Updated Analysis of Michigan Traffic Inputs for Pavement-ME Design

Final Report

The Michigan Department of Transportation
Construction & Technology Division
8885 Ricks Road
Lansing, MI 48909

By

Syed Waqar Haider, Gopikrishna Musunuru, Neeraj Buch,
Olga Selezneva, Praveen Desaraju, and Joshua Li

Report # SPR-1678

Michigan State University
Department of Civil and Environmental Engineering
3546 Engineering Building
East Lansing, MI 48824

August 2018

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. MDOT Project Manager
SPR-1678	N/A	Justin Schenkel

4. Title and Subtitle Updated Analysis of Michigan Traffic Inputs for Pavement-ME Design	**5. Report Date** May 2018
	6. Performing Organization Code N/A
7. Author(s) Syed W. Haider, Gopikrishna Musunuru, Neeraj Buch, Olga Selezneva, Praveen Desaraju, and Joshua Li	**8. Performing Org. Report No.** N/A
9. Performing Organization Name and Address Michigan State University Department of Civil and Environmental Engineering 3546 Engineering Building East Lansing, MI 48824 Tel: (517) 355-5107, Fax: (517) 432-1827	**10. Work Unit No. (TRAIS)** N/A
	11. Contract No. Contract 2013-0066 Z8
	11(a). Authorization No.
12. Sponsoring Agency Name and Address Michigan Department of Transportation Construction and Technology Division P.O. Box 30049, Lansing, MI 48909	**13. Type of Report & Period Covered** Final Report, 10/1/2016 to 8/31/2018
	14. Sponsoring Agency Code N/A

15. Supplementary Notes

16. Abstract

The purpose of this study is to characterize traffic inputs in support of the new Mechanistic-Empirical Pavement Design Guide for the State of Michigan. These traffic characteristics include monthly adjustment factors (MAF), hourly distribution factors (HDF), vehicle class distributions (VCD), axle groups per vehicle (AGPV), and axle load distributions for different axle configurations. Weight and classification data were obtained from 41 Weigh-in-Motion (WIM) sites located throughout the State of Michigan to develop Level 1 (site-specific) traffic inputs. Cluster analyses were conducted to group sites with similar characteristics for development of Level 2A inputs. Also, PTR locations with similar attributes were grouped for developing Level 2B traffic inputs. Traffic data from all freeway and non-freeways sites were averaged to establish the statewide Level 3A inputs. Finally, traffic data from all sites were averaged to develop the statewide Level 3B inputs. The effects of the developed hierarchical traffic inputs on the predicted performance of rigid and flexible pavements were investigated using the Pavement-ME. Based on statistical and practical significance of the life differences, appropriate levels were established for each traffic input. Specific recommendations about frequency of updating road groups, and additional WIM locations in different regions are included in the report. The methodology for developing traffic inputs is intuitive and can be adopted by MDOT for future updates.

17. Key Words	18. Distribution Statement
Pavement-ME sensitivity, pavement analysis and design, traffic inputs, rigid and flexible pavement performance.	No restrictions. This document is available to the public through the Michigan Department of Transportation.

19. Security Classification - report	20. Security Classification - page	21. No. of Pages	22. Price
Unclassified	Unclassified		N/A

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

Abbreviations:

AADT: Average Annual Daily Traffic
AADTT: Average Annual Daily Truck Traffic
AASHO: American Association of State Highway Officials
AASHTO: American Association of State and Highway Transportation Officials
AGPV: Axle Groups Per Vehicle
ANOVA: Analysis of Variance
API: Application Programming Interface
ATR: Automatic Traffic Recorder
AVC: Automatic Vehicle Classification
COHS: Corridors of Highest Significance
CI: Confidence Interval
CLA: Classification
DDF: Directional Distribution Factor
DOT: Department of Transportation
ESAL: Equivalent Single Axle Load
FHWA: Federal Highway Administration
GIS: Geographic Information System
GVW: Gross Vehicle Weight
HDF: Hourly Distribution Factor
HPMS: Highway Performance Monitoring System
IRI: International Roughness Index
JPCP: Jointed Plain Concrete Pavements
LDF: Lane Distribution Factor
LTPP: Long-term Pavement Performance
MAF: Monthly Adjustment Factor
ME: Mechanistic-empirical
MEPDG: Mechanistic-empirical Pavement Design Guide
MLD: Maximum Life Difference
NALS: Normalized Axle Load Spectra
NCHRP: National Cooperative Highway Research Program
PTR: Permanent Traffic Recorder
QALS: Quad Axle Load Spectra
QC: Quality Control
SALS: Single Axle Load Spectra
SHA: State Highway Agency
SQL: Structured Query Language
SSE: Sum of Squared Error
TALS: Tandem Axle Load Spectra
TMG: Traffic Monitoring Guide
TMAS: Travel Monitoring Analysis System
TRALS: Tridem Axle Load Spectra
TTC: Truck Traffic Classification

