4 significantly differ from the ME default VCD. It has higher percentage of Class 5 and lower percentage of Class 9 than the default VCD. Figures 3.7(b), 3.7(c) and 3.7(d) show that the axle load spectra for Site 4 significantly differ from the ME default ALSs. Site 4 has higher percentage of light tandem axle than other two ALSs.



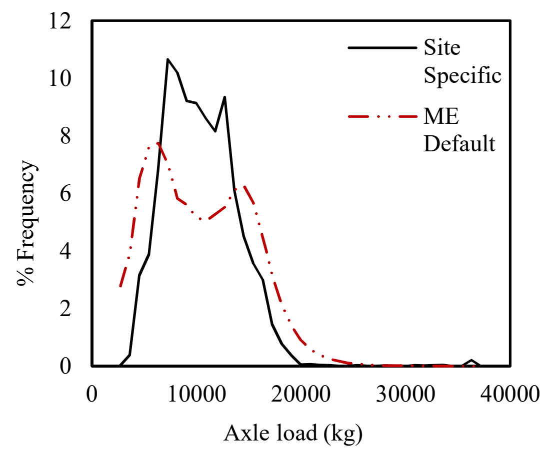
a) Vehicle class distribution



b) Single axle load spectra (Class 5)



c) Single axle load spectra (Class 9)

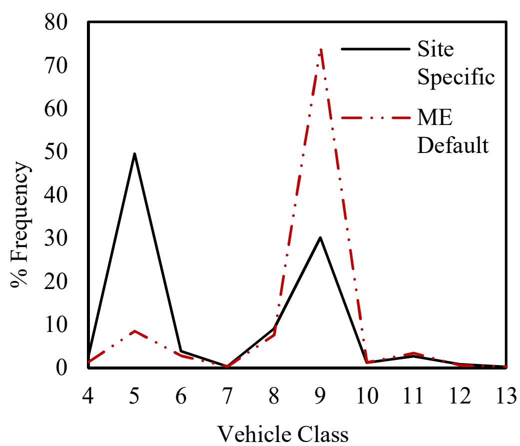


d) Tandem axle load spectra (Class 9)

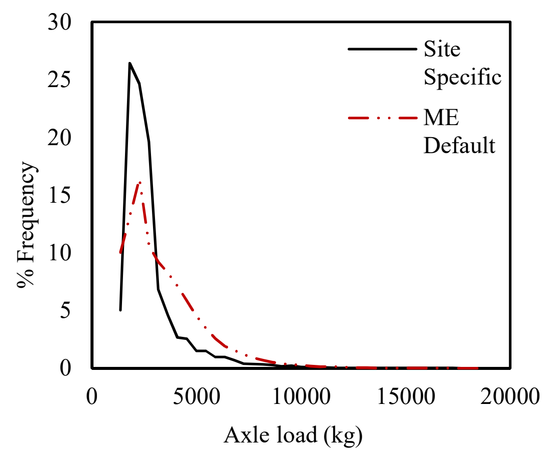
Figure 3.7 Site-specific traffic data at Site-4

Site 5: 2007

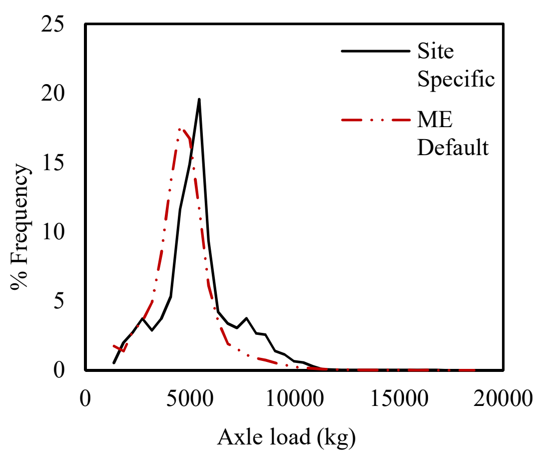
Figure 3.8 compares the site specific traffic inputs at Site 5 with the ME design default value. Figure 3.8(a) shows that the VCD of Site 5 has higher percentage of Class 5 and lower percentage of Class 9 than the default VCD. Figures 3.8(b), 3.8(c) and 3.8(d) show that the axle load spectra for Site 5 is different from the ME default ALS. Site 5 has higher percentage of heavy tandem axle than the ME default ALS.



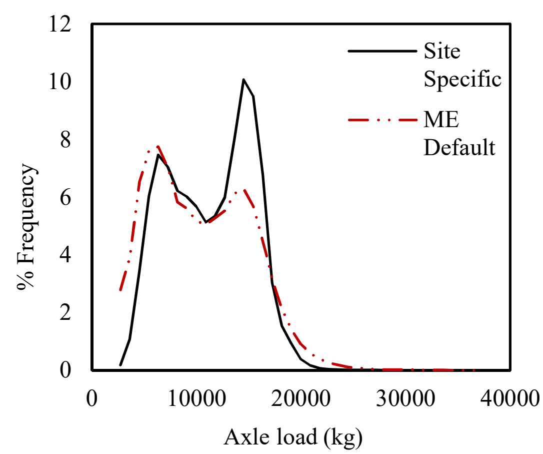
a) Vehicle class distribution



b) Single axle load spectra (Class 5)



c) Single axle load spectra (Class 9)



d) Tandem axle load spectra (Class 9)

Figure 3.8 Site-specific traffic data at Site-5

Site 6: 2118

Figure 3.9 compares the site specific traffic inputs at Site 6 with the ME design default value. Figure 3.9(a) shows that the VCD of Site 6 is closer to the ME default VCD. Figures 3.9(b) and 3.9(c) show that the single load spectra for both Class 5 and Class 9 are closed to the ME default ALS. Tandem axle load spectra for Class 9 vehicle at Site 6 differs from the regional average and ME default spectra (Figure 3.9(d)). It has higher percentage of light tandem axle than the default ALS.

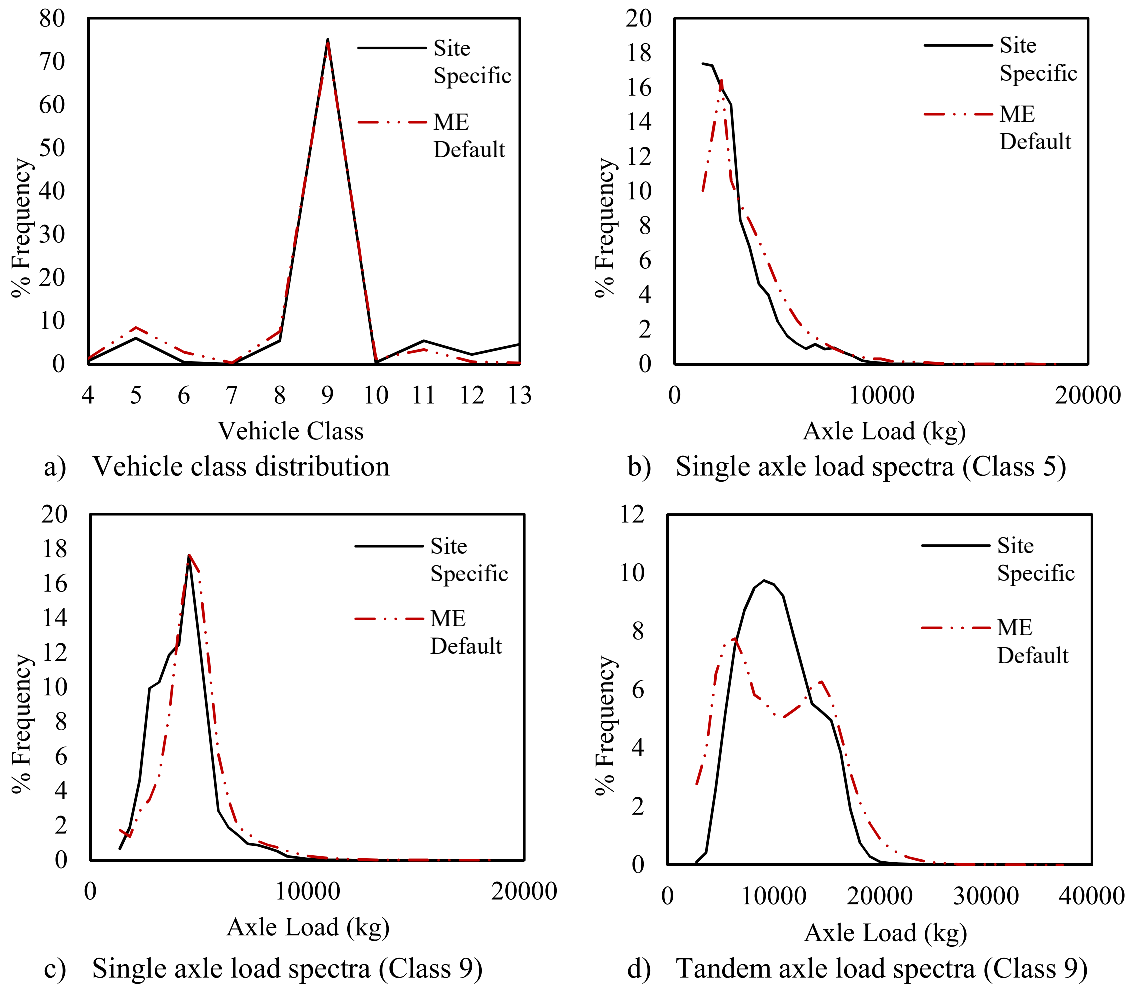
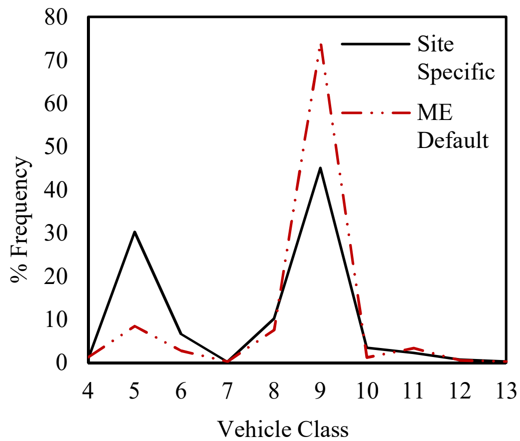


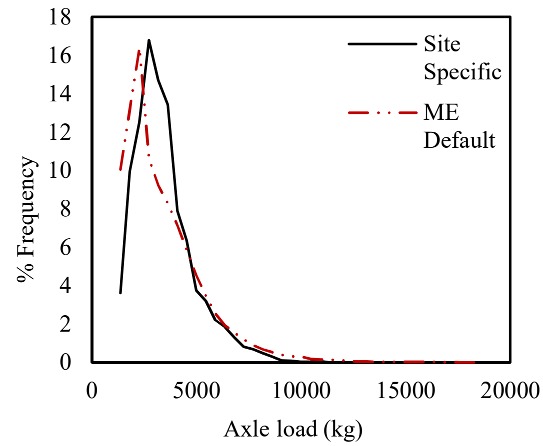
Figure 3.9 Site-specific traffic data at Site-6

Site 7: 3010

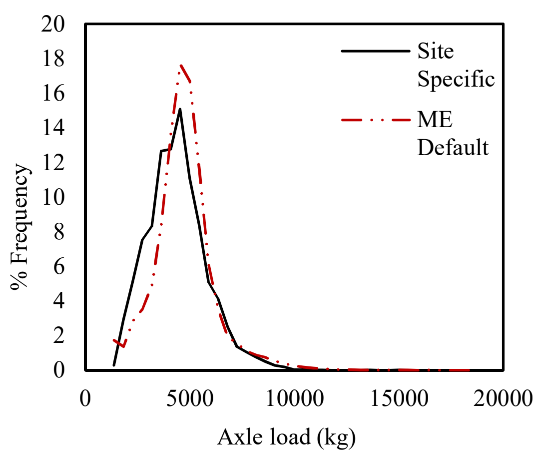
Figure 3.10 compares the site specific traffic inputs at Site 7 with the ME design default value. Figure 3.10(a) shows that the VCD of Site 7 has significantly higher percentage of Class 5 vehicle and lower percentage of Class 9 vehicle. Figures 3.10(b), 3.10(c) and 3.10(d) show that the axle load spectra for Site 7 significantly differ from the ME default ALSs. Site 7 has larger percentage of mid-weight tandem axle.



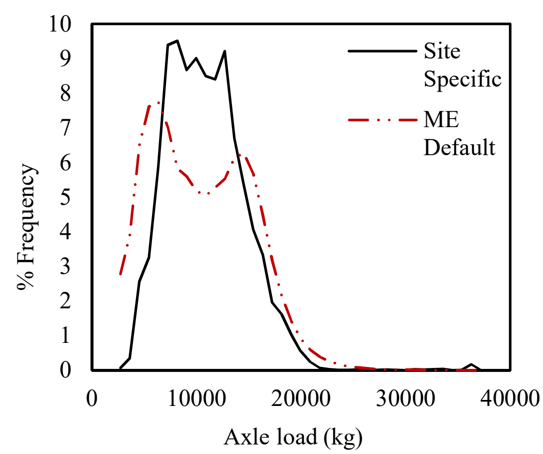
a) Vehicle class distribution



b) Single axle load spectra (Class 5)



c) Single axle load spectra (Class 9)

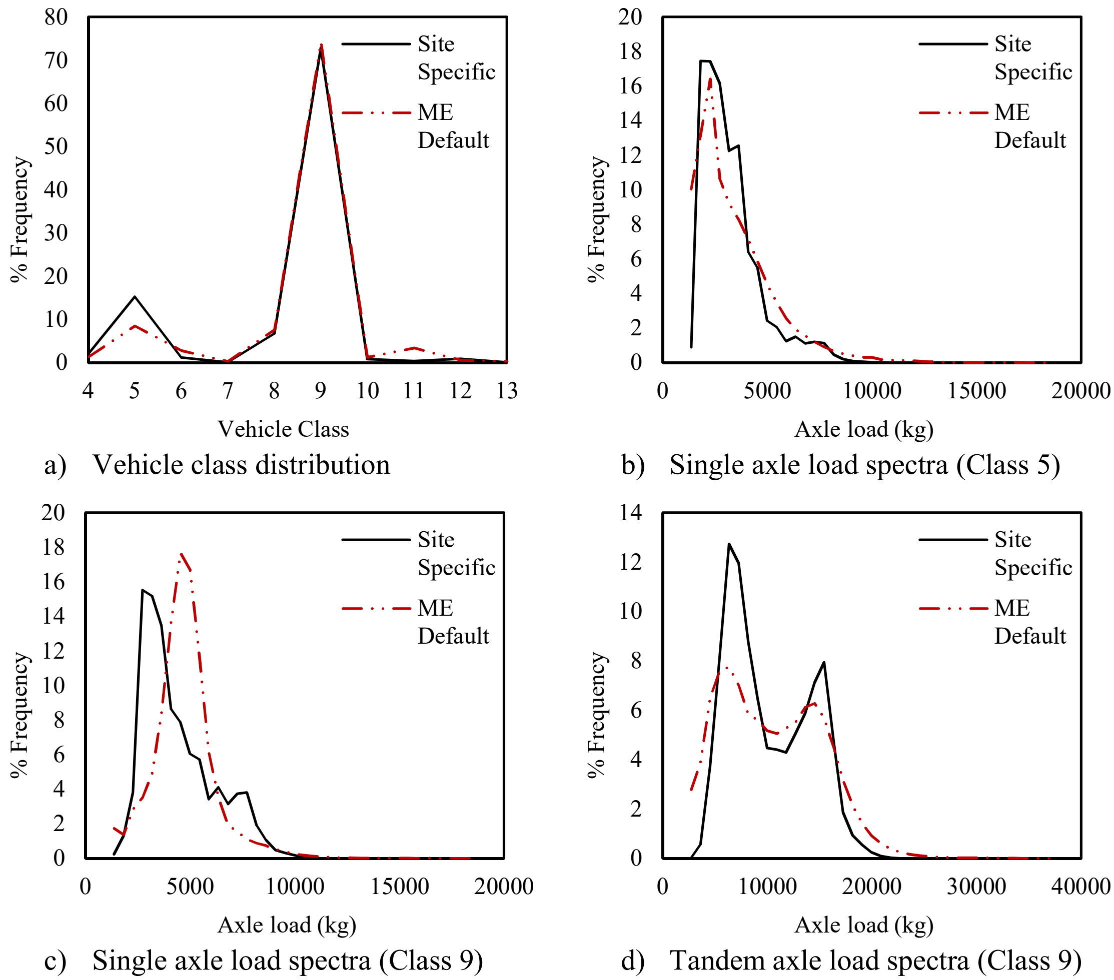


d) Tandem axle load spectra (Class 9)

Figure 3.10 Site-specific traffic data at Site-7

Site 8: 6035

Figure 3.11 compares the site specific traffic inputs at Site 8 with the ME design default value. Figure 3.11(a) shows that the VCD of Site 8 is closer to the ME default VCD. Figures 3.11(b), 3.11(c) and 3.11(d) show that the axle load spectra for Site 8 significantly differ from the ME default ALS. Site 8 has larger percentage of light tandem axle than the default ALS.



a) Vehicle class distribution

b) Single axle load spectra (Class 5)

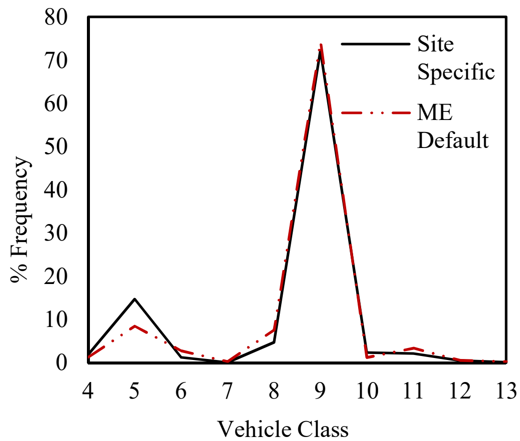
c) Single axle load spectra (Class 9)

d) Tandem axle load spectra (Class 9)

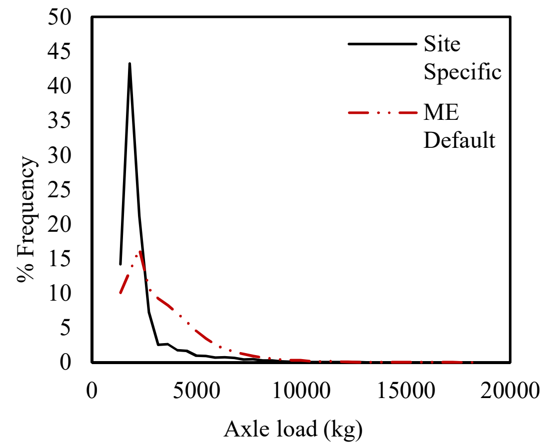
Figure 3.11 Site-specific traffic data at Site-8

Site 9: R01

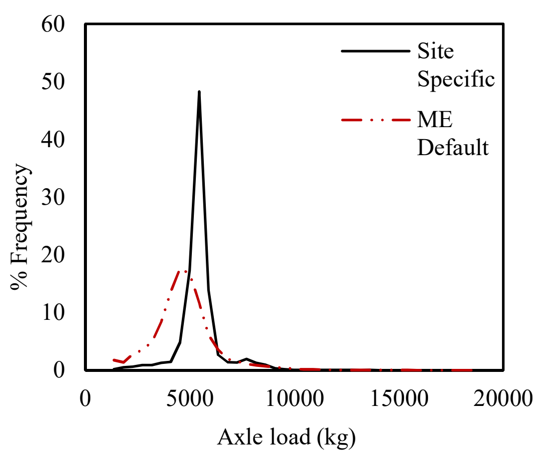
Figure 3.12 compares the site specific traffic inputs at Site 9 with the ME design default value. Figure 3.12(a) shows that the VCD of Site 8 is closed to the ME default VCD. Figures 3.12(b), 3.12(c) and 3.12(d) show that the axle load spectra for Site 9 significantly differ from the ME default ALS. Site 9 has larger percentage of heavy single and tandem axle than the ME default ALS.



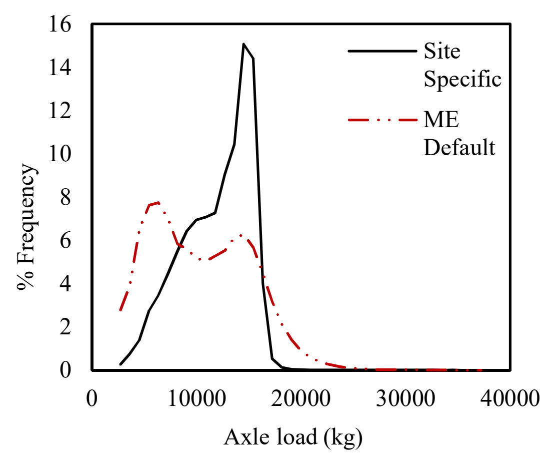
a) Vehicle class distribution



b) Single axle load spectra (Class 5)



c) Single axle load spectra (Class 9)

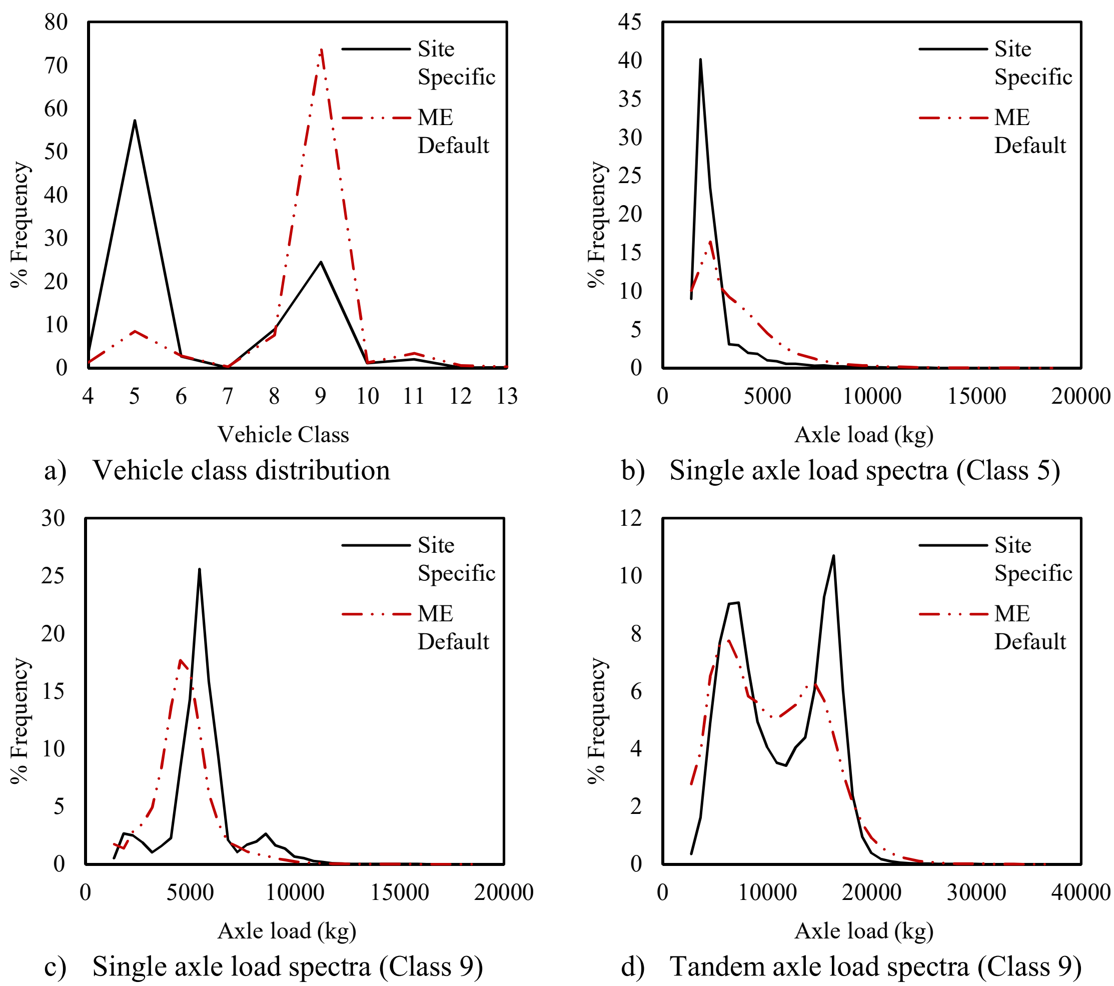


d) Tandem axle load spectra (Class 9)

Figure 3.12 Site-specific traffic data at Site-9

Site 10: R02

Figure 3.13 compares the site specific traffic inputs at Site 10 with the ME design default value. Figure 3.13(a) shows that the VCD of Site 10 significantly differ from the ME default VCD. It has significantly higher percentage of Class 5 and lower percentage of Class 9. Figures 3.13(b), 3.13(c) and 3.13(d) show that the axle load spectra for Site 10 significantly differ from the ME default ALS.



a) Vehicle class distribution

b) Single axle load spectra (Class 5)

c) Single axle load spectra (Class 9)

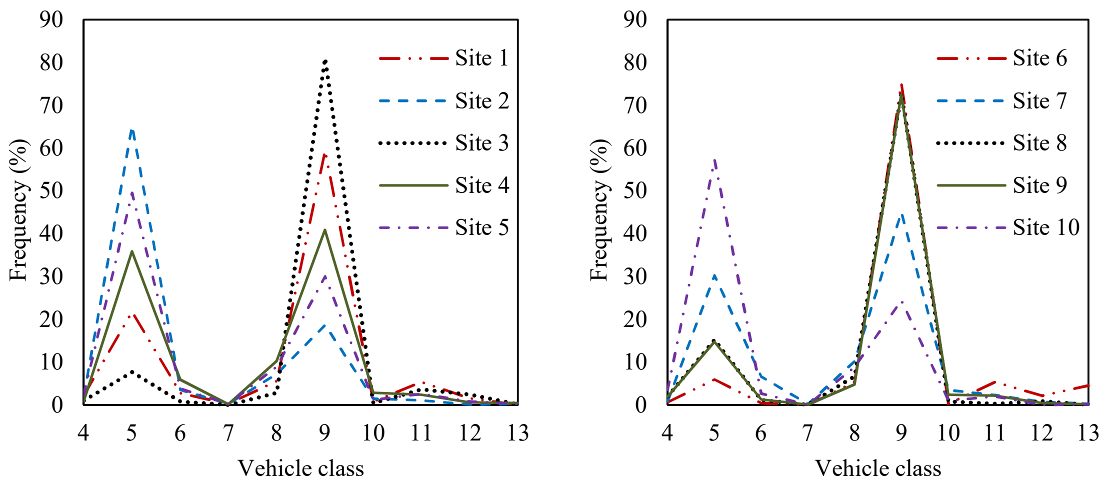
d) Tandem axle load spectra (Class 9)

Figure 3.13 Site-specific traffic data at Site-10

3.4 Summary of 10 Site Specific Data

3.4.1 VCDs

Figure 3.14 compares the 10 site-specific VCDs developed using the raw data from ten pavement sites. These VCDs are different from site to site. All sites are dominated by the single unit (Class 5) or the single trailer (Class 9) vehicle. Class 7 vehicles are rare for all sites. The percentage of multi-trailer vehicles is also low for all sites.

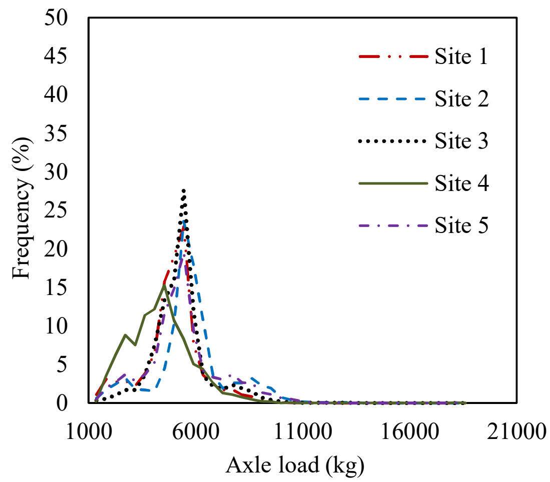


a) Site 1 to Site 5 b) Site 6 to Site 10

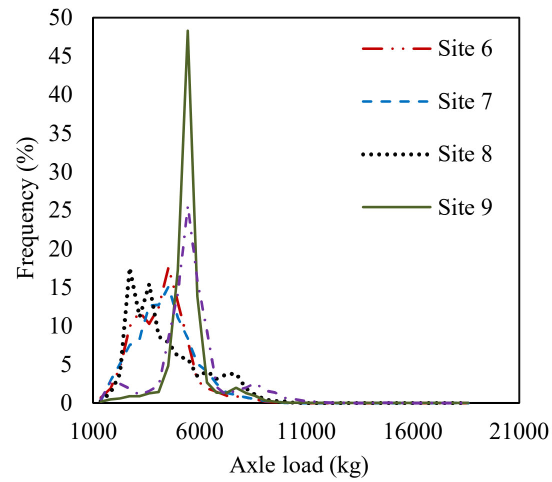
Figure 3.14 Vehicle class distribution for all sites

3.4.2 ALSs

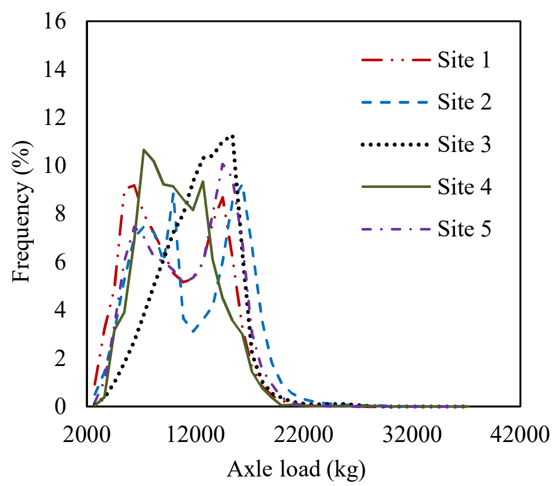
Figure 3.15 compares the 10 site specific ALSs for Class 9 vehicle developed using the raw data from ten pavement sites. It is observed that the site-specific ALSs vary significantly from site to site.



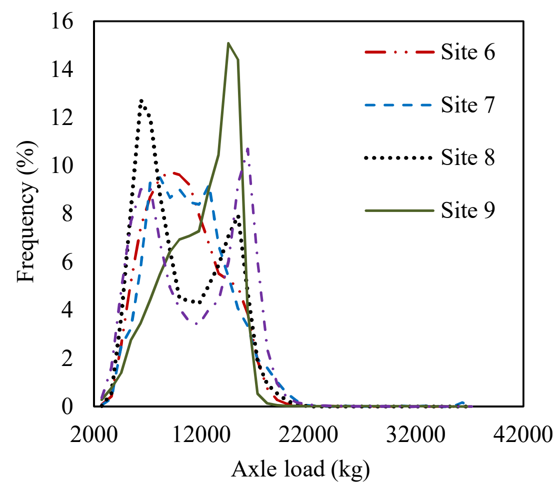
a) Single axle (Site 1 to Site 5)



b) Single axle (Site 6 to Site 10)



c) Tandem axle (Site 1 to Site 5)



d) Tandem axle (Site 6 to Site 10)

Figure 3.15 Axle load spectra of Class 9 vehicle for all sites

3.5 Regional Traffic Data (Level 2)

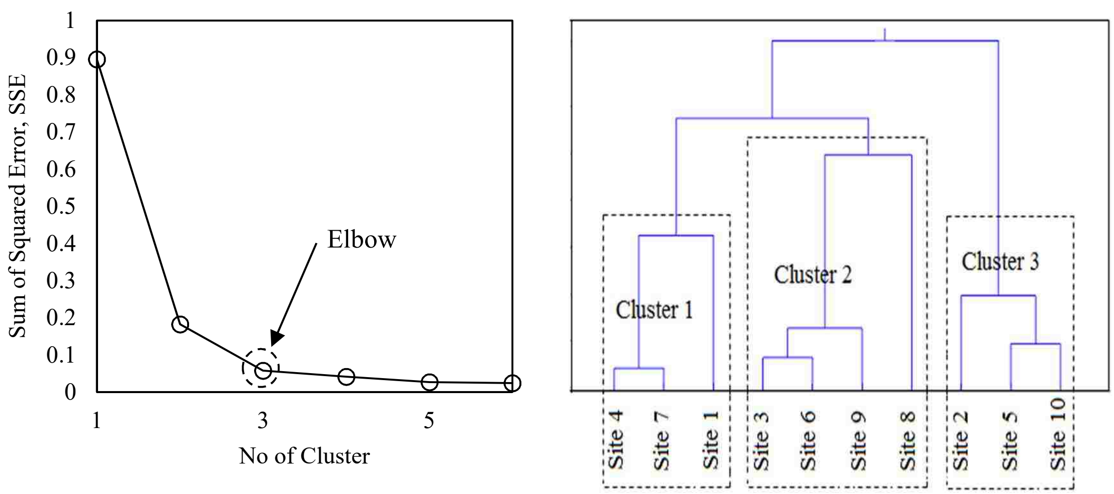
3.5.1 VCDs

Regional average VCD was calculated by arithmetic averaging of 10 site-specific VCDs. Then, K-means method was used to determine the optimum number of clusters. Cluster analysis was conducted using the MATLAB program. Sum of squared error was calculated for number of clusters of 1 to number of clusters of 6. Figure 3.16(a) shows the squared errors for different number of clusters. It shows that when the cluster number is equal 3, there is an elbow in the line. Thus, the optimum number of groups in this data set is found 3. Figure 3.16(b) shows the cluster tree obtained from the hierarchical cluster analysis using the ten VCD data. Euclidean distance matrix for hierarchical analysis is shown in Table 3.9. From the analysis, three different types of VCDs are obtained from the cluster analysis. These are mentioned below:

i) Cluster 1: Predominantly single-trailer trucks (Class 9) with a low to moderate amount of single-unit trucks (Class 5).

ii) Cluster 2: Predominantly single-trailer trucks (Class 9).

iii) Cluster 3: Predominantly single-unit trucks (Class 5) with a low to moderate amount of single-trailer trucks (Class 9).



a) Square error versus no of cluster

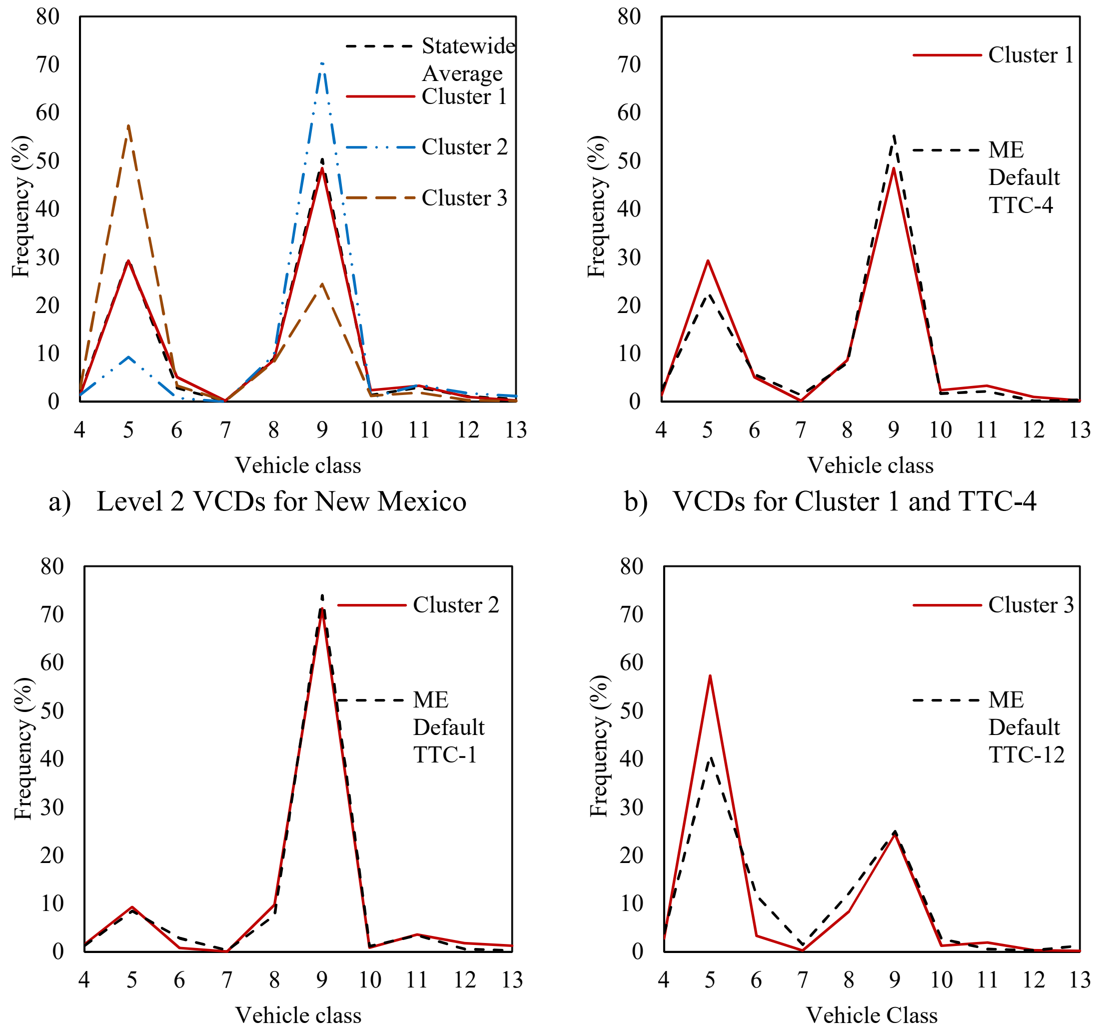
b) Cluster tree for VCDs

Figure 3.16 Cluster results for VCD data

Table 3.9 Euclidean distance matrix for VCDs

Site	1	2	3	4	5	6	7	8	9	10
1	0	0.60	0.26	0.24	0.41	0.23	0.18	0.16	0.15	0.50
2	0.60	0	0.85	0.37	0.20	0.82	0.44	0.74	0.74	0.10
3	0.26	0.85	0	0.50	0.66	0.08	0.44	0.12	0.12	0.76
4	0.24	0.37	0.50	0	0.18	0.46	0.07	0.39	0.39	0.27
5	0.41	0.20	0.66	0.18	0	0.63	0.25	0.55	0.55	0.10
6	0.23	0.82	0.08	0.46	0.63	0	0.40	0.12	0.11	0.72
7	0.18	0.44	0.44	0.07	0.25	0.40	0	0.32	0.32	0.34
8	0.16	0.74	0.12	0.39	0.55	0.12	0.32	0	0.03	0.64
9	0.15	0.74	0.12	0.39	0.55	0.11	0.32	0.03	0	0.64
10	0.50	0.10	0.76	0.27	0.10	0.72	0.34	0.64	0.64	0

The VCD for the statewide average and Clusters 1 to 3 are shown in Figure 3.17(a). It is observed that the statewide average VCD is close to Cluster 1. The ME design has a default (Level 3) VCD for the predominantly single-trailer trucks with a low to moderate amount of single-unit trucks which is known as Truck Traffic Class-4 (TTC-4). Therefore, Cluster 1 (Level 2) was compared with the default TTC-4 in Figure 3.17(b). It is observed that Cluster 1 has a lower percentage of Class 9 vehicles and a higher percentage of Class 5 vehicles compared to the TTC-4. Similarly, the ME design default VCDs for predominantly single-trailer trucks (similar to Cluster 2) and predominantly single-trailer trucks with a low to moderate amount of single-unit trucks (similar to Cluster 3) are known as TTC-1 and TTC-12 respectively. The Cluster 2 and the Cluster 3 were compared with the TTC-1 and the TTC-12 as shown in Figures 3.17(c) and 3.16(d) respectively. It is found that the Cluster 2 and the TTC-1 are almost the same. However, there is a significant difference between the Cluster 3 and the TTC-12. Statewide average and clustered VCDs are presented in tabulated form in appendices.



a) Level 2 VCDs for New Mexico

b) VCDs for Cluster 1 and TTC-4

c) VCDs for Cluster 2 and TTC-1

d) VCDs for Cluster 3 and TTC-12

Figure 3.17 Comparison of VCDs among different input levels

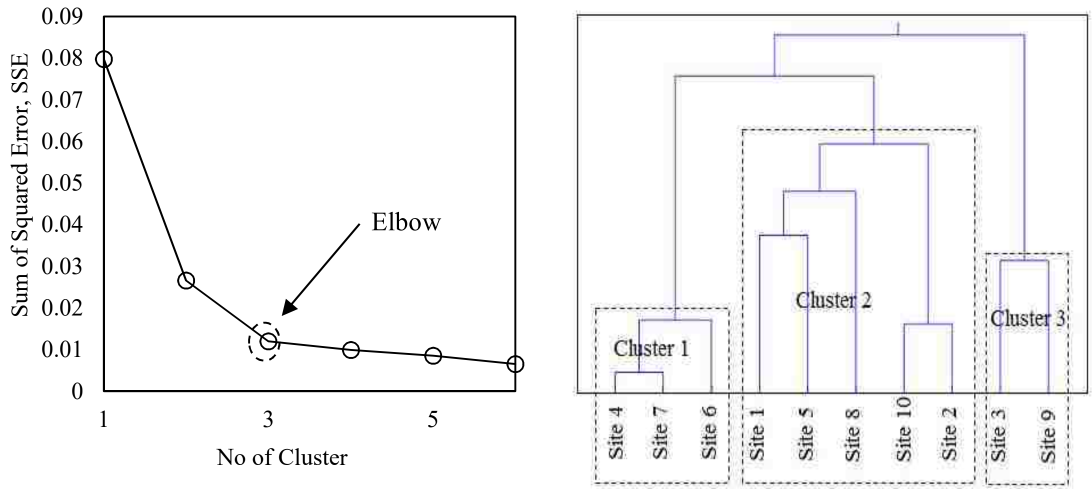
3.5.2 ALSs

Regional average ALS was calculated by arithmetic averaging of 10 site-specific ALSs. As Class 9 vehicles are frequent and consistent for all sites, the cluster analysis was performed based on the tandem axle load spectra of Class 9 vehicles. K-means method was used to determine the optimum number of clusters. Cluster analysis was conducted using the MATLAB program. Sum of squared error was calculated for number of clusters of 1 to number of clusters of 6. Figure 3.18(a) shows the squared errors for different number of clusters. It shows that when the cluster number is equal 3, there is an elbow in the line. Thus, the optimum number of groups in this data set is found 3. Figure 3.18(b) shows the cluster tree obtained from the hierarchical cluster analysis using the ten ALS data. Euclidean distance matrix for hierarchical analysis is shown in Table 3.10. From the analysis, three different types of ALSs are obtained from the cluster analysis. These are mentioned below:

i) Cluster 1: Predominated light weight vehicle.

ii) Cluster 2: Mix traffic with light weight and heavy weight vehicle.

iii) Cluster 3: Predominated heavy weight vehicle.



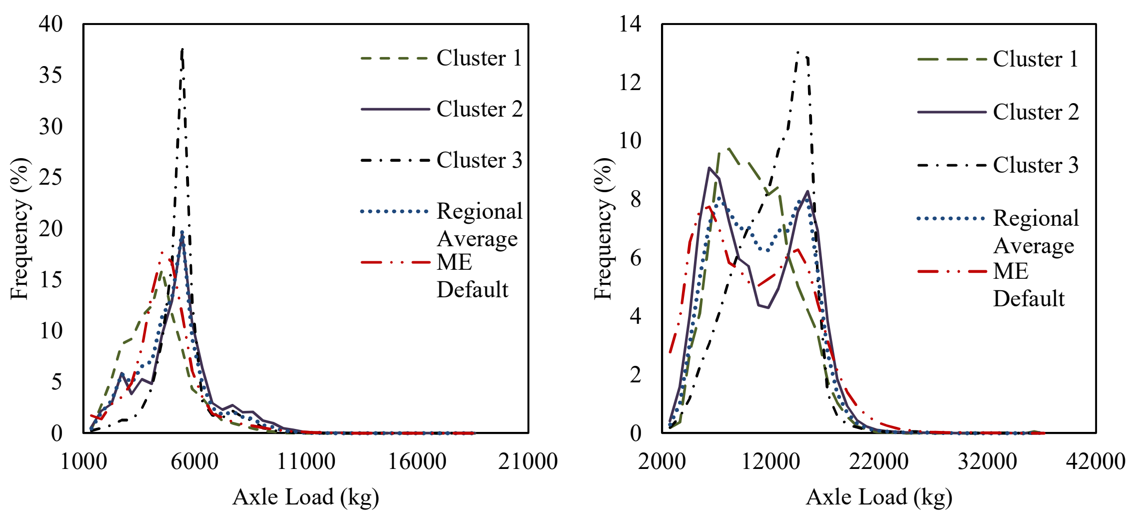
a) Square error versus no of cluster b) Cluster tree for ALSs

Figure 3.18 Cluster results for ALS data

Table 3.10 Euclidean distance matrix for ALSs

Site	1	2	3	4	5	6	7	8	9	10
1	0	0.08	0.15	0.12	0.07	0.10	0.12	0.07	0.16	0.06
2	0.08	0	0.15	0.14	0.06	0.12	0.13	0.08	0.15	0.05
3	0.15	0.15	0	0.16	0.11	0.15	0.14	0.19	0.07	0.16
4	0.12	0.14	0.16	0	0.13	0.04	0.03	0.13	0.19	0.14
5	0.07	0.06	0.11	0.13	0	0.11	0.12	0.09	0.11	0.06
6	0.10	0.12	0.15	0.04	0.11	0	0.04	0.12	0.17	0.12
7	0.12	0.13	0.14	0.03	0.12	0.04	0	0.13	0.17	0.14
8	0.07	0.08	0.19	0.13	0.09	0.12	0.13	0	0.19	0.07
9	0.16	0.15	0.07	0.19	0.11	0.17	0.17	0.19	0	0.16
10	0.06	0.05	0.16	0.14	0.06	0.12	0.14	0.07	0.16	0

The statewide average ALS was calculated by averaging all ten measured ALSs. Finally, ALSs for the statewide average and Cluster 1 to 3 are compared with the ME default values in Figure 3.19. Figure 3.19(a) compares the single axle load spectra of Class 9 vehicles. It shows the Cluster 1 ALS closely matches with the ME default ALS. The statewide average, the Cluster 2, and the Cluster 3 have a higher percentage of heavier single axle than the ME default value. Figure 3.19(b) compares the tandem axle load spectra of Class 9 vehicles. It shows that the Cluster 2 and the statewide average follow the two peak tandem axle load spectra described by Ramachandran et al. (2011). Cluster 3 has significantly heavier vehicles than the ME default ALS. Statewide average and clustered ALSs are presented in tabulated form in appendices.



a) Single axle (Class 9)   b) Tandem axle (Class 9)

Figure 3.19 Comparison of ALSs among different input levels

CHAPTER 4

EFFECTS OF ALTERNATIVE TRAFFIC DATA ON PREDICTED PAVEMENT PERFORMANCE

4.1 Introduction

In this section, effects of different traffic input levels on predicted pavement performance will be analyzed. There are several traffic inputs required in the ME design software. However, it is still ambiguous that among the thirteen values which affect more on predicting pavement distresses. Therefore, a comparative study was done to categorize the traffic inputs depending on their influences. Later, a comparative study was done to see the effects of traffic input levels on predicted performance.

4.2 Effects of Site Specific Data on Predicted Pavement Performance

Effects of different site-specific traffic inputs on predicted pavement distresses in New Mexico were investigated in this section. Two major interstate highways were considered in this study: Interstate-40 (I-40) and Interstate-25 (I-25). Site-specific traffic inputs were developed using Weigh-in-Motion (WIM) data collected from the pavement sites. WIM data was analyzed using an advanced and updated software, which can take care of error data, if any. Then a comparative study was conducted using the ME design Software. Different input parameters such as site-specific axle load spectra, vehicle class distribution, monthly adjustment factor, and hourly distribution, etc., were studied.

4.2.1 Design Inputs

The measured traffic data was finally used in the ME design software to determine the effects of site-specific data traffic inputs on pavement performance. Actual pavement section was used for this study. For example, a pavement section with 10.5 in (263 mm) Asphalt Concrete (AC) of PG 76 – 22 was chosen for I-40. Effective binder content and air void were considered as 8.8% and 6% respectively. Under the AC layer a 350 mm (14 in) crushed stone base course with a modulus 280 MPa (40000 psi) underlain by natural subgrade was considered. Subgrade was chosen as A-3 ME default subgrade with resilient modulus 170 MPa (24500 psi), and design lane width was 3.60 m (12 ft). A traffic growth factor of 4% with compound rate was used for all analysis. Climate data were generated for both sites using the site-specific longitude, latitude and ground water table data. The AADTT of I-40 and I-25 were 8950 and 7330 respectively. The analysis period was 20 years for all cases.

4.2.2 Effects of Different Inputs

Two major performance measures namely alligator cracking and rutting were considered to analyze the effects of the site specific parameters.

Effect of Site Specific Design Distribution

Unless a roadway has an unbalanced travel for trucks, the percentage of truck traffic in the design direction is 50%. Figures 4.1(a) and 4.1(b) show the directional distribution of truck traffic measured on I-40 and I-25 respectively. Figure 4.1(a) shows there are 53% truck passes through the negative direction (West) of I-40. For I-25 both of the directions have almost the equal traffic (Figure 4.1(b)).

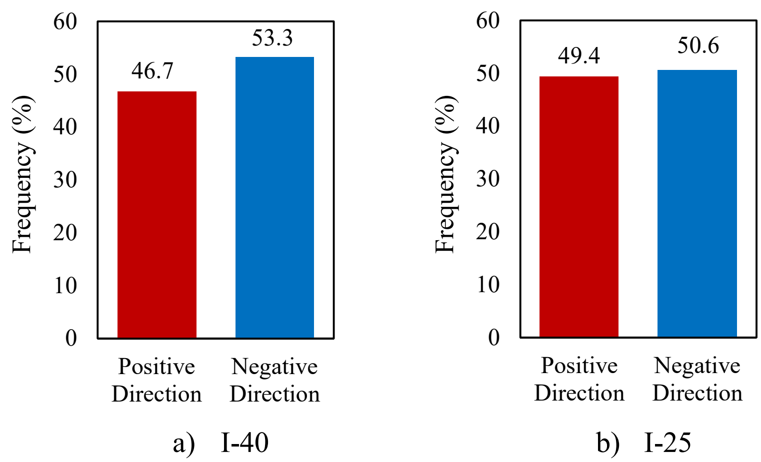
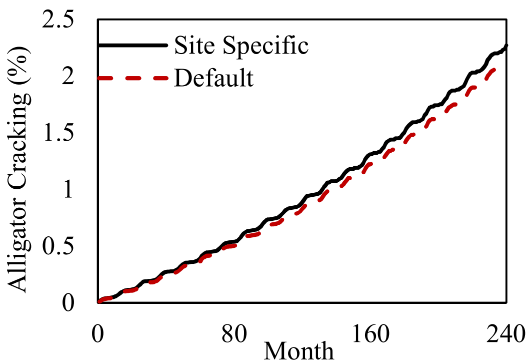
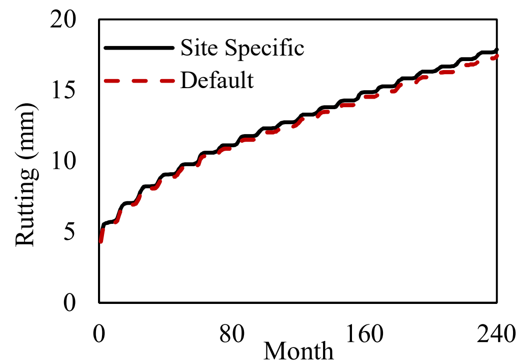


Figure 4.1 Directional Distribution

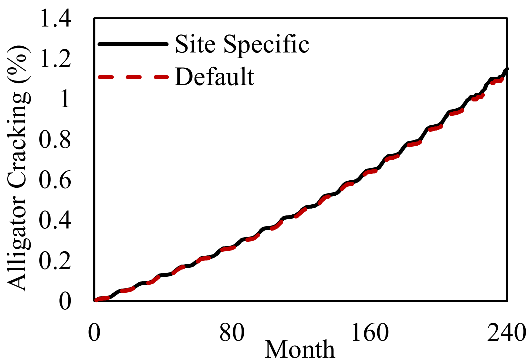
To evaluate the effect of site specific directional distribution, all parameters except the directional distribution were assigned default values while determining the performance (alligator cracking and rutting) using the ME design software. Figure 4.2 shows the effect of directional distribution on predicted alligator cracking and rutting. Site specific directional distribution in I-40 results in 7% higher predicted alligator cracking after 20 years compared to that by the ME default value as shown in Figure 4.2(a). For rutting, the site specific directional distribution produces 2.5% higher rutting compared to that by the ME default value as shown in Figure 4.2(b) after 20 years. As I-25 has almost symmetric directional distribution, both alligator cracking and rutting are almost the same for both of the site specific and the ME default values as shown in Figures 4.2(c) and 4.2(d).