TWRG: Truck Weight Road Group
UPGMA: Unweighted Pair Group Method with Arithmetic Mean
VC: Vehicle Class
VCD: Vehicle Class Distribution
VRC: Variance Ration Criterion
WGT: Weight
WIM: Weigh-in Motion
XML: Extensible Markup Language

DISCLAIMER

"This publication is disseminated in the interest of information exchange. The Michigan Department of Transportation (hereinafter referred to as MDOT) expressly disclaims any liability, of any kind, or for any reason, that might otherwise arise out of any use of this publication or the information or data provided in the publication. MDOT further disclaims any responsibility for typographical errors or accuracy of the information provided or contained within this information. MDOT makes no warranties or representations whatsoever regarding the quality, content, completeness, suitability, adequacy, sequence, accuracy or timeliness of the information and data provided, or that the contents represent standards, specifications, or regulations."

EXECUTIVE SUMMARY

The purpose of this study is to characterize traffic inputs in support of the new Mechanistic-Empirical Pavement Design Guide for the State of Michigan. These traffic characteristics include monthly adjustment factors (MAF), hourly distribution factors (HDF), vehicle class distributions (VCD), axle groups per vehicle (AGPV), and axle load distributions for different axle configurations. Weight and classification data were obtained from 41 Weigh-in-Motion (WIM) sites located throughout the State of Michigan to develop Level 1 (site-specific) traffic inputs. Cluster analyses were conducted to group sites with similar traffic patterns for developing Level 2A inputs. Also, Permanent Traffic Recorder (PTR) locations with similar attributes (e.g., road class, development type etc.,) were grouped for developing Level 2B traffic inputs. Traffic data from all freeway and non-freeways sites were averaged to establish the statewide Level 3A inputs. Finally, traffic data from all the 41 WIM sites were averaged to develop the statewide Level 3B inputs. The effects of the developed hierarchical traffic inputs on the predicted performance of rigid and flexible pavements were investigated using the Pavement-ME. Based on statistical and practical significance of the life differences, appropriate levels were established for each traffic input. The hierarchical traffic inputs to be used in the Pavement-ME are listed below:

- Level 1 – Convert WIM and classification site-specific data to the Pavement-ME format using PrepME.
- Level 2 – Utilize groups based on the road attributes with similar traffic characteristics. The group traffic characteristics should be averaged to create Level 2B traffic inputs.
- Level 3 – Use average traffic characteristics from all PTR sites based on freeway and non-freeway to establish Level 3A inputs or use average traffic characteristics from all PTR sites to establish statewide Level 3B inputs.

VCD significantly impacts predicted rigid and flexible pavement performance. Thus, VCD groups (Level 2B) is suggested for use in flexible and rigid pavement design. MAF have negligible impact on predicted rigid and flexible pavement performance. Therefore, it is recommended that a statewide average (Level 3A) be used. HDF significantly impacts rigid pavement performance. Consequently, group average (Level 2B) HDFs should be utilized for rigid pavement design. AGPV had a negligible impact on predicted rigid and flexible pavement performance. Therefore, it is suggested that statewide averages (Level 3B) be used for this traffic input. Single axle load spectra have a significant effect on predicted flexible pavement performance for both cluster (2A) and group (2B) averages and produced comparable results. Also no significant difference was detected between Levels 2B and 3A. Therefore, it is recommended that statewide averages (Level 3A) be used for this traffic input. Tandem axle load significantly impacted rigid and flexible pavement performance. Therefore, group averages (Level 2B) are suggested for both rigid and flexible pavement designs. Tridem and quad axle load spectra do not have a significant impact on rigid and flexible pavement performance. Consequently, statewide average tridem and quad axle load spectra (Level 3A) can be used for this traffic input. The Pavement-ME defaults traffic inputs don’t accurately reflect the local traffic conditions in the state of Michigan. In general, statewide or cluster averages produced design lives that were closer to the site-specific values than the Pavement-ME defaults. Consequently, the Pavement-ME defaults are not recommended for use in the state of Michigan. Specific recommendations about the selection of traffic inputs for MDOT pavement designs,