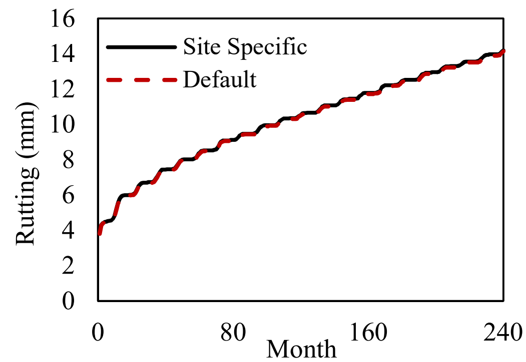
(a) Alligator cracking on I-40



(b) Rutting on I-40



(c) Alligator cracking on I-25



(d) Rutting on I-25

Figure 4.2 Effect of directional distribution on pavement performance

Effect of Site Specific Lane Distribution

Percentage Trucks in Design Lane means the percentage of total truck traffic that runs through the design lane, typically the outside lane (driving lane) in a multilane highway (more than one lane in each travel direction). This is because most of the traffic runs through the driving lane. Lane distributions of truck traffic for I-40 and I-25 are presented in Figure 4.3(a) and 4.3(b) respectively. For I-40 (Figure 4.3(a)), Lane 1 and Lane 2 are toward the positive direction (East) where Lane 3 and Lane 4 are toward the negative direction (West) of I-40. In the east bound lane, 85% trucks drives through the driving lane and 15% trucks uses the passing lane. The M-E Design software default value is 95% for the design lane/driving lane which is way conservative for I-40. In the west bound lane of I-40, 69% trucks drive through the driving lane and 31% trucks use the passing lane. Lane distribution on I-25 shows that the middle lanes in both directions (Lane 2 in north direction, Lane 4 in south direction) carry equal amount of truck. The outer lane, for example Lane 4 in south direction, carries the smallest amount of truck (25%). Therefore, it is not necessary that the outer lane has the lowest truck. In that case, the busiest lane is the design lane.

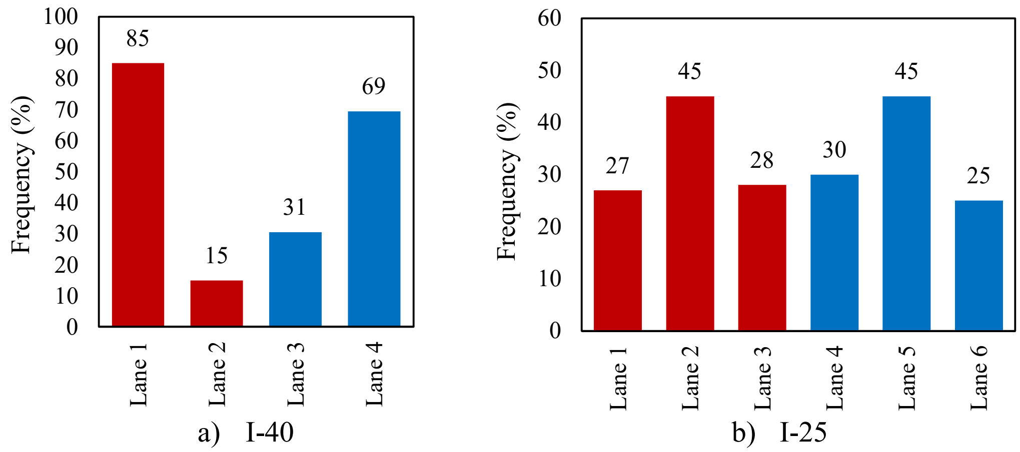
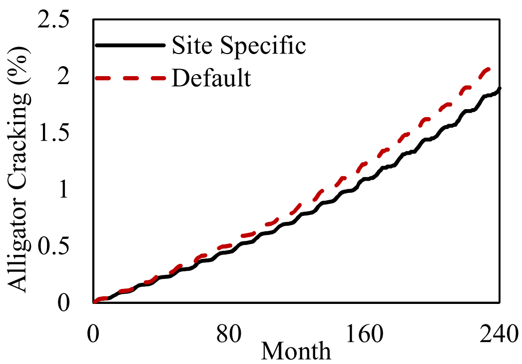
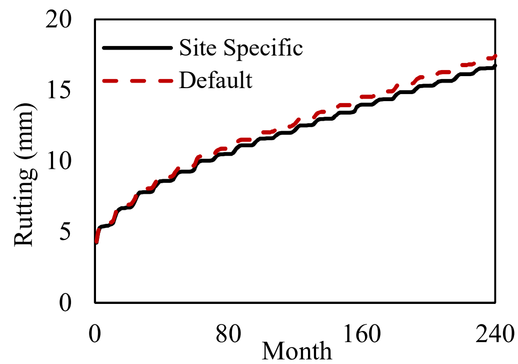


Figure 4.3 Lane Distribution

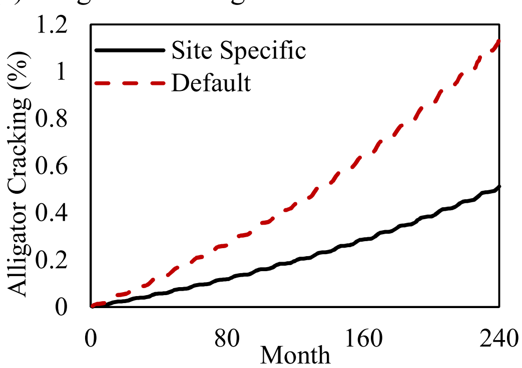
To analyze the effect of lane distribution, all parameters except the lane distribution were assigned default values while analyzing the section using the ME design software. Figure 4.4 shows the effect of site specific lane distribution on predicted alligator cracking and rutting. As site specific lane distribution for I-40 is 85% which is smaller than the ME default 95% distribution, the predicted alligator cracking and rutting after 20 years are 11% and 4% lower than that by the ME default value as shown in Figures 4.4(a) and 4.4(b) respectively. For the site specific lane distribution (45%), the predicted alligator cracking and rutting are 55% and 22% lower than those by the ME default values as shown in Figures 4.4(c) and 4.4(d) in I-25.



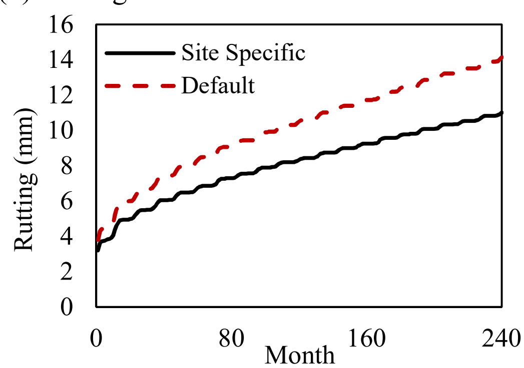
(a) Alligator cracking on I-40



(b) Rutting on I-40



(c) Alligator cracking on I-25

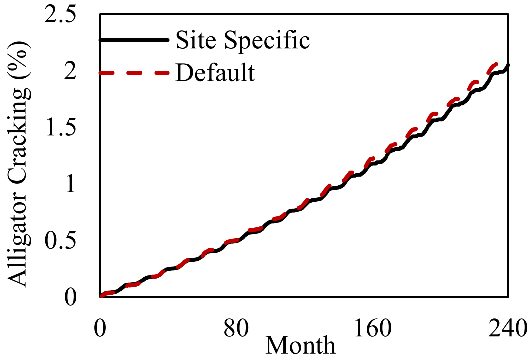


(d) Rutting on I-25

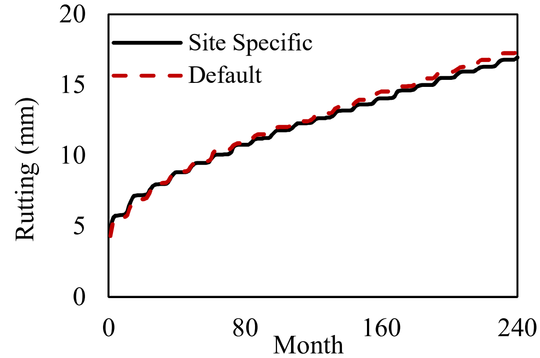
Figure 4.4 Effect of lane distribution on pavement performance

Effect of Site Specific Vehicle Operational Speed

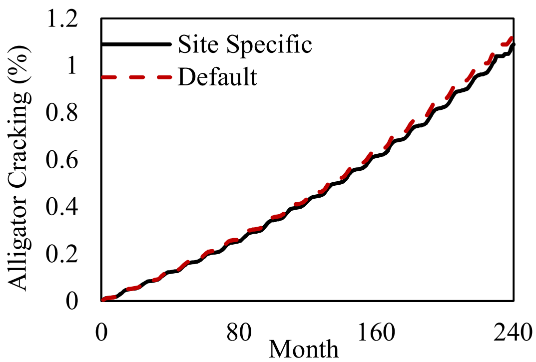
Vehicle operational speed can be obtained from the speed limit of the design site. For both I-40 and I-25 average vehicle speed is 70 mph. MEPDG default vehicle speed is 60 mph. All parameters except the operational speed were assigned default values while analyzing the effect of operational speed using the ME design software. Figures 4.5(a) and 4.5(b) show that predicted alligator cracking and rutting for site specific operational speed for I-40 are 3.5% and 3% less, respectively, compared to those by the ME default value. Figures 4.5(c) and 4.5(d) show that both predicted alligator cracking and rutting on I-25 is 4.5% and 3% less, respectively, compared to those by the ME default value.



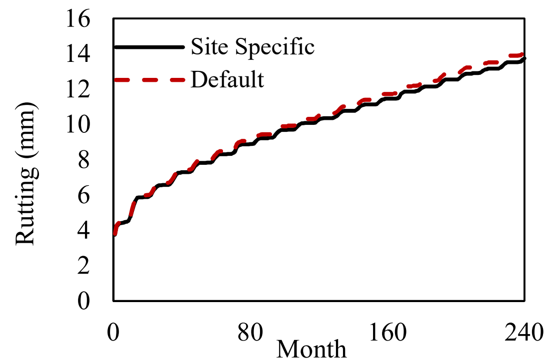
(a) Alligator cracking on I-40



(b) Rutting on I-40



(c) Alligator cracking on I-25



(d) Rutting on I-25

Figure 4.5 Effect of operational speed on pavement performance

Effect of Site Specific Vehicle Class Distribution

Vehicle Class Distribution (VCD) refers to AADTT distribution among the 10 vehicle types (Class 4 to 13). The TCDs measured on I-40 and I-25 is presented in Figure 4.6. On I-40, Class 9 truck is the governing vehicle (72% of the total truck) with a percentage of bus lower than 2% and percentage of multi-trailer higher than 2%. The measured distribution quite similar to the default TTC-1. But measured percentage of heavy vehicle (upper than class 8) (82%) is less than default value (87%). On I-25, Class 5 truck is the governing vehicle (57%) which is quite similar to default Truck Traffic Class 12 (TTC-12). For I-25, percentage of heavy vehicle is 36% which is small than default value for TTC-12 (42%).

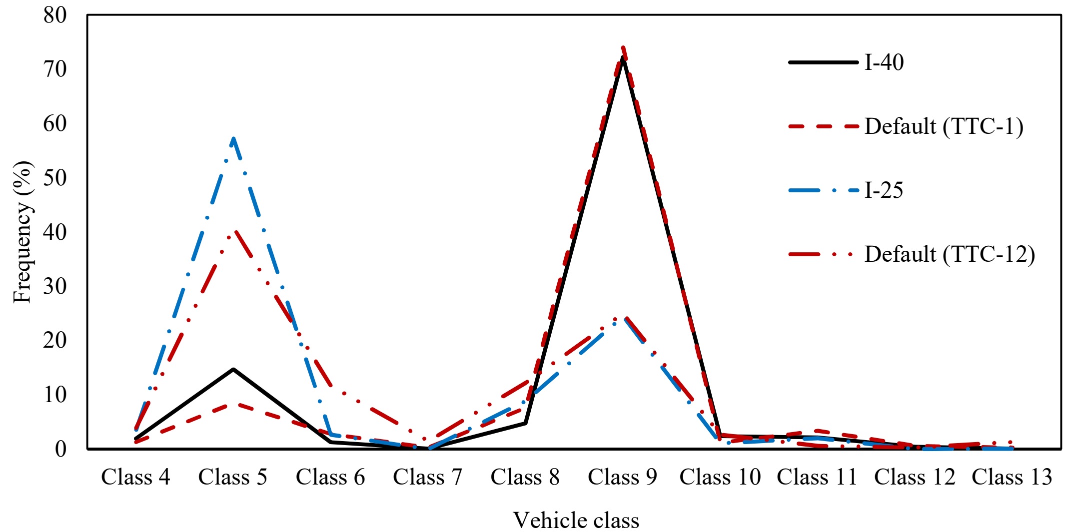
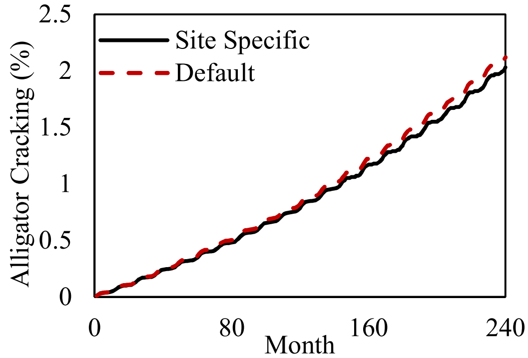
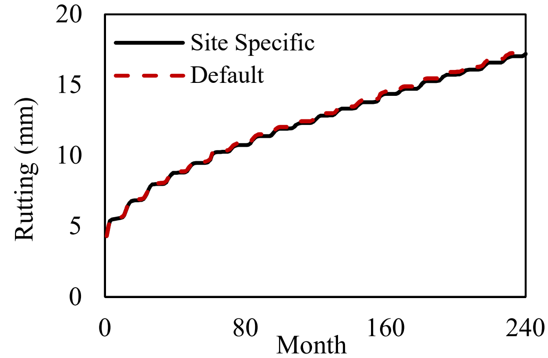


Figure 4.6 Vehicle Class Distribution

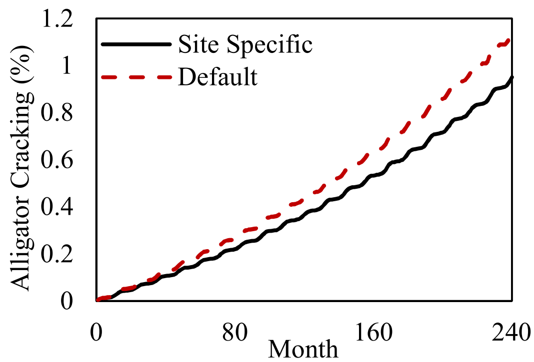
All parameters except the Vehicle Class Distribution (VCD) were assigned default values while analyzing the section to determine the alligator cracking and rutting using the AASHTOWare software. Figure 4.7 shows the effects of the site specific VCD on predicted alligator cracking and rutting. It can be seen from Figure 4.7(a) that the predicted alligator cracking after 20 years due to the site specific VCD for I-40 site is 4.25% lower than that by the ME default Truck Traffic Class-1 (TTC-1) available in the ME. The predicted rutting for site specific values for I-40 is 1.3% lower compared to that by the ME default value as shown in Figure 4.7(b). Figure 4.7(c) shows that the alligator cracking for the site specific classification on I-25 is 16.5% lower than that by the TTC-12. The rutting is 7% lower for the site specific classification in I-25 compared to that by the TTC-12 (Figure 4.7(d)). This is because, in I-25, the percentage of heavy vehicle is lower compared to that by the TTC-12. Therefore, it can be concluded that the site specific vehicle class distribution has a significant role in the predicted distresses.



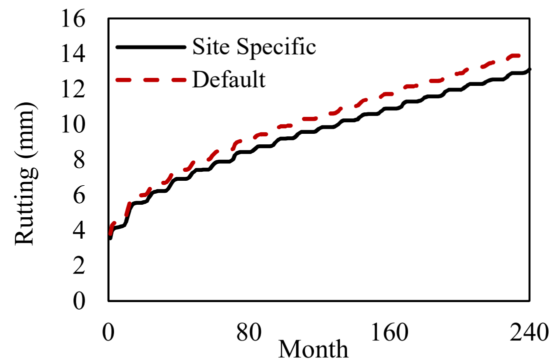
(a) Alligator cracking on I-40



(b) Rutting on I-40



(c) Alligator cracking on I-25



(d) Rutting on I-25

Figure 4.7 Effect of vehicle class distribution on pavement performance

Effect of Site Specific Hourly Distribution

Hourly Distribution (HD) refers to the percentage of hourly AADTT among a 24 hour period starting at midnight. There are 24 HDs in 24 hours of a day. To understand the importance the determining the HD, the measured HD from I-40 and I-25 site were compared with the ME design default values. The comparison is presented in Figure 4.8. It can be seen that the measured HD and ME design default HD distribution are not close to the ME design default values, especially in early morning and late afternoon to evening.

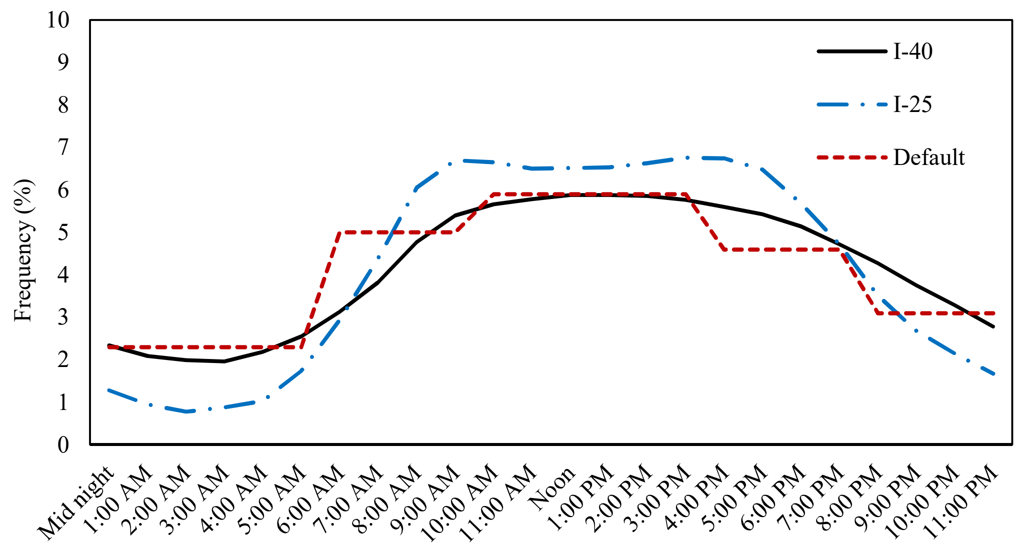
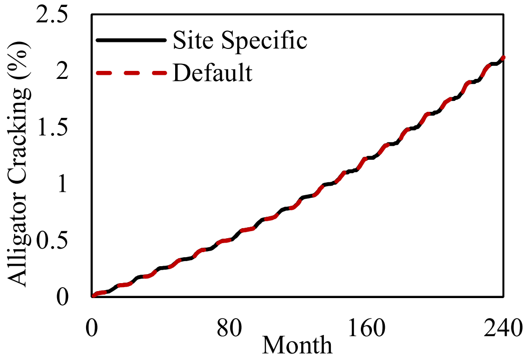
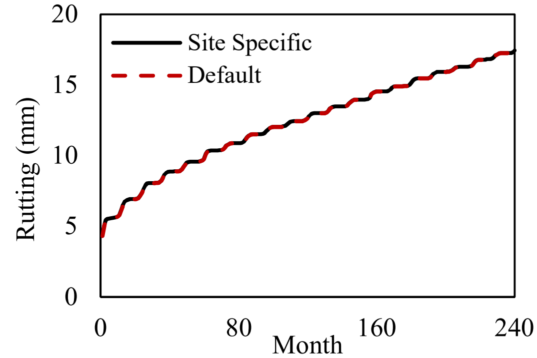


Figure 4.8 Hourly Distribution

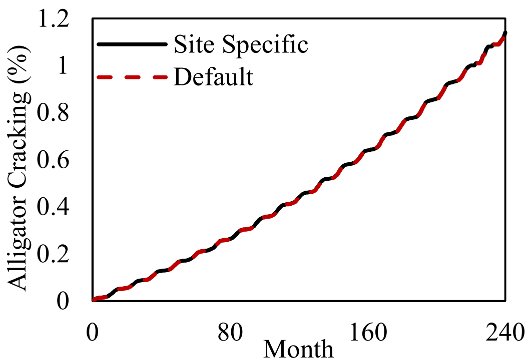
All parameters except the hourly distribution were assigned default values while determining the effect of hourly distribution using the ME design software. Figure 4.9 shows predicted distress values due to the ME default and site specific inputs of hourly distributions in both I-40 and I-25. It shows that hourly distribution has no influence on both predicted alligator cracking and rutting.



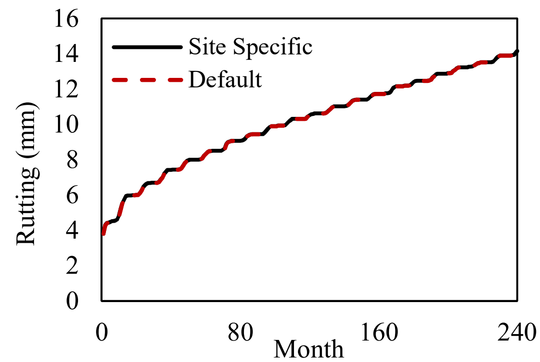
(a) Alligator cracking on I-40



(b) Rutting on I-40



(c) Alligator cracking on I-25



(d) Rutting on I-25

Figure 4.9 Effect of hourly distribution on pavement performance

Effect of Site Specific Monthly Adjustment Factor

The Truck Monthly Adjustment Factor (MAF) reflects truck travel patterns throughout the year. There are 10 truck types (FHWA vehicle Class 4-13) that result 10 potential different temporal patterns over a 12 month period. Mathematically, the monthly adjustment factor for a given vehicle class and a given month is obtained by dividing the average Monthly Average Daily Truck Traffic (MADTT) for the month by the summation of all the 12 month MADTTs and then, multiplied by 12. There are a total of 120 MAFs [10 vehicle classes × 12 months = 120 individual MAF]. The measured MAF for Class 4 to Class 13 on I-40 and I-25 is shown in Tables 4.1 and 4.2 respectively. The ME design default values are unity for all months and classes. This means the ME design assumes the vehicles are equally distributed in each month. The measured values from I-40 are very different than the ME design default ones. For example, the Class 12 vehicle is 0.38 instead of 1 in the month of January (60% less than the default value).

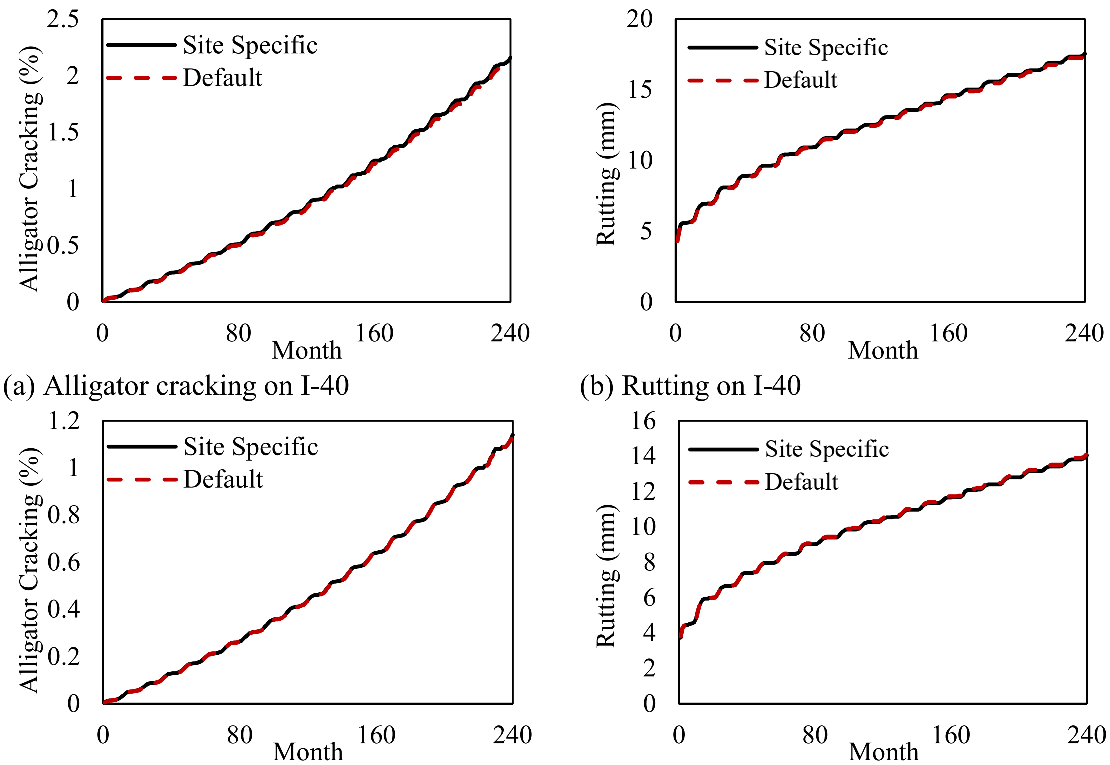
Table 4.1 Monthly Adjustment Factor (MAF) for I-40

MAF	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13
Jan	0.85	0.94	1.00	0.62	0.77	0.98	0.92	0.99	0.38	0.61
Feb	0.84	0.86	0.95	0.76	0.75	0.91	0.89	0.87	0.49	0.72
Mar	1.02	1.00	1.05	1.02	1.03	1.05	1.07	1.05	0.93	1.28
Apr	1.00	0.93	1.02	0.79	1.1	0.99	1.1	1.05	0.96	1.02
May	1.04	1.03	1.02	1.2	1.12	1.02	1.06	1.02	1.13	1.04
Jun	1.1	1.1	0.96	1.38	1.19	0.98	1.01	0.98	1.38	1.29
Jul	1.06	1.14	1.02	1.24	1.1	0.99	1.01	1.02	1.19	1.12
Aug	1.07	1.08	1.02	1.52	1.04	1.03	1.02	1.04	1.63	1.09
Sep	1.11	0.96	1.00	1.44	1.06	1.02	1.01	1.01	1.69	1.15
Oct	1.22	1.00	1.08	1.18	1.26	1.11	1.13	1.16	1.31	1.12
Nov	0.88	0.93	0.98	0.44	0.84	1.01	0.98	0.93	0.48	0.71
Dec	0.81	1.03	0.9	0.41	0.74	0.91	0.8	0.88	0.43	0.85
Total	12	12	12	12	12	12	12	12	12	12

Table 4.2 Monthly Adjustment Factor (MAF) for I-25

MAF	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13
Jan	0.97	0.99	1.06	1.25	0.81	1.09	1.10	1.08	0.67	0.80
Feb	1.00	0.97	1.16	1.25	0.81	1.11	1.09	1.00	0.67	1.10
Mar	1.01	0.99	0.93	1.25	0.93	1.06	1.03	0.97	1.00	1.00
Apr	1.04	0.99	0.96	1.00	0.98	1.03	0.93	1.03	1.00	1.00
May	1.04	1.01	0.90	1.00	1.06	0.96	0.91	0.93	1.33	1.10
Jun	1.01	1.03	0.86	0.75	1.18	0.90	0.90	0.84	0.67	0.80
Jul	0.96	1.05	0.87	0.75	1.18	0.85	0.84	0.98	1.67	1.00
Aug	0.91	1.07	0.88	0.50	1.11	0.84	0.82	0.90	1.33	0.80
Sep	1.09	0.95	1.14	0.75	1.13	1.03	1.11	1.10	1.67	1.20
Oct	1.07	0.93	1.15	0.75	1.14	1.06	1.14	1.11	1.00	1.20
Nov	0.96	0.99	1.12	1.00	0.88	1.07	1.09	1.02	1.00	0.80
Dec	0.94	1.04	0.97	0.75	0.78	1.00	1.07	1.04	0.67	0.90
Total	12	12	12	12	12	12	12	12	12	12

All parameters except the monthly adjustment factor were assigned default values while analyzing the effect of monthly adjustment factor using the ME design software. Figures 4.10(a) and 4.10(b) show that predicted alligator cracking and rutting for site specific monthly adjustment factor for I-40 are almost the same as that for the ME default value. The observation was found for I-25.



(a) Alligator cracking on I-40

(b) Rutting on I-40

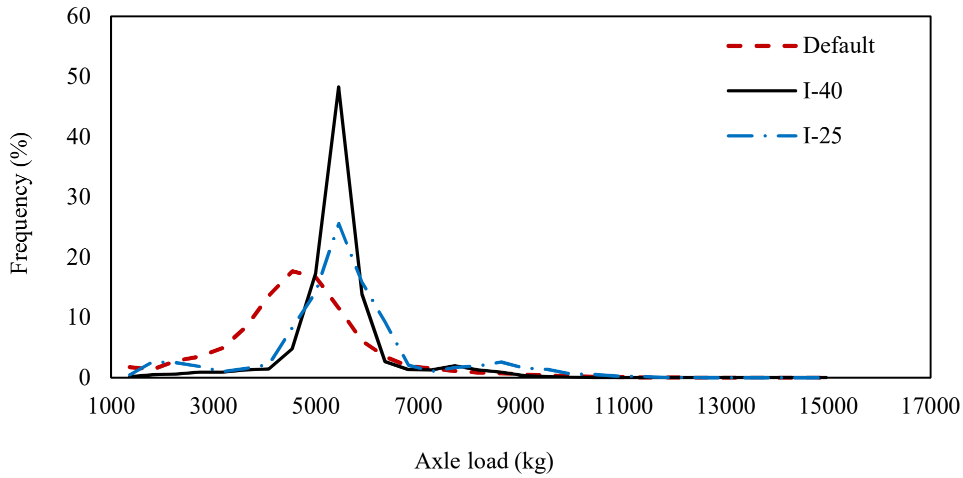
(c) Alligator cracking on I-25

(d) Rutting on I-25

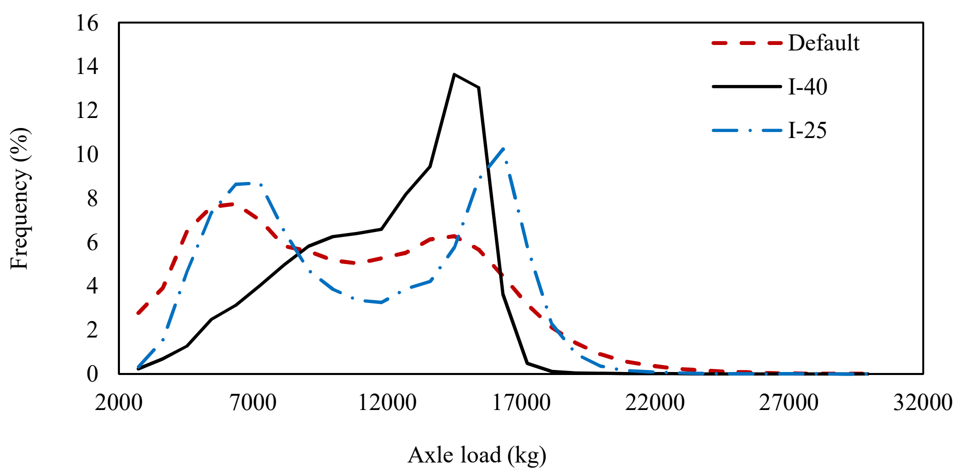
Figure 4.10 Effect of monthly adjustment factor on pavement performance

Effect of Site Specific Axle Load Spectra

Figure 4.11 shows the annual (January to December) average axle load spectra for single, tandem, tridem and quad axles on I-40 and I-25 sites. For both sites, the axle load spectra are significantly different from the ME design software default values. For example, Figure 4.11(a) shows that the ME design software default value has the maximum frequency of 17.7% at axle load of 4500 kg for Class 9 vehicle. However, the measured data from I-40 shows the maximum frequency of 48.2% at axle load of 5500 kg. For I-25, it shows the maximum frequency of 25% at axle load of 5500 kg. For I-40 tandem axle load spectra for Class 9 vehicle, it does not follow the double peak trend as the AASHTOWare software default spectra (Figure 4.11(b)). There are significantly more loaded Class 9 vehicles compared to the ME default value. It is observed that 13% of Class 9 vehicles have 15,000 kg whereas the AASHTOWare software default value has the maximum frequency of 6% at axle load of 14,500 kg for Class 9 vehicles. However, for I-25 Class 9 vehicles, load spectra has two peaks, but the corresponding values are different from ME design default.



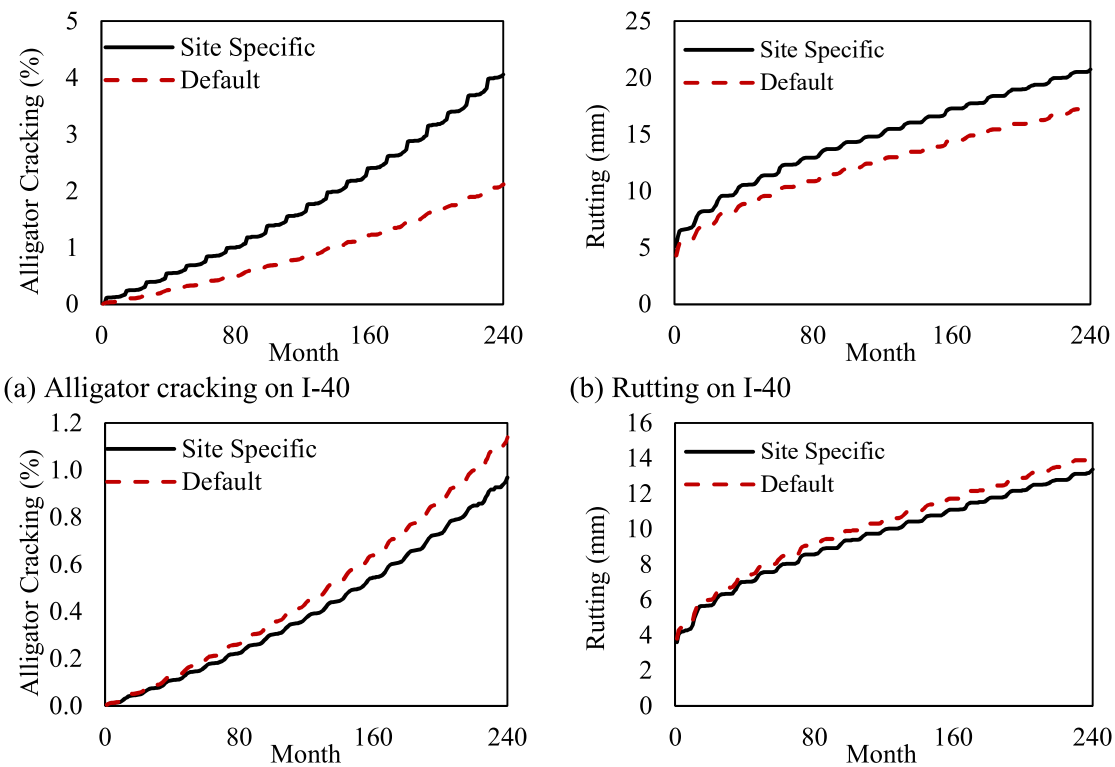
a) Single axle (Class 9)



b) Tandem axle (Class 9)

Figure 4.11 Axle Load Spectra for Class 9 Vehicles

All parameters except the axle load spectra were assigned default values while determining the performance using the ME design software. Figure 4.12 shows predicted alligator cracking and rutting values due to the site specific and ME default load spectra. Figure 4.12(a) shows that alligator cracking is 90% higher after 20 years by the site specific load spectra compared to that by the ME default load spectra. Similarly, rutting due to the site specific axle load spectra for I-40 is 32.5% higher than that by the ME default spectra as shown Figure 4.12(b). I-25 alligator cracking is found to be 15% lower than that by the ME default spectra as shown in Figure 4.12(c). Similarly, rutting is 5.5% lower as shown in Figure 4.12(d).



(a) Alligator cracking on I-40 (b) Rutting on I-40

(c) Alligator cracking on I-25 (d) Rutting on I-25

Figure 4.12 Effect of axle load spectra on pavement performance

Effect of Site Specific Axle per Truck

The number of axles per vehicle class for a given axle configuration is an annual average number of axles per vehicle category (per vehicle class and vehicle axle configuration). Tables 4.3 and 4.4 list the measured number of axle per truck on I-40 and I-25 respectively.

Table 4.3 Axle per truck on I-40

Vehicle Class	Single	Tandem	Tridem	Quad
Class 4	1.70 (1.62)	0.3 (0.39)	0 (0)	0 (0)
Class 5	2.00 (2.00)	0 (0)	0 (0)	0 (0)
Class 6	1.00 (1.02)	1.00 (0.99)	0 (0)	0 (0)
Class 7	0.48 (1.00)	1.04 (0.26)	0.48 (0.83)	0 (0)
Class 8	2.12 (2.38)	0.88 (0.67)	0 (0)	0 (0)
Class 9	1.16 (1.13)	1.92 (1.93)	0 (0)	0 (0)
Class 10	1.03 (1.19)	1.04 (1.09)	0.96 (0.89)	0 (0)
Class 11	3.00 (4.29)	0.88 (0.26)	0.08 (0.06)	0 (0)
Class 12	1.72 (3.52)	1.91 (1.14)	0.15 (0.06)	0 (0)
Class 13	1.25 (2.15)	1.69 (2.13)	0.08 (0.35)	0.06 (0)

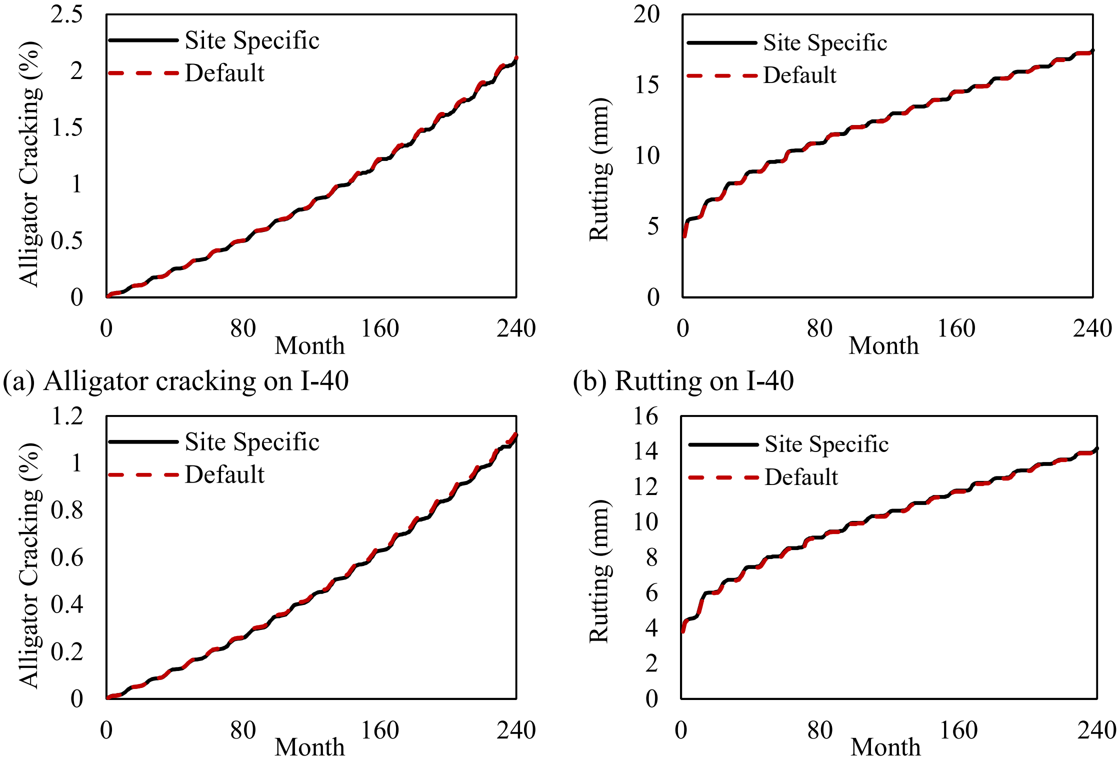
* Values shown in parenthesis represent the default value.

Table 4.4 Axle per truck on I-25

Vehicle Class	Single	Tandem	Tridem	Quad
Class 4	1.72(1.62)	0.28 (0.39)	0 (0)	0 (0)
Class 5	2.00 (2.00)	0 (0)	0 (0)	0 (0)
Class 6	1.00 (1.02)	1.00 (0.99)	0 (0)	0 (0)
Class 7	0..54 (1.00)	0.93 (0.26)	0.54 (0.83)	0 (0)
Class 8	2.14 (2.38)	0.86 (0.67)	0 (0)	0 (0)
Class 9	1.34 (1.13)	1.82 (1.93)	0 (0)	0 (0)
Class 10	1.01 (1.19)	1.01 (1.09)	0.99 (0.89)	0 (0)
Class 11	3.83 (4.29)	0.54 (0.26)	0.03 (0.06)	0 (0)
Class 12	2.35 (3.52)	1.81 (1.14)	0.01 (0.06)	0 (0)
Class 13	1.15 (2.15)	1.00 (2.13)	1.20 (0.35)	0.13 (0)

* Values shown in parenthesis represent the default value.

All parameters except the axle per vehicle were assigned default values while analyzing the effect of operational speed using the ME design software. Figure 4.13 shows the predicted alligator cracking and rutting values due to the site specific inputs of axle per vehicle and ME default value. Figure 4.13(a) shows predicted alligator cracking due to the site specific axle per vehicle for I-40 and the ME default values are almost the same. Similarly, predicted rutting using the site specific and ME default values are almost the same as shown in Figure 4.13(b). Similar observation was also found for I-25 as shown in Figures 4.13(c) and 4.13(d).



(a) Alligator cracking on I-40

(b) Rutting on I-40

(c) Alligator cracking on I-25

(d) Rutting on I-25

Figure 4.13 Effect of axle per vehicle on pavement performance

Effect of Site Specific Axle Configurations

Several types of input are required to specify the axle configuration such as axle spacing, axle width, mean wheel location, traffic wander and lane width. Axle spacing is the distance between two consecutive tandem, tridem, and quad axles. Figure 4.14 shows the average measured spacing for different wheel configurations from WIM data found for I-40 and I-25. The other ME design Pavement M-E Design software default values (average axle width, dual tire spacing, and tire pressure) are very close to the measured value on I-40. Therefore, the default values can be used reasonably.

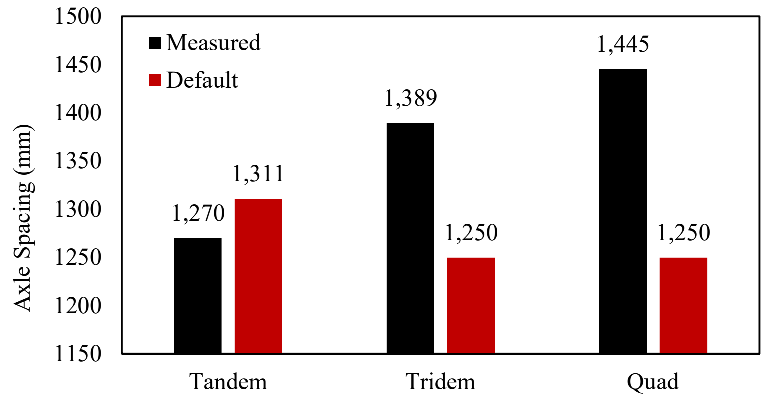
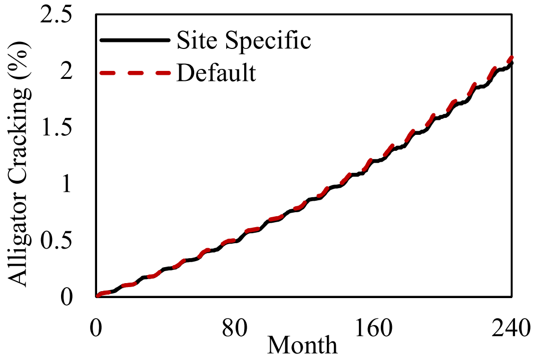
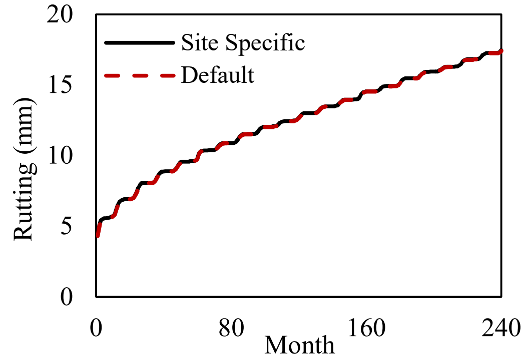


Figure 4.14 Average axle spacing

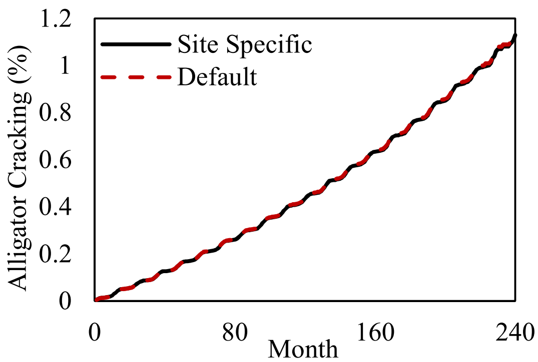
All parameters except the axle spacing were assigned default values while analyzing the performance using the ME design software. The site specific axle spacing predicts lower alligator cracking by 2.5% in I-40 and 1% in I-25 than that by the ME default value as shown in Figures 4.15(a) and 4.15(c). Axle spacing has an insignificant effect on predicted rutting shown in Figures 4.15(b) and 4.15(d).



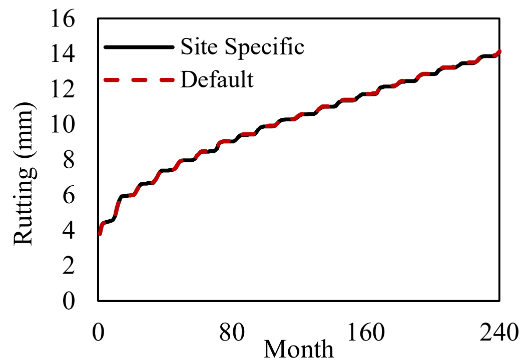
(a) Alligator cracking on I-40



(b) Rutting on I-40



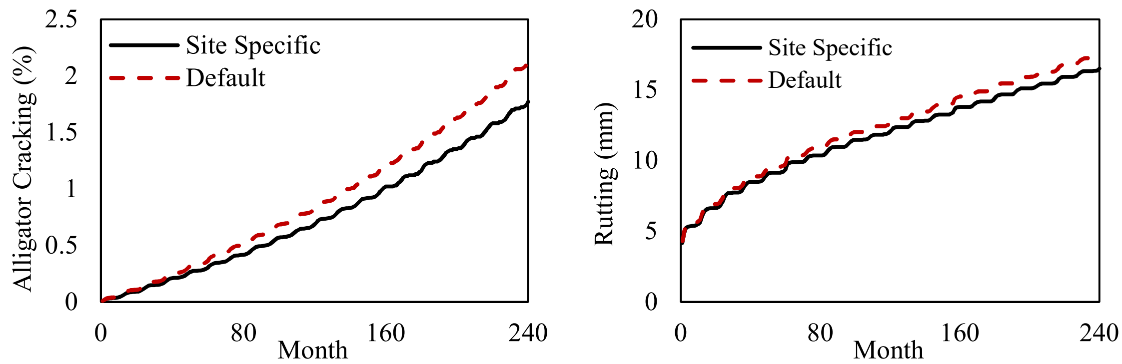
(c) Alligator cracking on I-25



(d) Rutting on I-25

Figure 4.15 Effect of axle spacing on pavement performance

The mean wheel location is the distance of the centerline of the wheel from the outer edge of the lane. Using axle strip sensing, it is measured to be 673 mm (26.5 in) with a standard deviation of 323 mm (12.7 in) for I-40 which are not close to the ME Design default values (300 mm and 250 mm respectively). However, the mean wheel location does not affect the structural response or performance of flexible pavement. However, the lateral wheel distribution may affect it. Parametric study was also conducted to determine the effect of lateral distribution using the ME design software. The predicted alligator cracking after 20 years is 16.5% lower due to site specific lateral wander (323 mm) compared to that by the ME default value (250 mm.) as shown in Figure 4.16(a) on I-40. Figure 4.16(b) shows that predicted rutting after 20 years is 5% lower due to the site specific input compared to that by the ME default value for I-40.

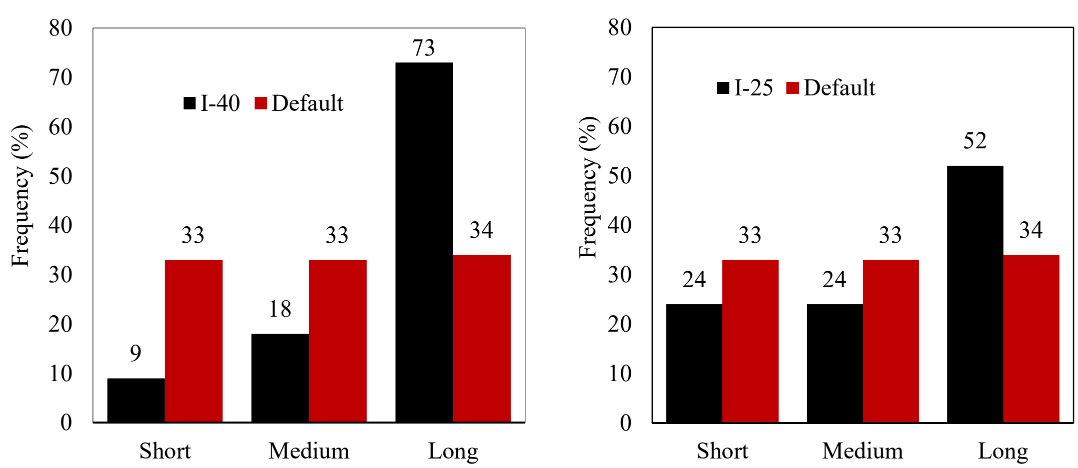


(a) Alligator cracking on I-40 (b) Rutting on I-40

Figure 4.16 Effect of lateral wander on pavement performance

Effect of Site Specific Wheelbase Distribution

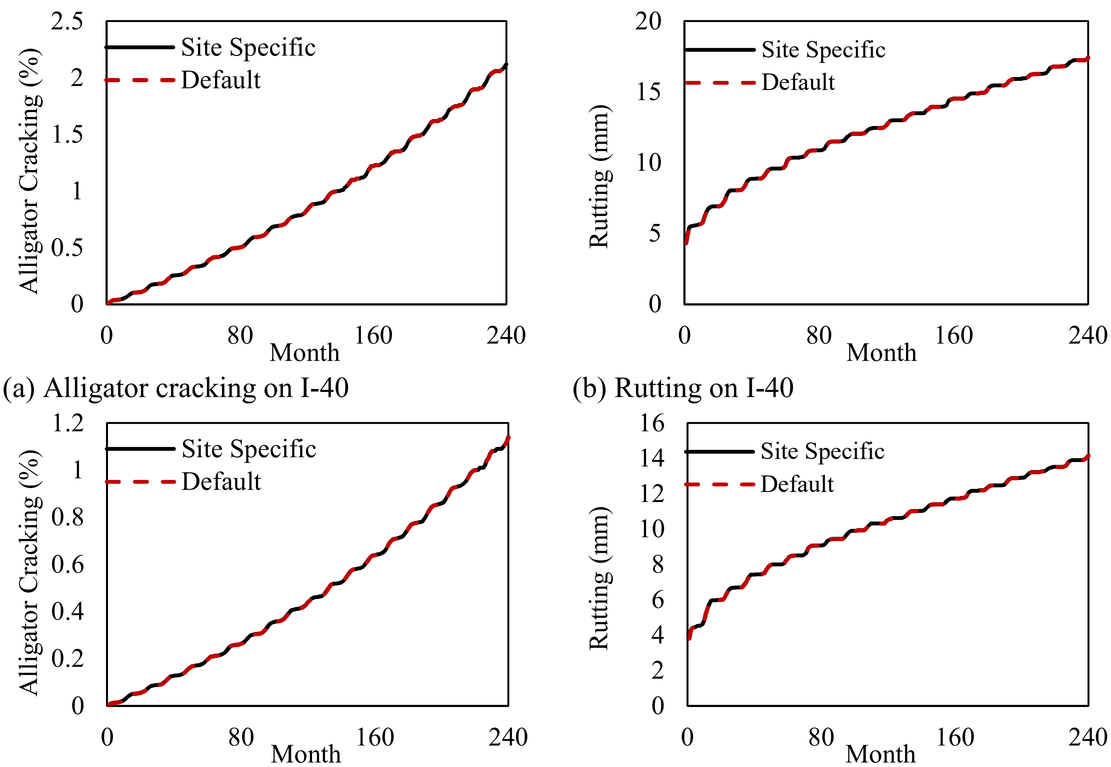
The distance between the steering and the first axle of a tractor or a heavy single unit is used to classify the truck as short, medium or long vehicle. The recommended values are 3.6 m (12 ft), 4.5 m (15 ft) and 4.8 m (18 ft) for short, medium and long axle spacing, respectively. The measured wheelbase configurations on I-40 and I-25 are shown in Figure 4.17(a) and 4.17(b). It shows that the measured values are way different compared to the ME design default values.



a) I-40 b) I-25

Figure 4.17 Wheelbase Distribution

All parameters except the wheelbase distribution were assigned default values while analyzing the alligator cracking and rutting using the ME design software. Figure 4.18 shows the predicted alligator cracking and rutting values due to the ME default and site specific inputs of wheelbase distributions for both I-40 and I-25 sites. It can be seen that predicted alligator and rutting are not dependent on wheelbase distribution.