frequency of updating road groups, and additional WIM locations in different regions are included in the report. The methodology for developing traffic inputs is straightforward and based on the data readily available to MDOT. As a result, it can be adopted by MDOT for future updates.

CHAPTER 1 - INTRODUCTION

1.1 PROBLEM STATEMENT AND BACKGROUND

In the AASHTO 93 pavement design procedure, the truck traffic is converted to an equivalent number of 18-kip single-axle loads (ESALs) using the load equivalency factors (LEFs) developed based on Present Serviceability Index (PSI) concept. Several studies have found that the complex failure modes of pavement structures cannot be explained by this single value (*1, 2*). The mechanistic-empirical pavement design guide (Pavement-ME) addresses these limitations by incorporating mechanistic models to estimate stresses, strains, and deformations in pavement layers using site-specific climatic, material, and traffic characteristics (*3*). The Pavement-ME uses different performance parameters for each pavement type (e.g., fatigue cracking, rutting, and surface roughness in the case of flexible pavements) and does not consider PSI. Therefore, the use of ESALs to characterize traffic loadings is not compatible with the Pavement-ME. This new analysis and design approach requires specific types of traffic data to design new or rehabilitated pavement structures. These traffic inputs include:

- Annual average daily truck traffic (AADTT),
- Vehicle class distribution (VCD),
- Monthly adjustment factors by vehicle class (MAF),
- Hourly truck volume distribution factors (HDF),
- Number of axle groups per vehicle (AGPV), and
- Axle load distributions by vehicle class and axle group.

The Pavement-ME addresses when detailed traffic data are not available or incomplete. Hierarchical input levels are used depending on the level of detail of the available traffic data (*3-5*). These input levels range from site-specific input values to “best-estimate” or default values and are classified as follows:

- Level 1 – There is a very good knowledge of past and future traffic characteristics. At this level, it is assumed that the past traffic volume and weight data have been collected along or near the roadway segment to be designed.
- Level 2 – There is a modest knowledge of past and future traffic characteristics. At this level, only regional truck volume and weight data may be available for the roadway in question.
- Level 3 – There is poor knowledge of past and future traffic characteristics. At this level, the designer will have little truck volume information. In this case, a statewide or some other default value must be used.

Traffic patterns in terms of truck volumes, vehicle class distributions, and axle loads vary considerably along various roads and locations even along the same route. The designer’s ability to assess the current and future traffic patterns is considered significant if WIM sites are present in the proximity to the design project. In the event, inputs are available only at a regional or a network level (Level 2), the designer's ability to evaluate current and future traffic patterns is reasonable. Finally, if the designer has to rely on default inputs based on national or state traffic patterns, the designer has insufficient knowledge (Level 3) of the current and future traffic characteristics. An improved understanding of the traffic inputs significance and their impact on performance predictions make the transition from a purely empirical to a mechanistic-empirical (ME) design procedure smoother.

To address the above-mentioned needs, a study entitled "*Characterization of Truck Traffic in Michigan for the New Mechanistic-Empirical Pavement Design Guide*," was completed in 2009 (*4*). The study analyzed permanent traffic recorder (PTR) traffic volumes and WIM axle load data in Michigan for evaluating and characterizing traffic-related inputs for the Pavement-ME. The traffic characteristics included MAF, HDF, VCD, AGPV, and axle load distributions for different axle configurations. Axle weight and vehicle classification data were obtained from 44 WIM and classification stations located throughout the State of Michigan to develop Level 1 (site-specific) traffic inputs. Cluster analyses were conducted to group sites with similar characteristics to develop Level 2 (regional) inputs. Finally, data from all sites were averaged to establish the statewide Level 3 inputs. While the traffic characterization was based on data collected from 2005 to 2007, the same study recommended that traffic inputs, especially Level 2 clusters should be re-evaluated every five years because of the following reasons (*4, 6*):

a. Addition of new classification and WIM sites at different geographical locations or change in the status of the existing site (e.g., down- or up-grading from WIM to classification or vice versa).
b. Significant changes in the land use in the vicinity of the existing WIM locations.
c. Changes in the WIM technology for some locations. For example, if less accurate piezo-polymer sensors are replaced with more accurate piezo-quartz or bending plate sensors.

During the last eight (8) years, new traffic data were collected reflecting the recent economic growth, additional, and downgraded WIM sites. Consequently, the current traffic inputs should be re-evaluated and developed with the latest traffic data collected at all the PTR locations. Also, the following significant developments, related to the Pavement-ME analysis and design method in the State of Michigan during the last few years further necessitate the re-evaluation of the current traffic inputs:

- The performance models for the Pavement-ME design were recently calibrated to the local conditions in the State of Michigan (*6*). It will be appropriate to incorporate such changes in the re-evaluation of traffic inputs while conducting their sensitivity analyses to identify the most important ones. It should be noted that the global performance models were used in the previous traffic study.
- TrafLoad software was used in the previous traffic study for extracting the traffic volumes (by class) and axle load data, and to ascertain the quality of the data in the previous study (*4*). TrafLoad has since lost endorsement nationally and is no longer supported. However, recently the PrepME software was developed through the Transportation Pooled-Fund Study TPF-5(242), "*Traffic and Data Preparation for AASHTO Pavement-ME Analysis and Design*." This software is capable of pre-

processing, importing, checking the quality of raw WIM traffic data, and generating three levels of traffic data inputs with built-in clustering methods for the ME design. Therefore, there is a need to employ such tools to improve the quality of traffic data in the re-evaluation of traffic inputs.

- While the PrepME has improved capabilities as compared to TrafLoad software (discussed later), it has incorporated the built-in traffic clustering for Michigan based on the previous traffic study(*4*). However, if the cluster method or type is impacted by this research, the impacts to the PrepME software also needs to be identified, and modifications may be necessary.
- Lastly, to reduce the frequency of future new traffic studies and streamline the process of generating ME traffic inputs, there is a need to re-evaluate the current methodology, provide enhancements, if found necessary. Also, there is a need for documenting a step-by-step procedure that would allow MDOT to analyze future traffic data and create traffic clusters for ME use.

Based on the above discussion, it is very likely that the new traffic data, changes in the Pavement-ME software, and performance model calibrations will affect the existing clusters methodology and their characteristics. Thus, it was important to re-evaluate the traffic inputs for the ME analysis and design procedures in the State of Michigan.

1.2 RESEARCH OBJECTIVES

The following are the specific objectives of the study:

1. Evaluate other states' experiences with developing ME traffic inputs and traffic clustering methodologies, as well as recommendations from the new Traffic Monitoring Guide (TMG) (*7*) and the LTPP Pavement Loading User Guide (*8*, *9*).
2. Compare the 2009 cluster analysis methodology to other methodologies and/or literature from objective one. Determine the best-suited methodology for MDOT use. Alternatives include the original 2009 cluster methodology, revised version of the 2009 cluster methodology, one of the methodologies from objective 1, or a new methodology altogether. From these alternatives, provide a recommendation for MDOT use.
3. Document the recommendations or changes to the cluster methodology and develop a tool or procedure for MDOT to evaluate and create the clusters for the specific traffic inputs to update traffic clusters in the future. This tool or procedure should lessen the need for future research and reduce demand for MDOT resources.
4. Establish new and/or updated traffic clusters, descriptions, equations, and associated inputs.
5. Review PrepME and identify possible errors or changes required. Document the findings and recommendations for PrepME enhancements.
6. Develop a research report documenting findings, new developments, and future recommendations.

1.3 RESEARCH PLAN

To accomplish the above objectives, the research was conducted in eight (8) tasks briefly discussed below.

Task 1: Literature Review

In this task, the team documented the state-of-the-practice for traffic clustering methods used in other states. In addition, the Federal Highway Administration (FHWA) recommendations for clustering traffic inputs among different locations (*7*, *9*) were reviewed.