(a) Alligator cracking on I-40 (b) Rutting on I-40

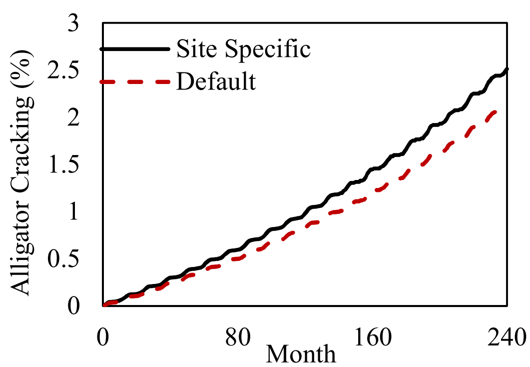
(c) Alligator cracking on I-25 (d) Rutting on I-25

Figure 4.18 Effect of wheelbase distribution on pavement performance

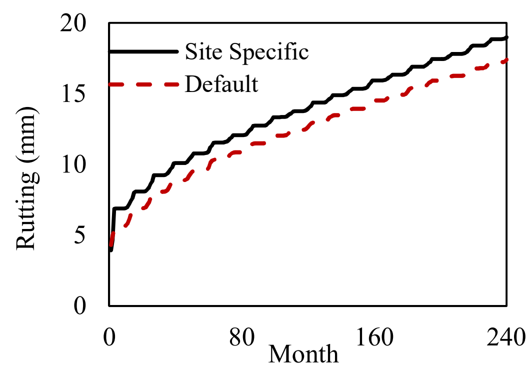
Effect of Overall Site Specific Traffic Input (Level 1 vs. Level 3)

In this case, the site specific traffic input (Level 1) was compared with the ME design software default value (Level 3). Figure 4.19 shows predicted alligator cracking and rutting due to the site specific and ME default traffic inputs for I-40 and I-25. It shows that the predicted alligator cracking after 20 years due to the site specific traffic input for I-40 is

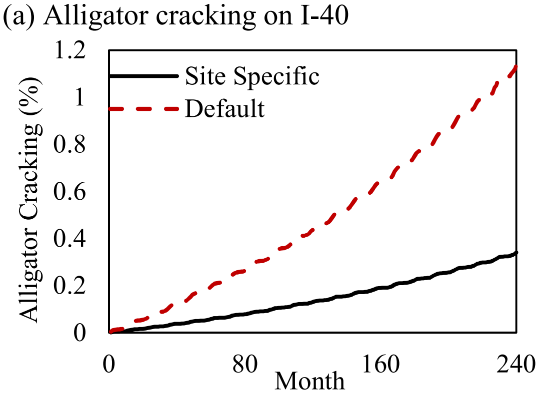
18.5% higher than that by the ME default value as shown in Figure 4.19(a). Similarly, the predicted rutting due to the site specific inputs for I-40 is 9% higher than that by the ME default value as shown in Figure 4.19(b). However, for I-25, the predicted alligator cracking and rutting by the site specific inputs are 70% and 32% lower than that by the ME default value (Figures 4.19(c) and 4.19(d)). This means the distresses vary significantly with the change in traffic input from Level 3 to Level 1.



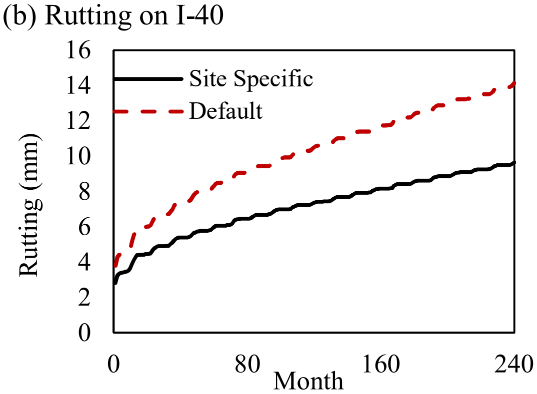
(a) Alligator cracking on I-40



(b) Rutting on I-40



(c) Alligator cracking on I-25)



(d) Rutting on I-25

Figure 4.19 Effect of overall site specific traffic input on pavement performance

4.2.3 Summary of the Results

Table 1 summarized the percentage difference of predicted pavement performance. Here, absolute difference in predicted pavement performance using site-specific from predicted pavement performance using the ME default value was used. Then, maximum percentage difference was chosen between alligator cracking and rutting. Finally, effects of different site-specific inputs are categorized based on maximum percentage difference of predicted pavement performance into following four groups:

i. Great: maximum percentage difference is greater than 20%.

ii. Moderate: maximum percentage difference within 5% to 20%.

iii. Little: maximum percentage difference within 1% to 5%.

iv. No effect: maximum percentage difference is 0.

Table 4.5 Effect levels of different site-specific input type

Site-specific input type	I-40 % of difference		I-25 % of difference		Maximum % difference	Effect level
	Alligator Cracking	Rutting	Alligator Cracking	Rutting		
Axle load spectra	58	19	15	5.5	58	Great
Vehicle class distribution	4.25	1.3	16.67	7.18	16.67	Moderate
Directional distribution	7.08	2.48	0.88	0.36	7.08	Moderate
Lane distribution	10.85	3.94	55.09	22.26	55.09	Great
Hourly distribution	1.89	0.73	0	0.72	1.89	Little
Monthly adjustment factor	0	0	0	0	0	No effect
Operational speed	3.3	2.77	4.39	2.87	4.39	Little
Axle per vehicle	0.47	0.15	1.75	0.18	1.75	Little
Wander distribution	16.51	5.25	-	-	16.51	Moderate
Axle spacing	2.5	0.15	0.88	0.36	2.5	Little
Wheelbase distribution	0	0	0	0	0	No effect

Results show that axle load spectra, and lane distribution have the highest impact on predicted pavement performances. Whereas, vehicle class distribution, directional distribution, and lateral wander distribution have moderate impact. Result also revealed that monthly adjustment factor, axles per vehicle, axle spacing, and operational speed affect the predicted alligator cracking and rutting very slightly. Hourly distribution and wheelbase distribution have no effect.

4.3 Effects of Input Levels on Pavement Distresses

From above discussion, it is found that both measured VCDs and ALSs (Level 1) vary significantly from site to site. The generated regional VCDs and ALSs (Level 2) differ from the ME default values (Level 3). Therefore, it is important to evaluate and compare the predicted distresses using these three input levels.

4.3.1 Design Inputs

For the comparative study, a trial pavement section with 200 mm (8 in) Asphalt Concrete (AC), 250 mm (10 in) crushed stone base course underlain by natural subgrade was considered for all sites. Design lane width was considered as 3.6 m (12 ft). Performance Grade (PG) 76-22 was used in this study. Base course modulus was chosen as 280 MPa (40000 psi) for crushed stone. Subgrade was chosen as A-3 ME software default subgrade with resilient modulus 170 MPa (24500 psi). Climate data were generated for both sites using the site specific longitude, latitude and ground water table data. A traffic growth factor of 4% with compound rate was used for all analysis. The analysis period was 20 years for all cases. For analysis, respective measured Annual Average Daily Truck Traffic (AADTT) for each site were used. Two major performances namely alligator cracking and rutting were considered to analyze the effects of the parameters.

4.3.2 Effects of VCDs

To evaluate the effect of VCD on pavement performance, Site-9 was analyzed using the cluster generated VCDs. Site-9 was chosen arbitrarily. The predicted alligator cracking and rutting on Site-9 for three cluster generated VCDs are shown in Figures 4.20(a) and 4.20(b). It is observed that both alligator cracking and rutting for Cluster 2 are highest among three clusters, because Cluster 2 has more single trailers (Class 9) than other two clusters, whereas Cluster 3 has the least Class 9 vehicles. For this reason, this cluster VCD provides the least distresses value. Therefore, it can be concluded that the predicted performances vary a lot for different VCDs.

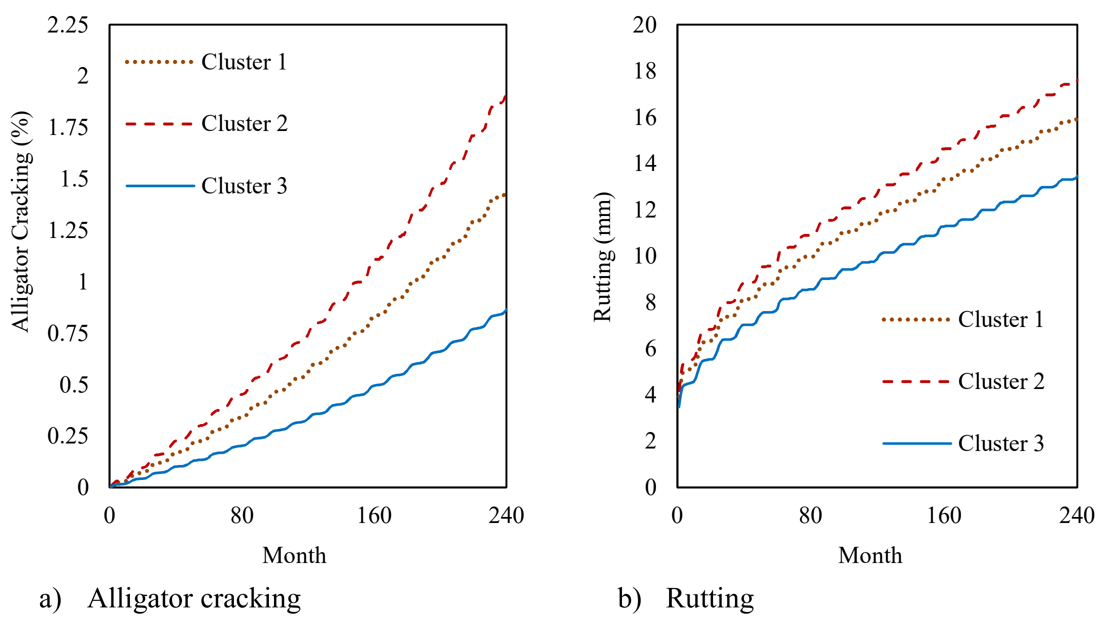
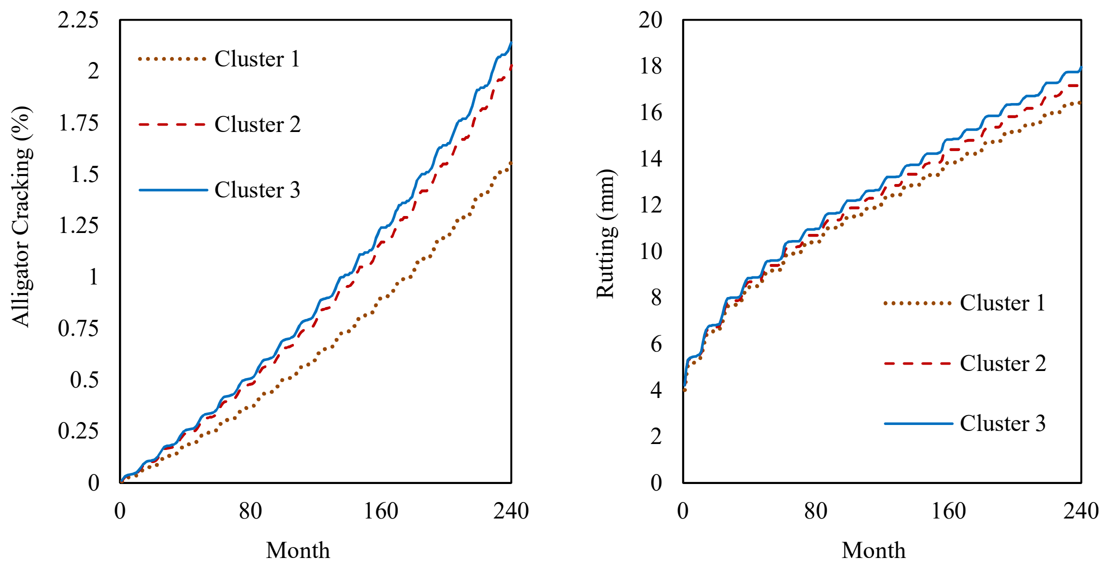


Figure 4.20 Predicted distresses for different VCDs on Site-9

4.3.3 Effects of ALSs

To evaluate the effect of ALS on pavement performance, Site-9 (chosen arbitrarily) was analyzed using cluster generated and ME default ALSs. The predicted alligator cracking and rutting on Site-9 for four different ALSs are shown in Figures 4.21(a) and 4.21(b). It is observed that both alligator cracking and rutting for Cluster 3 are the highest among four ALSs, because Cluster 3 has more loaded (heavy) Class 9 vehicles than other two clusters, whereas, Cluster 1 has more unloaded (light) Class 9. For this reason for this cluster ALS provides lower distresses value. It is also observed that predicted distresses by the ME default ALS is close to that for the Cluster 2. Therefore, it can be concluded that the pavement performances especially alligator cracking vary for different ALSs.

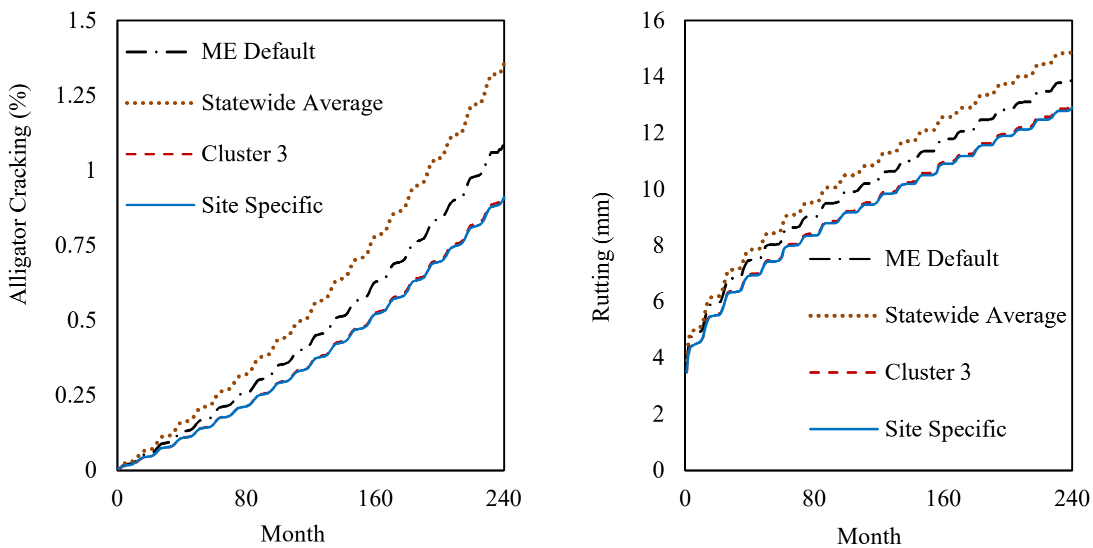


a) Alligator cracking b) Rutting

Figure 4.21 Predicted distresses for different ALSs on Site-9

4.3.4 Effects of Input Levels of VCD

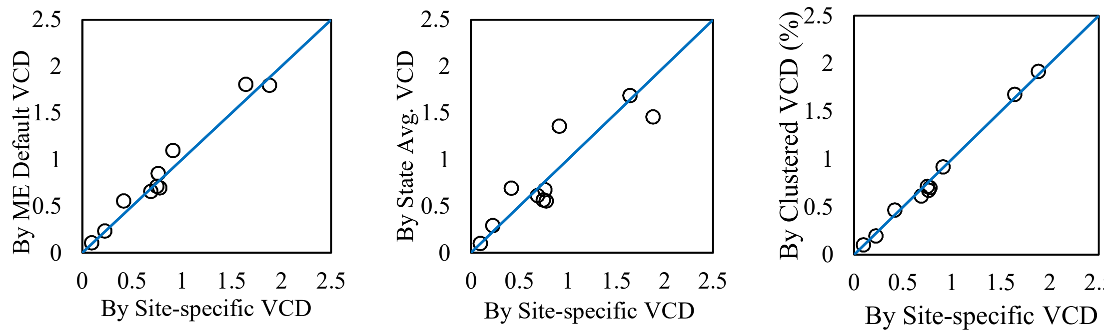
To evaluate the effect of input levels of VCD, all ten sites were analyzed using site-specific VCD, respective cluster generated VCD, the statewide average VCD and the ME default values. The predicted alligator cracking and rutting on Site-10 stations (chosen arbitrarily) by different VCDs are shown in Figure 4.22. Figure 4.22(a) shows that the predicted alligator cracking over the service life for different VCD inputs on Site-10 sections. It can be seen that the predicted alligator cracking using the cluster generated VCD matches well with that by the site-specific value. The ME default value produces more alligator cracking than that by the site-specific value. The statewide average VCD causes the most alligator cracking considering all options. Similar observation was made for the rutting as shown in Figure 4.22(b).



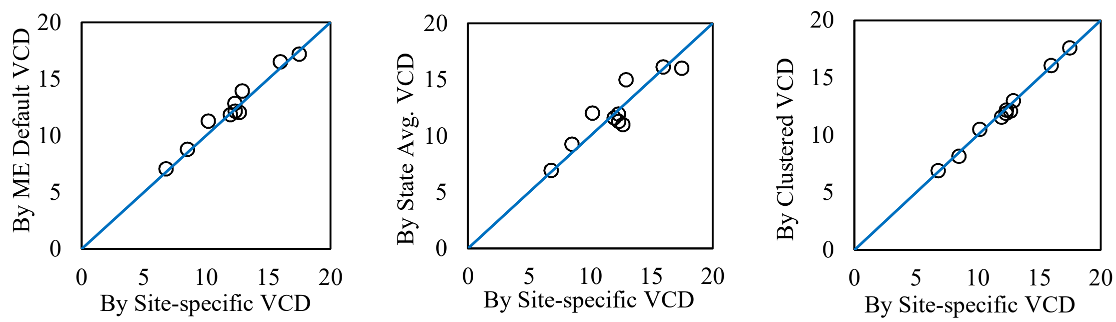
a) Alligator cracking   b) Rutting

Figure 4.22 Predicted distresses for different input levels of VCD on Site-10

Figure 4.23 shows the comparisons of the predicted distresses using the site-specific (Level 1), the statewide average (Level 2), the cluster generated (Level 2), and the ME default (Level 3) VCDs. Figure 4.23(a) compares the predicted alligator cracking using different VCD input levels with that by the site-specific VCD input. The Root Mean Square of Errors (RMSEs) of the predicted alligator cracking with regard to that by the site-specific VCD are also presented. It shows that the ME default, the statewide average, and the cluster generated VCDs produce RMSEs of 0.104%, 0.236% and 0.05% compared to that by the site-specific VCD. It implies that, the cluster generated VCD predicted alligator cracking is closer to that by site-specific value. The statewide average VCD provides the highest amount of error among three inputs. Similar observation was found for rutting as shown in Figure 4.23(b). It shows that the ME default, the statewide average, and the cluster generated VCDs produce RMSEs of 1.56 mm, 1.23 mm, and 0.60 mm compared to that by the site-specific VCD. This means the cluster generated VCD predicted rutting is closer to that by site-specific value. In addition, the statewide average VCD gives the highest amount of error among three inputs.



a) Alligator Cracking (%)

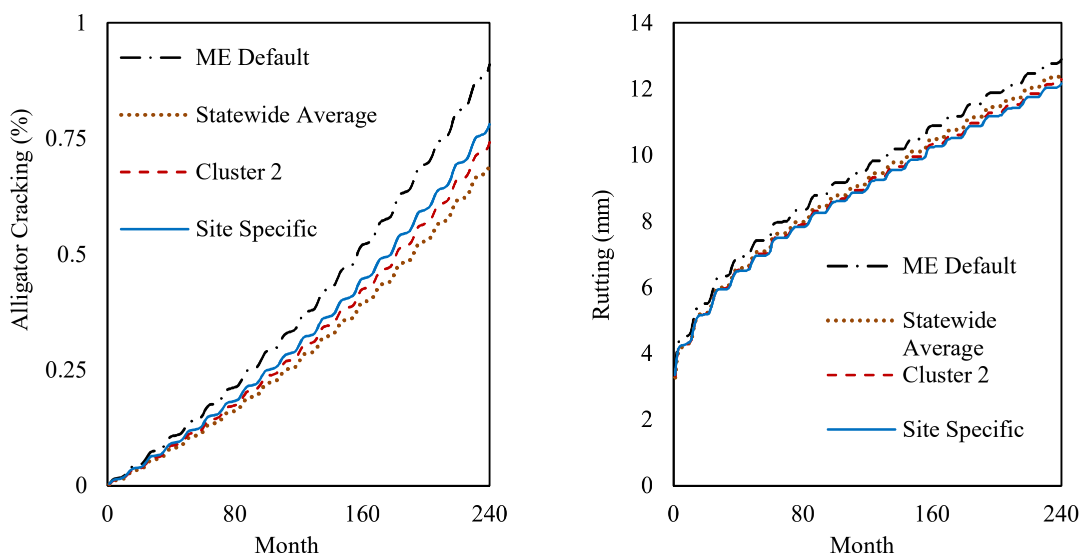


b) Rutting (mm)

Figure 4.23 Comparison of different levels of VCDs on pavement performances

4.3.5 Effects of Input Levels of ALS

To evaluate the effect of input levels of ALS, all ten sites were analyzed using the site-specific ALS, respective cluster generated ALS, the statewide average ALS and the ME default ALS. The predicted alligator cracking and rutting on Site-10 stations (chosen arbitrarily) by different ALSs are shown in Figure 4.24. Figure 4.24(a) shows that the predicted alligator cracking over time for different ALS inputs on Site-10 sections. It is found that the predicted alligator cracking using the cluster generated ALS is close to that by the site-specific value. The ME default ALS value predicts more alligator cracking than that by the site-specific value. The statewide average predicted the least alligator cracking. Similar observation was found for the rutting as shown in Figure 4.24(b).



a) Alligator cracking b) Rutting

Figure 4.24 Predicted distresses for different input levels of ALS on Site-10

Figure 4.25 shows the comparisons of the predicted distresses using the site-specific (Level 1), the statewide average (Level 2), the cluster generated (Level 2), and the ME default (Level 3) ALSs. Figure 4.25(a) compares the predicted alligator cracking using different ALS input levels with that by the site-specific ALS input. The RMSEs of the predicted alligator cracking with regard to that by the site-specific ALS are also presented. It shows that the ME default, the statewide average, and the cluster generated ALSs produces RMSEs of 0.336%, 0.176% and 0.09% compared to that by the site-specific ALS. It indicates that, the cluster generated ALS predicted alligator cracking is closer to that for site-specific value. The ME default ALS provides the highest amount of error among three inputs. Similar observation was found for rutting as shown in Figure 4.25(b). It shows that the ME default, the statewide average, and the cluster generated ALSs produces RMSEs of 0.60 mm, 1.21 mm, and 0.29 mm compared to that by the site-specific ALS. This means the cluster generated ALS predicted rutting is closer to that for site-specific value. Moreover, ME default ALS gives the highest amount of error among three inputs.

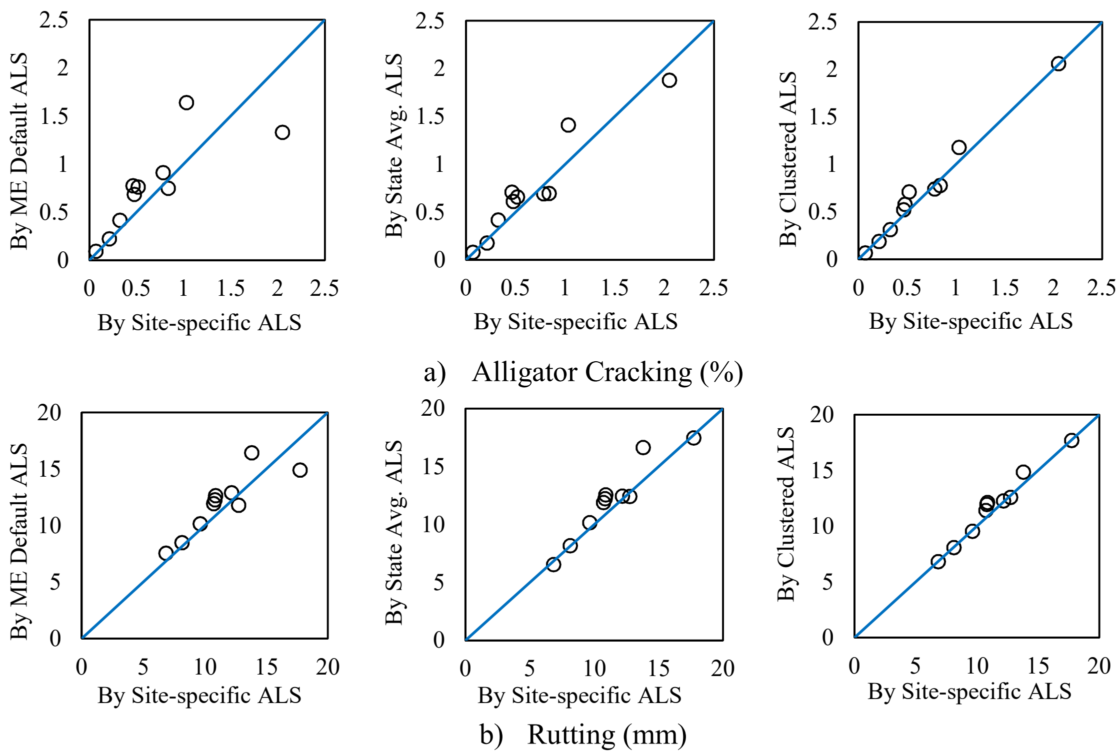


Figure 4.25 Comparison of different input levels of ALS on pavement performances

4.3.6 Summary of the Results

This study investigates the effects of different input levels of VCDs and ALSs on predicted pavement performances using the ME design software. A total ten sites are used to develop the site specific (Level 1) data. Then both arithmetic average and cluster methodologies are used to generate regional data (Level 2). Then a parametric study is conducted using the ME software to determine the effects of different input levels of VCD and ALS on the alligator cracking and rutting. Based on the results, the following conclusions can be made:

- The predicted pavement performances based on the cluster generated VCD and ALS match well with those based on the site specific data.
- The ME default VCD provides better results than the statewide average. On the other hand, statewide average ALS predicts pavement performances better than the ME default ALS.

4.4 Decision for Selecting Appropriate Cluster Combination

The predicted performance is dependent on both VCD and ALS inputs. The VCD can be generated easily by 48-h class counts even there is no WIM station. However, it is difficult to choose the appropriate ALS inputs without a WIM station. Therefore, it is greatly needed to develop a relation generated cluster VCDs with clustered ALSs so that it appropriate ALS input can be determine based on the counted VCD.

4.4.1 Interaction between Clustered VCDs and Clustered ALSs

Figure 4.26 shows the interaction between VCD and ALS clusters. The interaction diagram shows that there is a relationship between VCD and ALS clusters though there are some anomalies. Most of the sites in a VCD group also present in same ALS group. For example, two out of three sites (Site 4 and Site 7) of the VCD Cluster 1 present in the ALS Cluster 1. However, Site 1 presents in the ALS Cluster 2. Similarly, two out of four sites (Site 3 and Site 9) of the VCD Cluster 2 present in the ALS-Cluster 3. On the other hand, Site 6 presents in the ALS Cluster 1 whereas Site 8 presents in the ALS Cluster 2. The sites of the VCD Cluster 3 shows better interaction with the ALS clusters. All of the sites of the VCD Cluster 3 (Site 2, Site 5 and Site 10) present in the ALS Cluster 2.

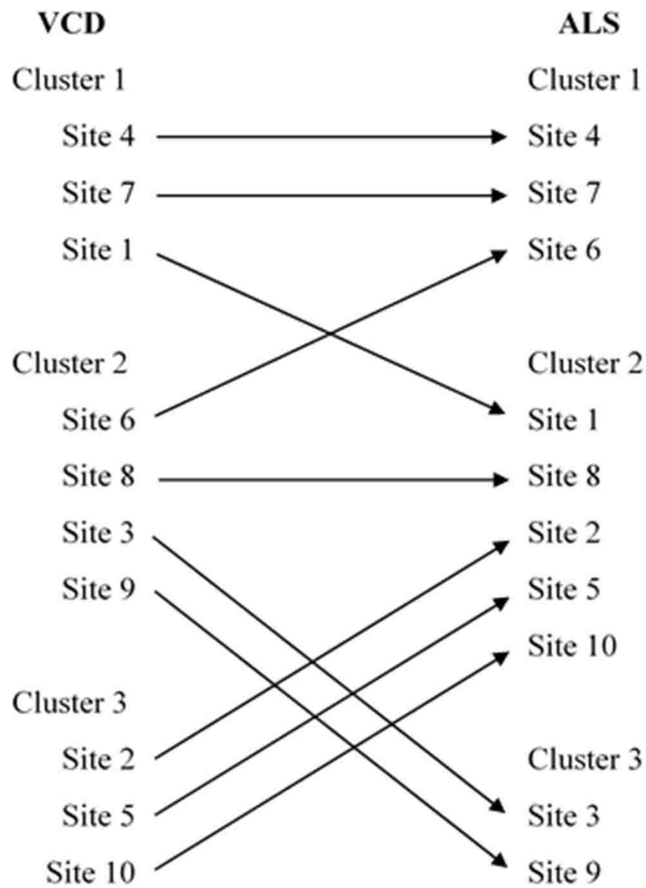


Figure 4.26 Interaction between VCD cluster and ALS cluster

Based on this interaction diagram, proposed guideline to select appropriate ALS cluster is presented in Table 4.6. To use this guideline, a 48-h traffic count will be needed to generate the site specific VCD. Then, VCD cluster group can be identify by correlating the site specific VCD. Finally, ALS cluster group can be selected using Table 4.6.

Table 4.6 Proposed guideline for selecting appropriate ALS cluster

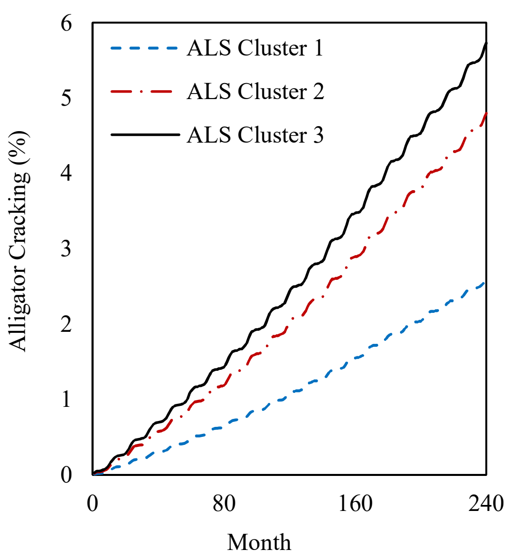
VCD Cluster	Description	Proposed ALS Cluster	Description
Cluster 1	Mix traffic of Class 5 & Class 9	Cluster 1	Lower percent of heavier tandem axles
Cluster 2	Predominately Class 9	Cluster 3	Higher percent of heavier tandem axles
Cluster 3	Predominately Class 5	Cluster 2	Mix with light and heavy tandem axle

4.4.2 Effects of Different Clustered VCD and ALS Combinations

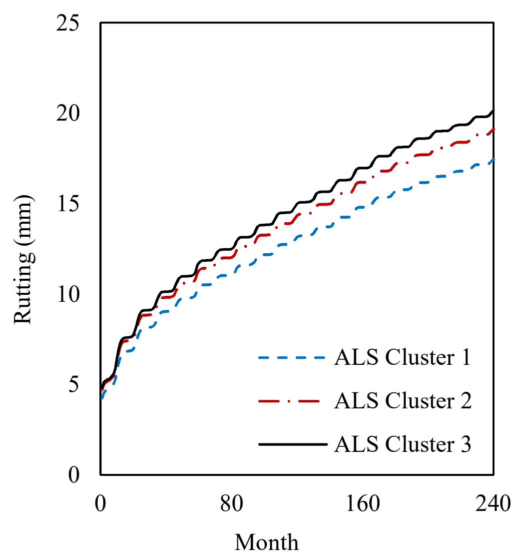
To evaluate the possible errors due to choosing wrong combination of VCD and ALS clusters, a comparative study was performance. A trial pavement section with 200 mm (8 in) Asphalt Concrete (AC), 100 mm (4 in) sandwich granular layer, 160 mm (6 in) crushed stone base course underlain by natural subgrade was considered for all sites. Design lane width was considered as 3.6 m (12 ft). Performance Grade (PG) 76-22 was used in this study. Base course modulus was chosen as 280 MPa (40000 psi). Subgrade was chosen as A-1-a ME software default subgrade with resilient modulus 125 MPa (18000 psi). A traffic growth factor of 3% with compound rate was used for all analysis. The analysis period was 20 years for all cases. For analysis, Annual Average Daily Truck Traffic (AADTT) was chosen as 8000. Two major performances namely alligator cracking and rutting were considered to analyze the effects of the parameters.

Figure 4.27 shows the effects of different clustered ALSs on VCD Cluster 1 in predicting pavement performance. Figures 4.27(a) and 4.27(b) compares predicted alligator cracking and rutting for different clustered ALSs on the VCD Cluster 1 respectively. The ALS

Cluster 1 has the higher percentage of light weight vehicles, therefore, the ALS Cluster 1 produce least alligator cracking and rutting compare to other two ALSs. On the other hand, the ALS Cluster 3 has higher percentage of heavier vehicles therefore it give highest alligator cracking and rutting. Compare to the ALS Cluster 1, the ALS Cluster 3 predicts 88.4% more alligator cracking and 15.4% more rutting. The ALS Cluster 2 has mix traffic with light and heavy weight vehicles therefore, it provides more distresses than the ALS Cluster 1 and less distresses than the ALS Cluster 3. Compare to the ALS Cluster 1, the ALS Cluster 2 predicts 67% more alligator cracking and 9.6% more rutting.



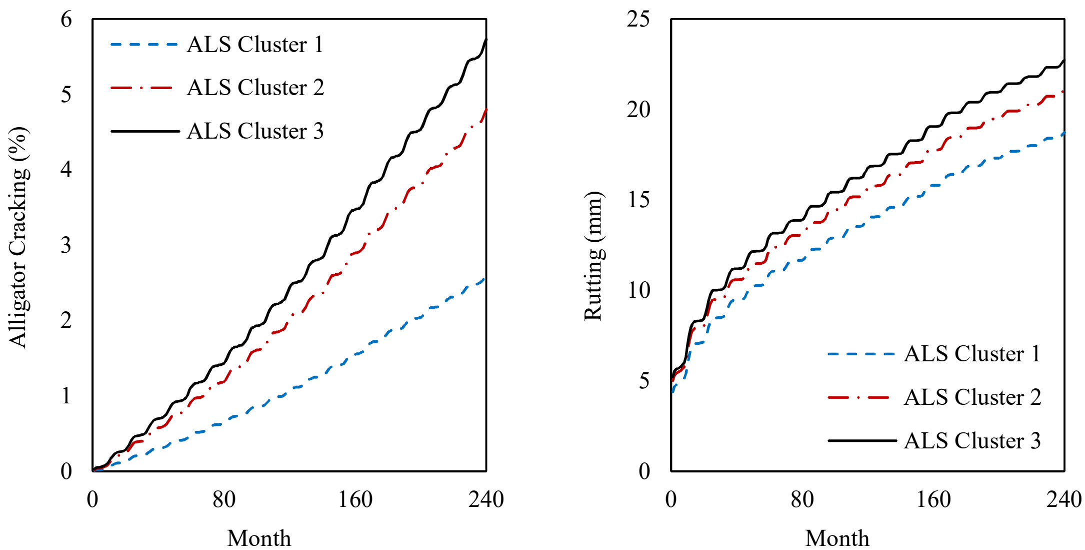
a) Alligator cracking



b) Rutting

Figure 4.27 Predicted distresses for different clustered of ALSs on VCD Cluster 1

Figure 4.28 shows the effects of different clustered ALSs on VCD Cluster 2 in predicting pavement performance. Figures 4.28(a) and 4.28(b) compares predicted alligator cracking and rutting for different clustered ALSs on the VCD Cluster 2 respectively. The ALS Cluster 1 has the higher percentage of light weight vehicles, therefore, the ALS Cluster 1 produce least alligator cracking and rutting compare to other two ALSs. On the other hand, the ALS Cluster 3 has higher percentage of heavier vehicles therefore it give highest alligator cracking and rutting. Compare to the ALS Cluster 1, the ALS Cluster 3 predicts 120.4% more alligator cracking and 21.3% more rutting. The ALS Cluster 2 has mix traffic with light and heavy weight vehicles therefore, it provides more distresses than the ALS Cluster 1 and less distresses than the ALS Cluster 3. Compare to the ALS Cluster 1, the ALS Cluster 2 predicts 84.6% more alligator cracking and 12.7% more rutting.

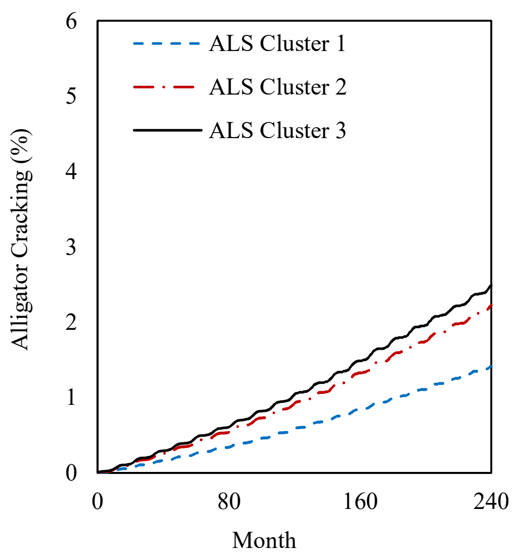


a) Alligator cracking b) Rutting

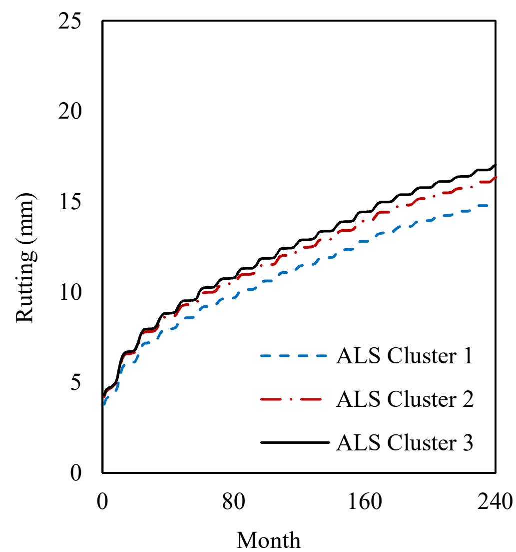
Figure 4.28 Predicted distresses for different clustered of ALSs on VCD Cluster 2

Figure 4.29 shows the effects of different clustered ALSs on VCD Cluster 3 in predicting pavement performance. Figures 4.24(a) and 4.24(b) compares predicted alligator cracking and rutting for different clustered ALSs on the VCD Cluster 3 respectively. The ALS Cluster 1 has the higher percentage of light weight vehicles, therefore, the ALS Cluster 1 produce least alligator cracking and rutting compare to other two ALSs. On the other hand, the ALS Cluster 3 has higher percentage of heavier vehicles therefore it give highest alligator cracking and rutting. Compare to the ALS Cluster 1, the ALS Cluster 3 predicts

75.4% more alligator cracking and 13.4% more rutting. The ALS Cluster 2 has mix traffic with light and heavy weight vehicles therefore, it provides more distresses than the ALS Cluster 1 and less distresses than the ALS Cluster 3. Compare to the ALS Cluster 1, the ALS Cluster 2 predicts 57% more alligator cracking and 8.8% more rutting.



a) Alligator cracking



b) Rutting

Figure 4.29 Predicted distresses for different clustered of ALSs on VCD Cluster 3

Figure 4.30 shows the effects of different clustered VCDs on ALS Cluster 1 in predicting pavement performance. Figures 4.30(a) and 4.30(b) compares predicted alligator cracking and rutting for different clustered VCDs on the ALS Cluster 1 respectively. The VCD Cluster 3 has lower percentage of Class 9 vehicles, therefore, the VCD Cluster 1 produce least alligator cracking and rutting compare to other two VCDs. On the other hand, the VCD Cluster 2 has higher percentage of Class 9 vehicles therefore it give highest alligator cracking and rutting. Compare to the VCD Cluster 3, the ALS Cluster 2 predicts 83.1% more alligator cracking and 24.7% more rutting. The VCD Cluster 1 has mix traffic of Class 5 and Class 9 vehicles therefore, it provides more distresses than the VCD Cluster 3 and less distresses than the VCD Cluster 2. Compare to the VCD Cluster 3, the VCD Cluster 1 predicts 16.1% more alligator cracking and 51.4% more rutting.

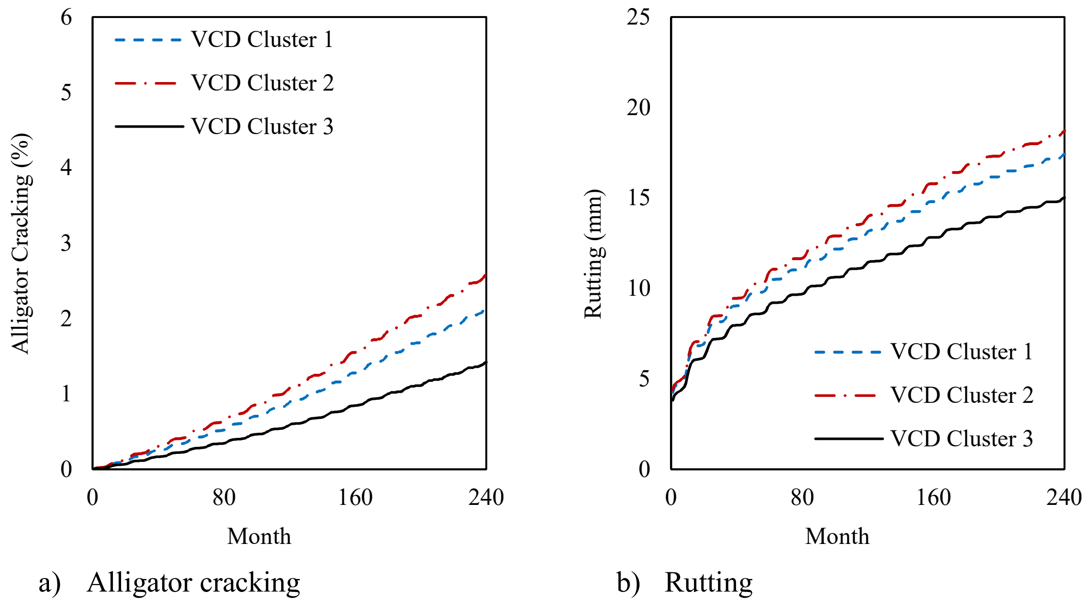
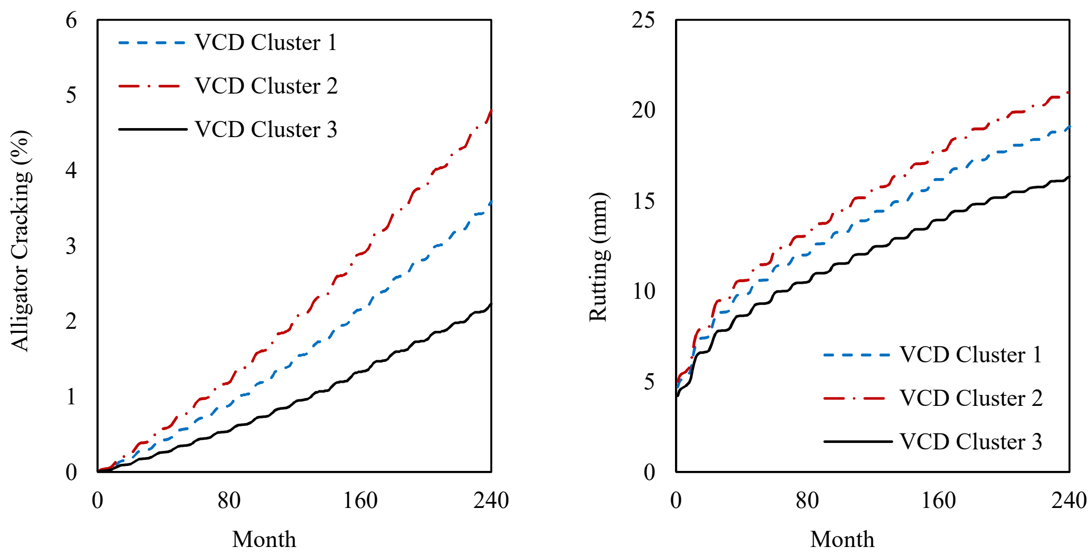


Figure 4.30 Predicted distresses for different clustered of VCDs on ALS Cluster 1

Figure 4.31 shows the effects of different clustered VCDs on ALS Cluster 2 in predicting pavement performance. Figures 4.31(a) and 4.31(b) compares predicted alligator cracking and rutting for different clustered VCDs on the ALS Cluster 2 respectively. The VCD Cluster 3 has lower percentage of Class 9 vehicles, therefore, the VCD Cluster 1 produce least alligator cracking and rutting compare to other two VCDs. On the other hand, the VCD Cluster 2 has higher percentage of Class 9 vehicles therefore it give highest alligator cracking and rutting. Compare to the VCD Cluster 3, the ALS Cluster 2 predicts 115.2% more alligator cracking and 29.1% more rutting. The VCD Cluster 1 has mix traffic of Class 5 and Class 9 vehicles therefore, it provides more distresses than the VCD Cluster 3 and less distresses than the VCD Cluster 2. Compare to the VCD Cluster 3, the VCD Cluster 1 predicts 17% more alligator cracking and 61% more rutting.



a) Alligator cracking

b) Rutting

Figure 4.31 Predicted distresses for different clustered of VCDs on ALS Cluster 2

Figure 4.32 shows the effects of different clustered VCDs on ALS Cluster 3 in predicting pavement performance. Figures 4.32(a) and 4.32(b) compares predicted alligator cracking and rutting for different clustered VCDs on the ALS Cluster 3 respectively. The VCD Cluster 3 has lower percentage of Class 9 vehicles, therefore, the VCD Cluster 1 produce least alligator cracking and rutting compare to other two VCDs. On the other hand, the VCD Cluster 2 has higher percentage of Class 9 vehicles therefore it give highest alligator cracking and rutting. Compare to the VCD Cluster 3, the ALS Cluster 2 predicts 130.1% more alligator cracking and 33.4% more rutting. The VCD Cluster 1 has mix traffic of Class 5 and Class 9 vehicles therefore, it provides more distresses than the VCD Cluster 3 and less distresses than the VCD Cluster 2. Compare to the VCD Cluster 3, the VCD Cluster 1 predicts 18.2% more alligator cracking and 62.7% more rutting.

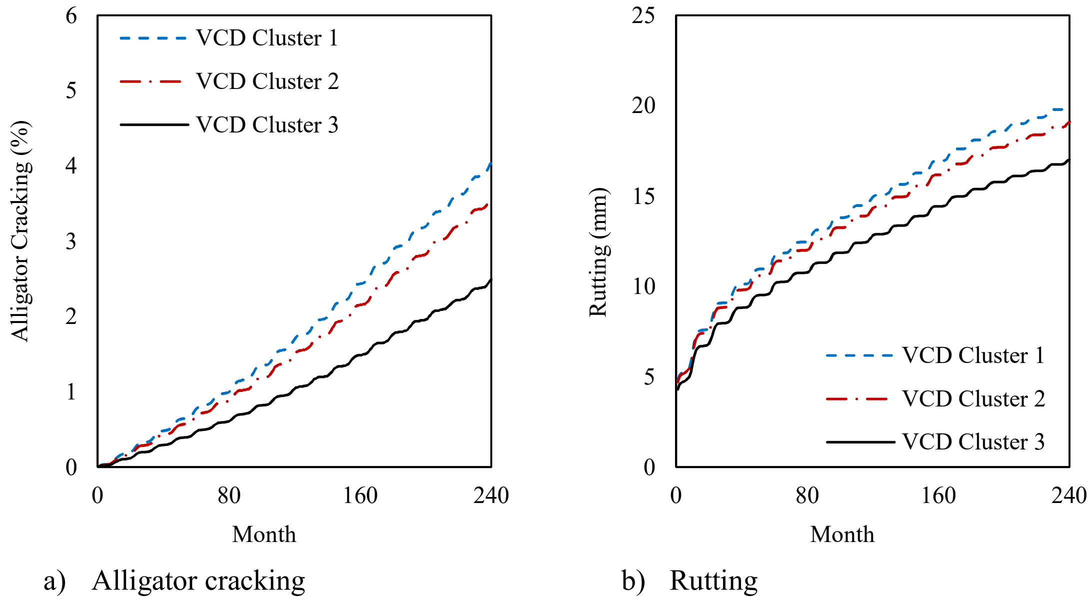


Figure 4.32 Predicted distresses for different clustered of VCDs on ALS Cluster 3

Table 4.7 shows the predicted distresses for different combinations of clustered ALSs and clustered VCDs for same other inputs. It shows that the VCD Cluster 3 and ALS Cluster 1 combination predicts the least alligator cracking and rutting. The reason is that, the VCD Cluster 3 has lowest percentage of Class 9 vehicles and ALS Cluster 1 has higher percentage of light weight vehicles. On the other hand, the VCD Cluster 2 and ALS Cluster 3 combination provides highest alligator cracking and rutting. The reason is that, the VCD Cluster 2 has highest percentage of Class 9 vehicle and ALS Cluster 3 has higher percentage of heavier vehicles. Table 4.8 shows the percent difference in predicting distresses compare to predicted distresses due VCD Cluster 3 and ALS Cluster 1 combination. It shows that alligator cracking can differ up to 303.5% for different combination of clustered VCD and clustered ALS. It also shows that rutting can differ up to 51.2% for different combinations of clustered VCD and clustered ALS.

Table 4.7 Predicted distresses due to different VCD and ALS combinations

VCD/ ALS	Alligator Cracking (%)			Rutting (mm)		
	ALS Cluster 1	ALS Cluster 2	ALS Cluster 3	ALS Cluster 1	ALS Cluster 2	ALS Cluster 3
VCD Cluster 1	2.15	3.59	4.05	17.44	19.12	20.13
VCD Cluster 2	2.60	4.80	5.73	18.72	21.09	22.72
VCD Cluster 3	1.42	2.23	2.49	15.02	16.34	17.03

Table 4.8 Percent difference with respect to VCD Cluster 3 and ALS Cluster 1

VCD/ ALS	Alligator Cracking (% difference)			Rutting (% difference)		
	ALS Cluster 1	ALS Cluster 2	ALS Cluster 3	ALS Cluster 1	ALS Cluster 2	ALS Cluster 3
VCD Cluster 1	51.41	152.82	185.21	16.13	27.29	34.02
VCD Cluster 2	83.10	238.03	303.52	24.65	40.43	51.25
VCD Cluster 3	0.00	57.04	75.35	0.00	8.81	13.38

4.4.3 Summary of the Results

This section proposed a guideline to select appropriate VCD and ALS cluster combinations for pavement design. Based on the interaction between sites present in both VCD and ALS clusters, a relationship between VCD clusters and ALS clusters was developed. In addition, the effects of different clustered VCDs and clustered ALSs combination on predicted pavement performances using the ME design software was investigated. Based on the results, the following conclusions can be made:

- Though there are a few anomalies, there is a good relationship between VCD clusters and ALS clusters. Most of the sites present in a VCD cluster also present in same ALS cluster.
- Wrong combination of VCD and ALS cluster can give erroneous distress prediction. Results shows that, alligator cracking can differ up to 303% and rutting can differ up to 51% for different clustered VCD and ALS combinations.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Several conclusions have been found following the completion of the study on the traffic data. The conclusions are as follows:

5.1.1 Effects of Site Specific Traffic Data on Predicted Pavement Performance

This study investigates the effects of different site-specific traffic inputs on predicted alligator cracking and rutting in asphalt pavement in New Mexico based on two major interstates. Site- specific traffic inputs were developed using WIM data collected from the pavement sites. Then a parametric study was conducted using the ME design software to determine the effects of Level 3 vs. Level 1 traffic input data, axle load spectra, class distribution, monthly adjustment factor, hourly distribution, etc., on the alligator cracking and rutting of asphalt pavement. The outcomes are as follows:

- Site specific traffic varies from site to site.
- Site specific traffic values are different from the ME design default values.
- Site specific axle load spectra and lane distribution have the highest impact on predicting pavement performance.
- Vehicle class distribution, directional distribution, and lateral wander have moderate impact on predicting pavement performance.
- Other inputs such as monthly adjustment factor, axles per vehicle, axle spacing, and operational speed affect the predicted alligator cracking and rutting very slightly.