Task 2: Review of the Existing Practices

The team reviewed the results and recommendations from the 2009 traffic study (*4*). The original methodology was assessed using findings from the literature review and experiences of other states with developing traffic inputs and clusters for the ME use. In evaluating the original MDOT clustering methodology, special attention was given to determine whether the existing cluster methodology still the “best” way for MDOT to cluster considering that there are other grouping techniques used by states (e.g., NCDOT or TTC clustering).

Task 3: Methodology for Clustering

The Task 3 proceeded with RAP approval. In this task, if there is not a conclusive methodology and multiple methodologies that could be to recommend from Task 2, then the research team will use part of Task 3 to finalize their recommendation by evaluating and comparing the methodology(s) using ME design results. Otherwise, if an existing cluster methodology is not recommended, then the research team will develop a reproducible grouping methodology (as discussed in Task 1 above) which will be applicable for future cluster updates.

Task 4: Generation of New Clusters for Level 2 Data

In this task, new clusters were generated for the traffic inputs based on the most appropriate grouping methodology identified in Tasks 2 and 3. These Level 2 traffic characteristics will provide common traffic inputs for those roadways without an appropriate PTR site. The detailed description is provided for each cluster along with the input values for AASHTOWare Pavement ME Design. The emphasis was given on documenting and explaining the procedure of clusters generation for each Level 2 input so that MDOT can generate new traffic cluster values independent of future research.

Task 5: Significant Traffic Inputs

Under this task, the team conducted a series of Pavement-ME sensitivity analyses. The purpose of the sensitivity analyses is to determine whether the accuracy of pavement designs using the AASHTOWare Pavement-ME software would improve from the use of multiple default values (supported by traffic clusters) for different traffic input parameters. The conclusions from these analyses will be used to identify traffic parameters that would require multiple default values. These default values will be developed based on traffic data clustering or other grouping techniques.

Task 6: Evaluation of PrepME

In this task, the research team will compare the cluster generated in Task 4 by the PrepME and the current cluster methodology. This comparison will be used to evaluate the current methodology in the PrepME. However, if it is determined that a new cluster methodology is more appropriate in Task 3, recommendations will be made to upgrade the PrepME software. If the 2009 clustering methodology is retained, an evaluation will determine if the software is currently applying the cluster methodology and correctly providing outputs as described in the 2009 research project. Finally, the team will determine if updates to PrepME are necessary due to any of the previous task findings. Consequently, explicit necessary corrections in the PrepME will be described for coding modifications to be made in the software.

Task 7: Data Collection Recommendations

Based on the traffic data analysis and grouping, specific recommendations are made to fill the gaps in loading data for different regions in the State of Michigan.

Task 8: Final Report and Technology Transfer

At the successful completion of the study, a final report will be submitted to MDOT containing all the deliverables. Also, if recommended by RAP, a technology transfer workshop will be developed and presented to MDOT engineers.

1.4 OUTLINE OF REPORT

The report consists of the following six chapters:

1. Introduction
2. Literature review
3. Development of traffic inputs for the Pavement-ME designs
4. Traffic inputs significance for pavement design
5. PrepME evaluation
6. Conclusion and recommendations

Chapter 1 outlines the problem statement, the research objectives, and an outline of the final report. Chapter 2 documents the traffic characterization in the Pavement-ME and findings from the past studies at the national and state levels (Tasks 1 and 2). It also includes clustering techniques and the review of existing practices in Michigan. Chapter 3 covers the traffic data collection and processing in Michigan. This chapter also reviews the clustering techniques, and the procedures used for developing Level 2 inputs (Tasks 3 and 4). Chapter 4 documents the impact of the developed Level 2 traffic inputs on pavement designs (Task 5). Also, the chapter includes the findings for appropriate traffic inputs levels (Level 2 or 3) in Michigan. Chapter 5 highlights intended modifications in the PrepME software. Chapter 6 summarizes the conclusions and recommendations for the implementation of modified traffic inputs in Michigan.

CHAPTER 2 - LITERATURE REVIEW

This chapter presents a review of literature and state-of-the-practice related to traffic inputs in the Pavement-ME. For ease of understanding, the review is further divided into the following topics:

- Pavement-ME traffic inputs
- National studies for traffic characterization
- Traffic studies in other states
- Review of existing practices in Michigan

The traffic inputs needed for pavement analysis and design by the Pavement-ME are briefly discussed below.