- On the other hand, predicted alligator cracking and rutting are insensitive to hourly distribution and wheelbase distribution.
- Therefore, it is recommended to develop the five types of site-specific data: axle load spectra, vehicle class distribution, directional distribution, lane distribution and lateral wander, instead of a larger number of traffic data. The ME default data may be considered good for other traffic inputs.

5.1.2 Effects of Input Levels on Predicted Pavement Performance

This study also investigates the effects of different input levels of VCDs and ALSs on pavement performances using the ME design software. A total of ten sites are used to develop the site-specific (Level 1) data. Then both arithmetic average and cluster methodologies are used to generate regional data (Level 2). Then a parametric study is conducted using the ME software to determine the effects of different input levels of VCD and ALS on the alligator cracking and rutting. Based on the results, the following conclusions can be made:

- K-means cluster technique along with elbow criterion can be an easy and successful technique to identify number of groups in traffic data.
- The predicted pavement performances based on the cluster generated VCD and ALS match well with those based on the site-specific data.
- The ME default VCD provides better results than the statewide average. On the other hand, statewide average ALS predicts pavement performance better than the ME default ALS.

5.1.3 Decision for Selecting Appropriate Cluster Combination

This study investigates the effects of different clustered VCD and ALS combinations on predicted pavement performances using the ME design software. Using the interaction between sites present in both VCD and ALS clusters, a guideline was proposed to select appropriate clustered VCD and ALS combinations. Based on the results, the following conclusions can be made:

- Though there are a few anomalies, there is a good relationship between VCD clusters and ALS clusters. Most of the sites present in a VCD cluster also present in same ALS cluster.
- Wrong combination of VCD and ALS cluster can give error result in distresses prediction.
- Therefore, this study recommends to use the proposed guideline given Table 4.6 to select appropriate clustered VCD and ALS combination if site specific data is not available. However, this guideline needs a 48-h traffic count to calculate AADTT and site specific VCD.

5.2 Recommendations for Future Work

- In this study, only ten site specific data were used. Adding more data may give more general conclusion.
- To further investigate into this study, it is recommended to correlate values attained from the field measurements.
- Detailed statistical analysis will provide strong support to the finds.

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APPENDICES

APPENDIX A

REGIONAL VEHICLE CLASS DISTRIBUTION FOR NEW MEXICO

Table A-1 Vehicle Class Distribution (VCD), Statewide Average

Class	Percentage
4	1.74
5	30.35
6	2.88
7	0.14
8	7.07
9	52.01
10	1.48
11	2.73
12	0.98
13	0.62

Table A-2 Vehicle Class Distribution (VCD), Cluster 1 (Mix with Class 5 & 9)

Class	Percentage
4	1.35
5	29.31
6	5.08
7	0.21
8	8.66
9	48.46
10	2.37
11	3.34
12	0.97
13	0.25

Table A-3 Vehicle Class Distribution (VCD), Cluster 2 (Predominately Class 9)

Class	Percentage
4	1.31
5	10.9
6	0.91
7	0.04
8	4.91
9	75.36
10	0.99
11	2.87
12	1.5
13	1.21

Table A-4 Vehicle Class Distribution (VCD), Cluster 3 (Predominately Class 5)

Class	Percentage
4	2.75
5	57.32
6	3.32
7	0.21
8	8.35
9	24.41
10	1.23
11	1.92
12	0.3
13	0.19

APPENDIX B

REGIONAL AXLE LOAD SPECTRA FOR NEW MEXICO

Table B-1 Single Axle Load Spectra (ALS), Statewide Average

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
3000	0.77	7.42	1	10	7.68	0.44	1.18	1.06	24.45	31.44
4000	2.39	23	2.55	3.43	9.34	2.02	0.66	2.81	1.82	1.55
5000	2.97	19.72	3.21	2.4	13.54	3.19	0.9	3.08	3.99	1.12
6000	5.12	15.78	5.46	3.49	14.28	5.81	3.05	5.78	6.42	3.77
7000	5.86	8.75	5.42	4.82	8.82	4.94	4.54	5.37	6.55	4.51
8000	10.06	7.67	7.16	5.27	9.04	6.55	4.89	6.84	7.49	5.37
9000	9.71	4.48	8.45	6.05	7.23	7.05	8.49	6.79	6.15	3.32
10000	10.32	3.8	13.25	6.41	7.63	11.42	10.79	12.04	8.9	5.48
11000	7.95	2.11	13.13	5.4	5.23	13.26	14.06	10.84	7.56	6.45
12000	8.59	1.79	15.02	6.25	4.42	19.79	17.61	9.4	9.56	8.77
13000	6.91	1.18	8.28	4.59	2.91	9.25	8.9	6.06	5.52	5.36
14000	7.87	1.11	6.74	3.41	2.41	4.83	7.01	6.66	4.65	5.04
15000	6.25	0.89	4.24	5.45	1.98	2.49	4.47	5.96	2.61	4.31
16000	4.11	0.62	2.14	3.84	1.33	1.81	2.42	4.36	1.47	3.31
17000	3.73	0.59	1.61	5.4	1.24	2.09	2.53	4.22	1.2	3.17
18000	2.32	0.39	0.88	3.64	0.82	1.56	3.21	3.13	0.51	1.58
19000	1.95	0.27	0.57	5.52	0.69	1.42	2.09	2.31	0.44	2.25
20000	1.16	0.13	0.31	4	0.43	0.78	1.11	1.32	0.25	0.89
21000	0.86	0.11	0.25	3.38	0.36	0.6	1.34	0.95	0.12	0.71

Table B-1 (cont.) Single Axle Load Spectra (ALS), Statewide Average

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
22000	0.43	0.06	0.12	2.74	0.18	0.27	0.18	0.41	0.14	0.42
23000	0.24	0.05	0.07	1.33	0.16	0.18	0.28	0.29	0.04	0.29
24000	0.14	0.03	0.04	0.56	0.09	0.08	0.06	0.1	0.03	0.11
25000	0.1	0.02	0.02	0.27	0.06	0.05	0.05	0.06	0.02	0.13
26000	0.06	0.01	0.02	0.35	0.04	0.02	0.03	0.02	0.02	0.05
27000	0.04	0.01	0.01	0.3	0.03	0.02	0.02	0.02	0.01	0.07
28000	0.02	0.01	0.02	0.32	0.02	0.02	0.02	0.02	0.01	0.08
29000	0.02	0	0.01	0.2	0.01	0.01	0.02	0.01	0.02	0.08
30000	0.02	0	0.01	0.36	0.01	0.01	0.02	0.01	0.01	0.06
31000	0.01	0	0	0.09	0	0.01	0.01	0.01	0	0.06
32000	0.01	0	0.01	0.2	0.01	0.01	0.01	0.01	0.01	0.06
33000	0.01	0	0	0.14	0	0.01	0.01	0	0	0.02
34000	0	0	0	0.16	0	0	0.01	0.01	0.01	0.06
35000	0	0	0	0.05	0	0	0.01	0	0	0.03
36000	0	0	0	0.03	0	0	0.01	0.01	0.01	0.01
37000	0	0	0	0.02	0	0	0.01	0	0.01	0.03
38000	0	0	0	0.05	0	0	0	0	0	0.01
39000	0	0	0	0.01	0	0	0	0	0	0.01
40000	0	0	0	0.07	0.01	0.01	0	0.04	0	0.02
41000	0	0	0	0	0	0	0	0	0	0

Table B-2 Tandem Axle Load Spectra (ALS), Statewide Average

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
6000	0.76	0	2.16	22.21	15.86	0.23	0.32	44.68	22.15	27.42
8000	0.83	0	6.06	2.59	8.22	1.02	0.3	4.37	1.1	1.14
10000	2.41	0	10.32	3.01	10.44	3.08	0.77	1.34	3.24	1.86
12000	4.18	0	8.51	3.67	10.56	5.31	1.97	2.38	4.57	3.43
14000	7.03	0	8.68	8.31	9.78	7.18	4.42	6.08	7.14	6.56
16000	7.79	0	8.16	7.89	8.56	8.05	4.49	4.79	9.63	5.66
18000	5.8	0	7.49	4.43	7.41	7.59	7.61	3.82	10.07	7.81
20000	6.45	0	6.31	2.38	6.39	7	8.96	5.83	11.38	6.41
22000	8.85	0	6.35	2.7	5.25	7.05	9.81	4.92	11.32	6.74
24000	8.76	0	5.12	4.87	4.11	6.32	13.03	4.62	7.12	3.5
26000	8.28	0	4.85	3.51	3.68	6.26	8.97	4.7	3.49	2.87
28000	9.23	0	4.87	3.14	2.98	6.94	7.06	4.11	1.81	3.24
30000	8.24	0	3.98	3.05	2.31	6.93	6.42	2.47	1.57	2.88
32000	6.91	0	3.47	2.55	1.74	7.91	4.89	1.6	1.38	2.72
34000	4.62	0	3.15	6.23	1.09	7.97	4.36	0.93	1.13	2.67
36000	3.29	0	2.63	3.18	0.61	5.52	4.7	0.75	0.91	2.69
38000	1.88	0	1.9	2.52	0.39	2.72	2.46	0.61	0.56	2.57
40000	1.2	0	1.46	2.37	0.17	1.36	2.89	0.58	0.4	2.54
42000	0.8	0	1.26	2.33	0.12	0.7	2.89	0.33	0.32	2.12
44000	0.46	0	1.29	1.88	0.1	0.33	1.14	0.28	0.11	1.88

Table B-2 (cont.) Tandem Axle Load Spectra (ALS), Statewide Average

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
46000	0.35	0	0.84	1.49	0.07	0.17	0.74	0.3	0.12	1.05
48000	0.32	0	0.46	1.22	0.05	0.09	0.61	0.24	0.12	0.63
50000	0.3	0	0.22	0.96	0.03	0.05	0.31	0.18	0.05	0.55
54000	0.22	0	0.07	0.72	0.01	0.03	0.16	0.05	0.08	0.16
56000	0.18	0	0.04	0.62	0.01	0.03	0.13	0.04	0.03	0.1
58000	0.14	0	0.04	0.49	0	0.02	0.07	0	0.07	0.06
60000	0.08	0	0.02	0.17	0	0.01	0.05	0	0	0.32
62000	0.12	0	0.01	0.25	0	0.01	0.03	0	0.05	0.03
64000	0.06	0	0.01	0.13	0.03	0.01	0.03	0	0	0.04
66000	0.04	0	0.01	0.07	0	0	0.04	0	0	0.03
68000	0.04	0	0.01	0.09	0	0.01	0.02	0	0	0.03
70000	0.02	0	0	0.03	0	0	0.01	0	0	0.02
72000	0.03	0	0	0.07	0	0.01	0.01	0	0	0.01
74000	0.02	0	0.03	0.02	0	0.01	0.01	0	0	0.01
76000	0.01	0	0	0.01	0	0	0.01	0	0.03	0.01
78000	0	0	0	0.02	0	0	0.01	0	0.01	0
80000	0.04	0	0.04	0.01	0.01	0.04	0.01	0	0	0.01
82000	0	0	0	0.01	0	0	0	0	0	0.01

Table B-3 Tridem Axle Load Spectra (ALS), Statewide Average

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
12000	0	0	2.16	22.21	15.86	0.23	0.32	44.68	22.15	27.42
15000	0	0	6.06	2.59	8.22	1.02	0.3	4.37	1.1	1.14
18000	0	0	10.32	3.01	10.44	3.08	0.77	1.34	3.24	1.86
21000	0	0	8.51	3.67	10.56	5.31	1.97	2.38	4.57	3.43
24000	0	0	8.68	8.31	9.78	7.18	4.42	6.08	7.14	6.56
27000	0	0	8.16	7.89	8.56	8.05	4.49	4.79	9.63	5.66
30000	0	0	7.49	4.43	7.41	7.59	7.61	3.82	10.07	7.81
33000	0	0	6.31	2.38	6.39	7	8.96	5.83	11.38	6.41
36000	0	0	6.35	2.7	5.25	7.05	9.81	4.92	11.32	6.74
39000	0	0	5.12	4.87	4.11	6.32	13.03	4.62	7.12	3.5
42000	0	0	4.85	3.51	3.68	6.26	8.97	4.7	3.49	2.97
45000	0	0	4.87	3.14	2.98	6.94	7.14	4.15	1.85	3.24
48000	0	0	3.98	3.05	2.31	6.93	6.42	2.43	1.57	2.88
51000	0	0	3.47	2.81	1.75	7.98	4.89	1.6	1.38	2.72
54000	0	0	3.15	6.23	1.09	7.97	4.36	0.93	1.13	2.67
57000	0	0	2.63	3.18	0.61	5.52	4.7	0.75	0.91	2.69
60000	0	0	1.98	2.52	0.39	2.72	2.46	0.61	0.56	2.57
63000	0	0	1.46	2.37	0.17	1.36	2.89	0.58	0.4	2.54
66000	0	0	1.26	2.33	0.12	0.7	2.89	0.33	0.32	2.12
69000	0	0	1.29	1.88	0.1	0.33	1.14	0.28	0.11	1.88

Table B-3 (cont.) Tridem Axle Load Spectra (ALS), Statewide Average

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
72000	0	0	0.84	1.49	0.07	0.17	0.74	0.3	0.12	1.05
75000	0	0	0.46	1.22	0.05	0.09	0.61	0.24	0.12	0.63
78000	0	0	0.22	0.96	0.03	0.05	0.31	0.18	0.05	0.55
81000	0	0	0.18	0.8	0.02	0.04	0.29	0	0.04	0.22
84000	0	0	0.07	0.72	0.01	0.03	0.16	0.05	0.08	0.16
87000	0	0	0.04	0.62	0.01	0.03	0.13	0.04	0.03	0.1
90000	0	0	0.04	0.49	0	0.02	0.07	0	0.07	0.06
93000	0	0	0.02	0.17	0	0.01	0.05	0	0	0.32
96000	0	0	0.01	0.25	0	0.01	0.03	0	0.05	0.03
99000	0	0	0.01	0.13	0.03	0.01	0.03	0	0	0.04
102000	0	0	0.01	0.07	0	0	0.04	0	0	0.03

Table B-4 Quad Axle Load Spectra (ALS), Statewide Average

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
12000	0	0	0	1.1	0	0.01	8.54	0	4	13.69
15000	0	0	0	1.91	0	14.61	2.75	0	4	2.33
18000	0	0	0	0.66	0	14.97	5.31	0	0	3.11
21000	0	0	0	6.55	0	0	3.16	0	4	3.8
24000	0	0	0	1.79	0	0	4.16	0	0	5.76
27000	0	0	0	3.29	0	0	1.85	0	0	4.36
30000	0	0	0	6.25	0	4.1	15.54	0	0	7.39
33000	0	0	0	3.12	0	10.2	1.67	0	0	4.54
36000	0	0	0	4.75	0	0.06	1.28	0	0	4.57
39000	0	0	0	4.87	0	0	1.39	0	0	3.17
42000	0	0	0	6.17	0	0	3.14	0	5	2.13
45000	0	0	0	4.45	0	2.43	10.1	0	10	2.28
48000	0	0	0	3.87	0	14.63	2.69	0	40	3.02
51000	0	0	0	5.91	0	0	4.41	0	0	2.43
54000	0	0	0	6.63	0	0	1.91	0	14	3.48
57000	0	0	0	8.3	0	0	6.82	0	0	5.21
60000	0	0	0	6.11	0	2.43	2.43	0	0	3.32
63000	0	0	0	2.65	0	2.43	6.91	0	0	4.38
66000	0	0	0	4.15	0	0	3.89	0	0	3.64
69000	0	0	0	8.37	0	2.93	2.85	0	0	3.41

Table B-4 (cont.) Quad Axle Load Spectra (ALS), Statewide Average

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
72000	0	0	0	1.78	0	2.93	0.27	0	4	1.8
75000	0	0	0	1.45	0	5.85	2.97	0	0	3.44
78000	0	0	0	2.28	0	2.93	3.7	0	15	1.58
81000	0	0	0	1.86	0	0	1.17	0	0	2.51
84000	0	0	0	1.42	0	17.06	0.23	0	0	1.86
87000	0	0	0	0.25	0	0	0.3	0	0	0.98
90000	0	0	0	0.04	0	0	0.15	0	0	0.76
93000	0	0	0	0	0	2.43	0.38	0	0	0.68
96000	0	0	0	0.02	0	0	0	0	0	0.31
99000	0	0	0	0	0	0	0	0	0	0.02
102000	0	0	0	0	0	0	0.03	0	0	0.04

Table B-5 Single Axle Load Spectra (ALS), Cluster 1 (Light tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
3000	1.04	13.04	1.97	24.74	6.44	0.39	1.72	1.22	66.78	92.87
4000	6.42	30.9	6.35	6.81	6.41	2.77	0.61	2.5	0.3	0.57
5000	8.16	21.84	6.9	3.85	8.33	5.33	1.56	3.66	0.56	0.38
6000	11.09	10.64	8.7	5.74	12.37	8.74	3.43	6.06	1.81	0.37
7000	10.52	4.7	8.41	10.47	10.36	9.23	5.56	5.69	2.08	0.31
8000	11.72	4.72	10.67	9.3	12.02	11.43	3.38	7.93	2.88	0.38
9000	9.62	3.18	11.85	10.6	10.25	12.46	8.24	7.4	3.19	0.33
10000	8.93	2.87	14.23	2.29	9.42	15.99	12.15	10.49	4.54	0.44
11000	6.75	1.64	9.61	2.39	6.24	11.62	11.05	10	4.17	0.49
12000	6.54	1.42	8.23	2.72	4.8	8.21	10.26	9.2	4.29	0.38
13000	4.23	0.96	4.4	3.41	3.49	4.31	4.76	6.79	2.87	0.3
14000	4.47	0.95	3.15	1.92	2.78	3.45	7.51	7.46	2.96	0.39
15000	3.08	0.89	2.04	6.24	2.26	2.19	6.91	5.99	1.73	0.31
16000	2.17	0.54	1.13	0.72	1.4	1.19	3.16	4.5	0.88	0.23
17000	1.7	0.53	0.91	3.72	1.2	0.98	3.13	4.29	0.55	0.17
18000	1.41	0.38	0.7	0.8	0.93	0.72	7.25	3.56	0.19	0.16
19000	0.98	0.29	0.29	0.37	0.53	0.48	3.4	1.64	0.11	0.11
20000	0.5	0.17	0.18	0.39	0.29	0.23	2.05	0.72	0.05	0.1
21000	0.38	0.13	0.13	0.21	0.19	0.16	3.16	0.42	0.04	0.12
22000	0.12	0.05	0.05	2.81	0.07	0.04	0.05	0.16	0.01	0.15

Table B-5 (cont.) Single Axle Load Spectra (ALS), Cluster 1 (Light tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
23000	0.07	0.05	0.04	0	0.08	0.03	0.62	0.12	0	0.16
24000	0.06	0.03	0.03	0	0.05	0.01	0.02	0.02	0	0.05
25000	0.02	0.02	0.01	0	0.01	0.01	0.01	0.01	0.01	0.02
26000	0.01	0.02	0	0.05	0.01	0	0.01	0.01	0	0.03
27000	0.01	0.01	0	0	0	0	0	0	0	0.08
28000	0	0.01	0	0.02	0	0	0	0	0	0.14
29000	0	0.01	0	0.02	0.01	0	0	0	0	0.18
30000	0	0.01	0.01	0	0.01	0	0	0	0	0.14
31000	0	0	0	0	0	0	0	0.01	0	0.15
32000	0	0	0	0.31	0.01	0	0	0	0	0.12
33000	0	0	0.01	0	0	0	0	0	0	0.03
34000	0	0	0	0.1	0	0	0	0	0	0.12
35000	0	0	0	0	0	0	0	0	0	0.07
36000	0	0	0	0	0	0	0	0.02	0	0.01
37000	0	0	0	0	0	0	0	0	0	0.05
38000	0	0	0	0	0	0	0	0	0	0.05
39000	0	0	0	0	0	0	0	0	0	0.03
40000	0	0	0	0	0.04	0.03	0	0.13	0	0.01
41000	0	0	0	0	0	0	0	0	0	0

Table B-6 Tandem Axle Load Spectra (ALS), Cluster 1 (Light tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
6000	1.56	0	4.09	67.41	8.76	3.35	0.28	97.28	66.81	88.88
8000	1.52	0	8	0	4.18	4.1	0.24	0.84	0.34	1.03
10000	4.13	0	7.46	0	10.86	6.73	0.99	0.84	0.51	0.94
12000	8.92	0	7.87	0.99	10.73	9.59	1.85	0.42	1.73	0.98
14000	12.37	0	8.92	8.15	11.37	9.73	2.8	0.21	3.83	0.78
16000	12.49	0	9.21	7.16	10.09	9.21	3.04	0.1	4	0.72
18000	7.29	0	8.79	7.16	9.21	9.25	5.75	0.31	4.66	0.65
20000	7.09	0	7.09	0	8.33	8.76	6.2	0	4.71	0.74
22000	7.05	0	6.52	0	5.82	8.17	4.66	0	5.25	0.79
24000	7.67	0	5.78	8.15	4.29	8.43	14.92	0	4.21	0.41
26000	6.85	0	6.6	0	4.8	6.11	9.81	0	2.24	0.33
28000	7.02	0	6.43	0	3.94	5.04	10.01	0	0.87	0.31
30000	5.43	0	4.39	0	2.91	4.19	7.07	0	0.58	0.66
32000	4.51	0	2.87	0	1.88	3.39	6.97	0	0.14	0.67
34000	2.25	0	2.42	0.49	1.26	1.77	5.72	0	0.08	0.61
36000	1.71	0	1.83	0	0.76	1.05	8.83	0	0.01	0.53
38000	0.69	0	0.68	0.49	0.38	0.56	2.15	0	0.03	0.42
40000	0.6	0	0.38	0	0.2	0.24	3.97	0	0	0.22
42000	0.33	0	0.35	0	0.08	0.12	3.53	0	0	0.13
44000	0.15	0	0.08	0	0.04	0.05	0.62	0	0	0.1

Table B-6 (cont.) Tandem Axle Load Spectra (ALS), Cluster 1 (Light tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
46000	0.11	0	0.12	0	0	0.03	0.07	0	0	0.02
48000	0.05	0	0.02	0	0.02	0.01	0.49	0	0	0.02
50000	0.02	0	0.04	0	0	0.01	0.03	0	0	0.01
52000	0.08	0	0	0	0	0.02	0	0	0	0
54000	0.02	0	0.02	0	0	0.01	0	0	0	0.01
56000	0.02	0	0	0	0	0.01	0	0	0	0
58000	0.02	0	0.04	0	0	0.01	0	0	0	0
60000	0	0	0	0	0	0.01	0	0	0	0.02
62000	0.05	0	0	0	0	0.02	0	0	0	0
64000	0	0	0	0	0.09	0.02	0	0	0	0.02
66000	0	0	0	0	0	0.01	0	0	0	0
68000	0	0	0	0	0	0	0	0	0	0
70000	0	0	0	0	0	0	0	0	0	0
72000	0	0	0	0	0	0	0	0	0	0
74000	0	0	0	0	0	0	0	0	0	0
76000	0	0	0	0	0	0	0	0	0	0
78000	0	0	0	0	0	0	0	0	0	0
80000	0	0	0	0	0	0	0	0	0	0
82000	0	0	0	0	0	0	0	0	0	0

Table B-7 Tridem Axle Load Spectra (ALS), Cluster 1 (Light tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
12000	0	0	0	16.8	0	14.39	3.15	0	0	78.39
15000	0	0	0	4.15	0	15.52	2.31	0	0	2.6
18000	0	0	0	5.84	0	3	3.69	0	5	1.92
21000	0	0	0	13.18	0	6.39	5.21	0	0	2.36
24000	0	0	0	16.49	0	2.2	3.98	0	0	1.17
27000	0	0	0	1.48	0	2.99	28.34	0	25	1.09
30000	0	0	0	5.75	0	1.89	3.58	0	10	1.41
33000	0	0	0	6.51	0	4.14	4.55	0	10	1.64
36000	0	0	0	6.33	0	4.4	3.66	0	25	1.47
39000	0	0	0	1.03	0	3.46	3.51	0	15	1.59
42000	0	0	0	12.76	0	2.62	3.87	0	10	1.73
45000	0	0	0	2.89	0	5.65	2.89	0	0	1.23
48000	0	0	0	1.67	0	7.27	1.74	0	0	1.17
51000	0	0	0	1.37	0	5.49	1.68	0	0	0.5
54000	0	0	0	0.42	0	4.63	1.44	0	0	0.52
57000	0	0	0	0.06	0	6.48	0.36	0	0	0.16
60000	0	0	0	0	0	3.28	25.39	0	0	0.41
63000	0	0	0	0	0	4.35	0.13	0	0	0.31
66000	0	0	0	3.27	0	1.22	0.14	0	0	0.15
69000	0	0	0	0	0	0.19	0.18	0	0	0.18

Table B-7 (cont.) Tridem Axle Load Spectra (ALS), Cluster 1 (Light tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
72000	0	0	0	0	0	0.44	0.01	0	0	0
75000	0	0	0	0	0	0	0.06	0	0	0
78000	0	0	0	0	0	0	0.09	0	0	0
81000	0	0	0	0	0	0	0	0	0	0
84000	0	0	0	0	0	0	0.02	0	0	0
87000	0	0	0	0	0	0	0	0	0	0
90000	0	0	0	0	0	0	0	0	0	0
93000	0	0	0	0	0	0	0.02	0	0	0
96000	0	0	0	0	0	0	0	0	0	0
99000	0	0	0	0	0	0	0	0	0	0
102000	0	0	0	0	0	0	0	0	0	0

Table B-8 Quad Axle Load Spectra (ALS), Cluster 1 (Light tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
12000	0	0	0	1.34	0	0	4.38	0	0	85.84
15000	0	0	0	0	0	0	0.43	0	0	3.09
18000	0	0	0	1.33	0	51.14	2.9	0	0	1.98
21000	0	0	0	13.52	0	0	1.3	0	0	1.9
24000	0	0	0	4	0	0	1.88	0	0	1.31
27000	0	0	0	5.33	0	0	0.87	0	0	0.93
30000	0	0	0	9.52	0	14.01	42.99	0	0	0.77
33000	0	0	0	2.67	0	34.85	1.3	0	0	0.88
36000	0	0	0	0	0	0	0	0	0	0.83
39000	0	0	0	0	0	0	0.72	0	0	0.76
42000	0	0	0	4	0	0	2.32	0	0	0.6
45000	0	0	0	0	0	0	27.31	0	0	0.23
48000	0	0	0	0	0	0	0.87	0	0	0.13
51000	0	0	0	2.67	0	0	2.46	0	0	0.14
54000	0	0	0	12.76	0	0	1.01	0	0	0.05
57000	0	0	0	14.29	0	0	0	0	0	0.14
60000	0	0	0	4.76	0	0	0.58	0	0	0.08
63000	0	0	0	0	0	0	2.17	0	0	0.06
66000	0	0	0	4.76	0	0	1.45	0	0	0.15
69000	0	0	0	19.05	0	0	1.16	0	0	0.09

Table B-8 (cont.) Quad Axle Load Spectra (ALS), Cluster 1 (Light tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
72000	0	0	0	0	0	0	0.14	0	0	0.03
75000	0	0	0	0	0	0	1.45	0	0	0.01
78000	0	0	0	0	0	0	1.16	0	0	0
81000	0	0	0	0	0	0	0.72	0	0	0
84000	0	0	0	0	0	0	0.43	0	0	0
87000	0	0	0	0	0	0	0	0	0	0
90000	0	0	0	0	0	0	0	0	0	0
93000	0	0	0	0	0	0	0	0	0	0
96000	0	0	0	0	0	0	0	0	0	0
99000	0	0	0	0	0	0	0	0	0	0
102000	0	0	0	0	0	0	0	0	0	0

Table B-9 Single ALS, Cluster 2 (Mix with light & heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
3000	0.42	4.82	0.44	4.1	5.06	0.61	0.71	1.23	4.38	3.87
4000	0.6	26.9	0.92	1.45	10.11	2.16	0.14	3.83	1.84	2.1
5000	0.57	22.98	1.61	1.35	15.78	2.86	0.33	3.34	4.27	1.6
6000	2.8	17.38	4.9	1.99	16.86	5.86	1.94	6.81	9.47	6.19
7000	3.93	7.78	4.82	2.28	8.81	3.82	1.63	6.27	10.54	6.88
8000	9.74	6.34	6.29	3.34	8.11	5.26	5.52	7.28	11.95	7.59
9000	9.95	3.4	6.61	4.18	6.13	4.84	10.64	6.8	9.09	4.8
10000	11.24	2.97	11.65	5.35	7.07	9.61	11.22	11.36	12.24	7.82
11000	7.77	1.53	13.37	5.17	4.97	12.9	13.49	9.79	8.06	8.75
12000	8.88	1.37	16.88	6.46	4.39	19.48	18.15	9.27	9.48	11.94
13000	7.69	0.86	9.92	5.1	2.65	10.8	11.97	5.12	5.38	7.71
14000	9.27	0.91	8.75	4.35	2.26	6.36	8.14	5.37	4.56	7.19
15000	7.38	0.68	5.76	5.65	1.84	2.95	4.21	5.01	2.97	5.78
16000	5.06	0.52	2.86	6.12	1.33	2.28	2.61	4.04	1.86	4.52
17000	4.82	0.5	2.12	7.58	1.28	2.73	2.87	4.11	1.6	4.38
18000	2.93	0.3	1.06	5.93	0.79	2.05	1.88	3.01	0.64	1.98
19000	2.55	0.22	0.74	8.85	0.77	2.06	2	2.72	0.59	3.41
20000	1.59	0.13	0.43	6.61	0.48	1.22	0.93	1.77	0.36	1.17
21000	1.23	0.13	0.35	5.87	0.43	0.99	0.73	1.35	0.17	0.9
22000	0.63	0.07	0.19	3.34	0.23	0.47	0.29	0.66	0.23	0.51

Table B-9 (cont.) Single ALS, Cluster 2 (Mix with light & heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
23000	0.36	0.06	0.09	2.25	0.22	0.31	0.16	0.46	0.07	0.24
24000	0.17	0.04	0.05	0.66	0.13	0.14	0.08	0.16	0.02	0.07
25000	0.14	0.04	0.04	0.23	0.1	0.08	0.08	0.1	0.04	0.2
26000	0.08	0.02	0.03	0.18	0.07	0.04	0.03	0.03	0.03	0.04
27000	0.07	0.01	0.02	0.22	0.05	0.03	0.03	0.03	0.02	0.07
28000	0.03	0.01	0.03	0.1	0.03	0.02	0.03	0.02	0.02	0.05
29000	0.03	0.01	0.02	0.06	0.02	0.02	0.03	0.01	0.03	0.04
30000	0.03	0	0.01	0.37	0.01	0.01	0.04	0.01	0.02	0.02
31000	0.01	0	0.01	0.09	0.01	0.01	0.02	0.01	0.01	0.02
32000	0.01	0	0.01	0.11	0.01	0.01	0.02	0.01	0.02	0.04
33000	0.01	0	0	0.17	0	0.01	0.01	0.01	0	0.02
34000	0.01	0.01	0	0.13	0	0.01	0.02	0.01	0.01	0.03
35000	0	0.01	0	0.08	0	0	0.02	0	0.01	0.02
36000	0	0	0.01	0.07	0	0	0.02	0	0.01	0.02
37000	0	0	0.01	0.05	0	0	0.01	0	0.01	0.03
38000	0	0	0	0.02	0	0	0	0	0	0
39000	0	0	0	0.01	0	0	0	0	0	0
40000	0	0	0	0.13	0	0	0	0	0	0
41000	0	0	0	0	0	0	0	0	0	0

Table B-10 Tandem ALS, Cluster 2 (Mix with light & heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
6000	0.23	0	1.11	2.44	16.39	1.97	0.38	23.94	3.32	1.36
8000	0.61	0	4.19	4.34	9.88	4.01	0.3	5.44	1.02	1.41
10000	1.49	0	9.31	4.81	10.11	7.25	0.52	1.04	5.29	2.63
12000	2.04	0	8.26	5.67	10.1	9.08	1.89	3.47	7.46	4.64
14000	5.22	0	8.99	9.93	9.6	8.7	5.83	11.04	10.61	9.63
16000	6.77	0	8.06	9.47	8.43	7.25	5.28	8.47	14.92	8.49
18000	5.79	0	7.32	2.59	6.92	5.97	9.15	5.48	11.83	10.76
20000	6.81	0	6.21	2.81	5.64	5.72	9	9.28	10.29	9.27
22000	10.34	0	6.69	3.2	4.93	4.37	8.09	5.97	12.82	10.58
24000	9.51	0	4.85	2.19	4.2	4.29	10.77	5.15	8.35	5.42
26000	8.74	0	4	4.17	3.35	4.94	8.22	5.71	4.01	4.48
28000	9.89	0	4.03	3.66	2.72	6.02	5.94	5.08	1.77	5.01
30000	8.39	0	3.43	3.03	2.31	7.58	7.06	3.1	1.12	3.85
32000	6.3	0	3.61	3.33	2.11	8.28	4.4	2.27	1.51	2.87
34000	4.66	0	3.37	5.16	1.31	6.93	4.32	1.45	1.27	2.99
36000	3.48	0	3.22	5.1	0.71	3.83	3.46	1.15	1.67	3.19
38000	2.33	0	2.9	4.14	0.38	1.86	3.19	0.42	0.8	2.34
40000	1.62	0	2.41	4.18	0.2	0.94	2.99	0.53	0.6	2.31
42000	1.2	0	2.16	4.04	0.18	0.45	3.31	0.38	0.5	1.8
44000	0.7	0	2.27	3.12	0.17	0.22	1.68	0.11	0.13	2.36

Table B-10 (cont.) Tandem ALS, Cluster 2 (Mix with light & heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
46000	0.56	0	1.58	2.39	0.13	0.12	1.23	0.17	0.12	1.26
48000	0.55	0	0.89	2.1	0.08	0.07	0.8	0.15	0.23	0.75
50000	0.55	0	0.4	1.73	0.05	0.05	0.52	0.1	0.02	0.9
52000	0.45	0	0.36	1.45	0.05	0.03	0.52	0	0.07	0.29
54000	0.4	0	0.12	1.31	0.02	0.02	0.3	0.03	0.07	0.24
56000	0.34	0	0.08	1.14	0.01	0.02	0.25	0.07	0	0.16
58000	0.26	0	0.05	0.98	0.01	0.01	0.13	0	0.14	0.06
60000	0.16	0	0.04	0.32	0.01	0.01	0.09	0	0.01	0.62
62000	0.22	0	0.02	0.47	0	0.01	0.06	0	0.01	0.06
64000	0.12	0	0.02	0.24	0	0	0.06	0	0.01	0.05
66000	0.08	0	0.02	0.13	0	0	0.07	0	0.01	0.05
68000	0.07	0	0.01	0.16	0	0	0.04	0	0	0.06
70000	0.04	0	0.01	0.04	0	0	0.02	0	0	0.04
72000	0.05	0	0.01	0.1	0	0	0.03	0	0.01	0.01
74000	0.01	0	0	0.02	0	0	0.02	0	0	0.02
76000	0.02	0	0	0.01	0	0	0.02	0	0	0.02
78000	0	0	0	0.02	0	0	0.03	0	0.01	0
80000	0	0	0	0	0	0	0.02	0	0	0.01
82000	0	0	0	0.01	0	0	0.01	0	0	0.01

Table B-11 Tridem ALS, Cluster 2 (Mix with light & heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
12000	0	0	32.78	13.6	0	25.04	4.81	20.27	5.15	3.64
15000	0	0	6.55	4.39	0	11.49	10.94	20.65	4.58	5.67
18000	0	0	15.47	2.44	0	9.33	14.22	14.25	2.4	3
21000	0	0	5.15	0.85	0	6.46	7.07	7.95	4.36	7.24
24000	0	0	2.74	1.02	0	4.91	6.42	2.54	3.22	1.6
27000	0	0	3.99	1.15	0	6.8	7.97	1.52	5.38	1.92
30000	0	0	3.6	1.66	13.64	5.43	6.53	0.58	7.92	5.48
33000	0	0	2.77	2.57	13.64	4.13	4.92	0.17	8.51	7.01
36000	0	0	1.66	4.35	13.64	4.3	7.01	1.36	12.09	3.82
39000	0	0	1.22	11.8	0	4.13	6.43	0.59	10.55	2.54
42000	0	0	0.82	12.63	13.64	5.09	5.95	0.97	13.28	3.73
45000	0	0	0.75	9.78	0	4.98	4.96	0.7	5.36	5.32
48000	0	0	7.93	15.64	13.64	3.34	3.64	1.54	7.12	8.29
51000	0	0	1.4	3.55	9.09	1.12	2.89	1.67	3.37	7.48
54000	0	0	0.45	2.93	0	1.12	1.93	0.71	0.71	8.36
57000	0	0	0.47	2.59	13.64	0.33	1.5	1.41	1.19	5.51
60000	0	0	0.2	2.28	0	1.07	1	3.56	2.25	6.33
63000	0	0	0.05	1.75	0	0.36	0.59	4.92	0.1	4.75
66000	0	0	0.11	1.45	0	0.1	0.45	4.77	1.01	4
69000	0	0	0.13	1.04	0	0.24	0.23	2.51	0.79	1.38

Table B-11 (cont.) Tridem ALS, Cluster 2 (Mix with light & heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
72000	0	0	0.12	0.77	0	0.03	0.19	2.91	0.26	1.24
75000	0	0	0.06	0.62	0	0.05	0.09	1.47	0.01	0.31
78000	0	0	0.14	0.52	0	0.04	0.07	1.98	0.03	0.48
81000	0	0	0.1	0.3	0	0.03	0.05	0.34	0.26	0.06
84000	0	0	0.1	0.15	0	0.01	0.04	0.39	0.03	0.42
87000	0	0	0.12	0.04	9.07	0	0.03	0.2	0.01	0.02
90000	0	0	10.85	0.04	0	0	0.02	0	0.01	0.06
93000	0	0	0.06	0.05	0	0.05	0.01	0.04	0.02	0.09
96000	0	0	0.1	0.02	0	0	0.02	0.01	0.01	0.21
99000	0	0	0.08	0.01	0	0.01	0.01	0.01	0.01	0.04
102000	0	0	0.03	0.01	0	0.01	0.01	0.01	0.01	0

Table B-12 Quad ALS, Cluster 2 (Mix with light & heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
12000	0	0	0	0.31	0	0	13.83	0	0	0.96
15000	0	0	0	3.85	0	33.33	3.26	0	0	2.15
18000	0	0	0	0.36	0	0	4.8	0	0	3.18
21000	0	0	0	4.21	0	0	2.6	0	0	4.21
24000	0	0	0	0.76	0	0	5.01	0	0	8.31
27000	0	0	0	2.82	0	0	2.11	0	0	5.33
30000	0	0	0	6.8	0	0	4.08	0	0	9.19
33000	0	0	0	2.64	0	0	0.66	0	0	3.93
36000	0	0	0	2.85	0	0	1.35	0	0	3.78
39000	0	0	0	5.92	0	0	2.03	0	0	3.23
42000	0	0	0	7.45	0	0	2.59	0	8.33	2.27
45000	0	0	0	5.04	0	0	2.4	0	16.67	3.19
48000	0	0	0	6.57	0	33.33	1.06	0	33.33	2.83
51000	0	0	0	7.29	0	0	4.73	0	0	2.1
54000	0	0	0	3.39	0	0	2.79	0	16.67	2.98
57000	0	0	0	5.24	0	0	11.88	0	0	7.42
60000	0	0	0	8.81	0	0	3.32	0	0	2.25
63000	0	0	0	3.89	0	0	10.6	0	0	4.2
66000	0	0	0	2.41	0	0	3.97	0	0	3.81
69000	0	0	0	3.5	0	6.67	4.27	0	0	4.59

Table B-12 (cont.) Quad ALS, Cluster 2 (Mix with light & heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
72000	0	0	0	3.16	0	6.67	0.07	0	0	1.01
75000	0	0	0	2.36	0	13.33	4.89	0	0	5.59
78000	0	0	0	4.09	0	6.67	5.28	0	25	2.27
81000	0	0	0	3.73	0	0	0.72	0	0	4.35
84000	0	0	0	1.84	0	0	0.2	0	0	3.16
87000	0	0	0	0.56	0	0	0.52	0	0	1.61
90000	0	0	0	0.1	0	0	0.26	0	0	0.87
93000	0	0	0	0	0	0	0.65	0	0	1.14
96000	0	0	0	0.05	0	0	0	0	0	0.03
99000	0	0	0	0	0	0	0	0	0	0.03
102000	0	0	0	0	0	0	0.07	0	0	0.03

Table B-13 Single ALS, Cluster 3 (Heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
3000	1.11	7.89	0.86	2.63	15.99	0.24	1.52	0.4	11.16	8.32
4000	0.84	11.31	0.94	3.32	11.81	0.51	2.06	0.73	4.03	1.63
5000	1.18	12.84	1.69	2.87	15.75	0.8	1.3	1.58	8.42	1.01
6000	1.97	16.52	1.99	3.89	10.73	1.29	5.26	2.78	5.7	2.81
7000	3.71	13.06	2.43	2.67	6.54	1.29	10.3	2.63	3.28	4.9
8000	8.36	11.84	4.06	4.07	6.89	2.45	5.59	4.12	3.26	7.27
9000	9.26	7.14	7.96	3.89	5.44	4.47	3.49	5.82	3.27	4.12
10000	10.13	5.82	15.76	15.25	6.33	9.08	7.68	16.04	7.12	7.17
11000	10.19	3.39	17.82	10.47	4.4	16.63	20.03	14.74	11.37	9.65
12000	10.96	2.75	20.56	11.03	3.94	37.96	27.29	10.01	17.65	13.4
13000	8.97	1.86	9.99	5.09	2.67	12.79	7.45	7.32	9.83	7.09
14000	9.46	1.55	7.14	3.29	2.2	3.09	3.44	8.69	7.41	6.64
15000	8.17	1.25	3.73	3.76	1.94	1.77	1.46	8.3	3.05	6.64
16000	4.65	0.83	1.85	2.83	1.21	1.55	0.86	4.95	1.38	4.89
17000	4.04	0.78	1.37	2.45	1.19	2.16	0.77	4.39	1.16	4.64
18000	2.18	0.56	0.7	2.17	0.74	1.59	0.5	2.8	0.66	2.69
19000	1.92	0.34	0.57	4.89	0.72	1.2	0.36	2.26	0.58	2.55
20000	1.07	0.12	0.23	2.91	0.55	0.51	0.16	1.1	0.29	1.38
21000	0.63	0.08	0.18	1.93	0.45	0.27	0.13	0.76	0.12	1.11
22000	0.42	0.03	0.07	1.14	0.2	0.12	0.07	0.17	0.09	0.6

Table B-13 (cont.) Single ALS, Cluster 3 (Heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
23000	0.18	0.02	0.05	1.04	0.12	0.06	0.06	0.13	0.02	0.63
24000	0.2	0.02	0.01	1.14	0.06	0.03	0.05	0.04	0.12	0.27
25000	0.11	0	0.01	0.78	0.04	0.02	0.05	0.03	0	0.15
26000	0.09	0	0.01	1.24	0.02	0.02	0.03	0.02	0	0.09
27000	0.03	0	0.01	0.94	0.02	0.02	0.02	0.03	0	0.07
28000	0.03	0	0.01	1.32	0.01	0.02	0.01	0.03	0	0.06
29000	0.02	0	0	0.86	0.01	0.02	0.01	0.03	0	0.04
30000	0.02	0	0	0.85	0.01	0.02	0.01	0.02	0	0.05
31000	0.01	0	0	0.21	0.01	0.01	0	0.01	0	0.01
32000	0.01	0	0	0.24	0.01	0.01	0.01	0.01	0	0
33000	0.01	0	0	0.3	0	0	0	0.01	0	0.01
34000	0.01	0	0	0.31	0	0	0	0.01	0	0.01
35000	0.01	0	0	0.03	0	0	0	0.01	0	0.01
36000	0.01	0	0	0	0	0	0.01	0.01	0.03	0
37000	0.01	0	0	0	0	0	0	0	0	0
38000	0.01	0	0	0.19	0	0	0.01	0.01	0	0
39000	0	0	0	0	0	0	0	0	0	0.01
40000	0.01	0	0	0	0	0	0.01	0.01	0	0.08
41000	0.01	0	0	0	0	0	0	0	0	0

Table B-14 Tandem ALS, Cluster 3 (Heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
6000	0.88	0	1.73	3.85	25.04	0.19	0.23	17.55	2.4	0.36
8000	0.63	0	8.2	2.11	10.2	0.56	0.4	7	2.43	0.65
10000	2.16	0	17.14	3.03	10.66	1.2	1.06	2.85	2.22	1.32
12000	2.44	0	10.08	2.72	11.45	2.28	2.35	2.6	1.62	4.08
14000	3.55	0	7.57	4.52	7.86	3.08	3.35	2.47	3.41	7.57
16000	3.31	0	6.85	5.02	6.61	4.13	4.7	2.62	4.87	5.98
18000	3.58	0	5.98	4.96	5.94	5.25	6.52	4.95	13.75	11.2
20000	4.57	0	5.41	4.85	5.36	6.28	13.02	5.95	24.1	7.77
22000	7.86	0	5.24	5.47	5.22	7.08	21.85	9.67	16.68	6.08
24000	8.49	0	4.82	6.63	3.61	7.54	15.82	10.23	8.4	3.33
26000	9.25	0	4.36	7.11	2.83	8.32	9.55	9.24	4.03	2.68
28000	10.92	0	4.62	6.56	2.16	9.68	5.44	7.87	3.32	3.23
30000	12.08	0	4.75	7.66	1.42	10.42	3.88	4.59	4.17	3.78
32000	12.05	0	4.02	4.45	0.61	13.04	3	2.31	2.91	5.4
34000	8.06	0	3.67	17.49	0.29	12.83	2.43	1.02	2.36	4.98
36000	5.22	0	2.34	3.15	0.15	5.18	1.6	0.86	0.36	4.7
38000	2.52	0	1.24	1.51	0.44	1.35	1.1	1.98	0.76	6.38
40000	1.05	0	0.72	1.42	0.05	0.59	1	1.61	0.49	6.58
42000	0.53	0	0.38	1.52	0.04	0.3	0.86	0.7	0.32	5.89
44000	0.3	0	0.67	1.6	0.02	0.2	0.58	1.16	0.22	3.34

Table B-14 (cont.) Tandem ALS, Cluster 3 (Heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
46000	0.18	0	0.09	1.45	0.01	0.12	0.49	1.09	0.3	2.06
48000	0.14	0	0.04	0.86	0.01	0.07	0.31	0.84	0	1.24
50000	0.09	0	0.03	0.48	0.01	0.05	0.18	0.64	0.19	0.49
52000	0.06	0	0.01	0.38	0.01	0.05	0.12	0	0	0.36
54000	0.04	0	0.02	0.34	0	0.05	0.05	0.2	0.21	0.17
56000	0.02	0	0.01	0.27	0	0.06	0.04	0	0.14	0.1
58000	0.01	0	0.01	0.02	0	0.05	0.03	0	0	0.13
60000	0	0	0	0.07	0	0.03	0.01	0	0	0.04
62000	0	0	0	0.07	0	0.01	0.01	0	0.21	0.02
64000	0.01	0	0	0.07	0	0.01	0.01	0	0	0.02
66000	0	0	0	0.02	0	0	0.01	0	0	0.01
68000	0	0	0	0.07	0	0	0	0	0	0.02
70000	0	0	0	0.04	0	0	0	0	0	0
72000	0	0	0	0.09	0	0	0	0	0	0
74000	0	0	0	0.04	0	0	0	0	0	0.02
76000	0	0	0	0	0	0	0	0	0.13	0.01
78000	0	0	0	0.04	0	0	0	0	0	0
80000	0	0	0	0.04	0	0	0	0	0	0
82000	0	0	0	0.02	0	0	0	0	0	0.01

Table B-15 Tridem ALS, Cluster 3 (Heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
12000	0	0	45.17	4.52	47.15	32.36	2.87	47.3	5.77	2.04
15000	0	0	6.6	4.11	0.62	15.08	4.41	28.99	4.54	1.84
18000	0	0	9.2	2.31	0.7	15.91	4.18	10.5	5.96	3.02
21000	0	0	9.21	2.3	0.48	6.19	4.2	3.43	6.9	5.47
24000	0	0	9.25	2.91	0.32	4.63	4.3	1.3	6.57	4.8
27000	0	0	8.56	2.2	0.27	4.19	4.96	0.49	14.33	2.47
30000	0	0	6.19	1.72	0.2	4.37	6.41	0.71	10.25	3.13
33000	0	0	2.42	5.94	0.61	1.88	9.74	0.91	9.18	3.12
36000	0	0	1.21	9.23	0.17	2.2	15.19	1.56	6.3	3.64
39000	0	0	0.49	9.8	49.41	1.96	14.81	1.48	10.25	4.7
42000	0	0	0.33	15.59	0.03	1.91	9.66	1.27	8.13	6.7
45000	0	0	0.22	11.57	0.01	2.07	5.02	0.98	4.47	8.32
48000	0	0	0.2	5.07	0.01	2.57	3.69	0.56	1.77	7.9
51000	0	0	0.31	8.25	0.01	2.23	3.21	0.32	2.72	11.35
54000	0	0	0.18	5.65	0.01	1.27	2.85	0.14	1.33	10.17
57000	0	0	0.18	2.6	0	0.36	2.11	0.03	0	8.84
60000	0	0	0.09	1.96	0	0.24	1.26	0.02	0.59	6.56
63000	0	0	0.08	0.63	0	0.15	0.67	0	0	3.09
66000	0	0	0.04	0.47	0	0.09	0.22	0	0	1.71
69000	0	0	0.02	0.47	0	0.1	0.09	0	0.36	0.44

Table A-15 (cont.) Tridem ALS, Cluster 3 (Heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
72000	0	0	0.02	0.47	0	0.06	0.07	0	0	0.14
75000	0	0	0	0.37	0	0.03	0.02	0	0.58	0.06
78000	0	0	0	0.3	0	0.06	0.03	0	0	0.26
81000	0	0	0	0.46	0	0.02	0.01	0.01	0	0.06
84000	0	0	0	0.24	0	0	0.01	0	0	0.02
87000	0	0	0	0.23	0	0.03	0.01	0	0	0.03
90000	0	0	0	0.18	0	0.02	0	0	0	0.03
93000	0	0	0	0.18	0	0	0	0	0	0.02
96000	0	0	0	0.14	0	0.01	0	0	0	0.02
99000	0	0	0	0.06	0	0.01	0	0	0	0.01
102000	0	0	0.03	0.07	0	0	0	0	0	0.04

Table B-16 Quad ALS, Cluster 3 (Heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
12000	0	0	0	2.3	0	0	1.49	0	20	2.66
15000	0	0	0	0.91	0	0	4.96	0	20	2.33
18000	0	0	0	0.26	0	0	10.23	0	0	3.54
21000	0	0	0	0.77	0	0	7.34	0	20	3.93
24000	0	0	0	0.52	0	0	5.45	0	0	2.92
27000	0	0	0	1.16	0	0	2.68	0	0	4.15
30000	0	0	0	0.26	0	0	2.77	0	0	7.13
33000	0	0	0	4.79	0	0	4.76	0	0	7.62
36000	0	0	0	15.68	0	0.22	3.05	0	0	8.05
39000	0	0	0	10.06	0	0	0.79	0	0	4.27
42000	0	0	0	6.85	0	0	5.76	0	0	2.62
45000	0	0	0	9.94	0	9.05	3.38	0	0	1.5
48000	0	0	0	4.27	0	0	9.51	0	0	4.86
51000	0	0	0	8.02	0	0	6.56	0	0	4.23
54000	0	0	0	3.89	0	0	1.09	0	20	6.23
57000	0	0	0	5.42	0	0	4.47	0	0	3.37
60000	0	0	0	2.73	0	9.05	2.97	0	0	7.09
63000	0	0	0	4.15	0	9.05	4.86	0	0	6.94
66000	0	0	0	6.74	0	0	7.35	0	0	5.05
69000	0	0	0	2.07	0	0	1.88	0	0	2.72

Table B-16 (cont.) Quad ALS, Cluster 3 (Heavy tandem)

Load bins (lb)	Vehicle Class									
	4	5	6	7	8	9	10	11	12	13
72000	0	0	0	1.68	0	0	0.99	0	20	4.27
75000	0	0	0	1.82	0	0	0.5	0	0	0.88
78000	0	0	0	2.07	0	0	3.58	0	0	1.01
81000	0	0	0	0.91	0	0	2.98	0	0	0.1
84000	0	0	0	2.73	0	63.58	0	0	0	0.2
87000	0	0	0	0	0	0	0.2	0	0	0.2
90000	0	0	0	0	0	0	0.1	0	0	0.92
93000	0	0	0	0	0	9.05	0.3	0	0	0.1
96000	0	0	0	0	0	0	0	0	0	1.01
99000	0	0	0	0	0	0	0	0	0	0
102000	0	0	0	0	0	0	0	0	0	0.1