2.1 PAVEMENT-ME TRAFFIC INPUTS

The Pavement-ME uses hierarchical input levels and provides flexibility to the designer in obtaining the design inputs based on the project importance. Three different input levels can be used in this hierarchical system ranging from site-specific input values to “best-estimate” or default values as classified below:

a) Level 1 – These inputs provide the highest level of accuracy because they are site/project specific and are measured directly,
b) Level 2 – These inputs provide an intermediate level of accuracy and are used when Level 1 inputs are unavailable. Correlation or regression equations are used to estimate these inputs.
c) Level 3 – These inputs are based on global or regional averages and provide the least amount of knowledge regarding the input parameters (Ideal for low volume roads).

The Pavement ME accepts an array of traffic inputs for use in design. Most of these inputs can be obtained through weigh-in-motion (WIM), automatic vehicle classification (AVC), and vehicle counts, etc. Table 2-1 summarizes each of these traffic inputs based on the available hierarchical levels (*1*). Each of these traffic inputs is briefly discussed below.

2.1.1 Directional distribution factor (DDF)

The traffic volume in the design direction expressed as a percentage of the overall volume of traffic in both directions. While a value of 50 percent is assumed, it usually depends on the commodities being transported as well as other regional/local patterns. The Pavement-ME assumes it to be constant over time and for vehicle classes. These values can be obtained from the AVCs or traffic count data measured over time.

2.1.2 Lane distribution factor (LDF)

Trucks in the design lane expressed as a percentage of trucks in the design direction. For two-lane, two-way highways (one lane in one direction), LDF is equal to 1. For multiple lanes in one direction, it depends on the AADTT and other geometric and site-specific conditions. LDFs can be calculated from the AVCs or traffic count data measured over time. They are assumed constant with time and for all truck classes.

Table 2-1 Traffic data required for the three Pavement ME input levels

Data Elements/Variables		Input Level		
		I	II	III
Truck Traffic & Tire Factors	Directional distribution factor (DDF)	Site-specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Truck lane distribution factor (LDF)	Site-specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Axle/truck class	Site-specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Axle and tire spacing	Hierarchical levels not applicable for these inputs		
	Tire pressure			
	Traffic growth			
	Vehicle operational speed			
	Lateral distribution (wheel wonder)			
	Monthly adjustment factor (MAF)	Site-specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Hourly distribution factor (HDF)	Site-specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
Truck Traffic Distribution and Volume	AADT or AADTT for the base year	Hierarchical levels not applicable for these inputs		
	Truck dist/spectra by truck class (VCD)	Site-specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Axle load dist/spectra by truck class and axle type (ALS)	Site-specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Truck traffic classification (TTC) group for design	Hierarchical levels not applicable for these inputs		
	% of trucks			

2.1.3 Axles per truck class

Axle types per truck class represent the average number of axles for each truck class (class 4 to 13) for each axle type (single, tandem, tridem, and quad). The default number of axle types per truck class in the Pavement-ME were estimated by using the LTPP data. Local values can be different from the default, especially for unique truck class definitions not included in the Pavement-ME software. However, most studies have found the values to be reasonable for the standard truck class definitions (*2*). The local defaults can be obtained from the WIM sites.

2.1.4 Axle and tire spacing

The computed pavement responses are sensitive to both wheel locations and the interaction between the various wheels on a given axle. A set of axle spacing defaults were developed from LTPP WIM data. Default axles spacing are limited to three axle types: tandem, tridem, and quads. Defaults for this input parameter can vary state-by-state and depend on the truck classes (*2*). These values can be obtained from the truck manufactures specifications.

2.1.5 Tire pressure

Pavement responses are dependent on the tire dimensions and inflation pressures. Tire pressure is constant between all truck classes and does not change over with time. A default value of hot inflation pressure of 120 psi is used in the Pavement-ME. The reasonableness of this default value is based on a limited number of tire pressure studies conducted by different agencies (*2*). These values can be obtained from the tire manufacturer specifications.

2.1.6 Traffic growth

Nationally, there is no default value, but a 2% to 4% linear growth is typically used. The value and function do not change over time for individual truck classes; values & growth function can change between truck classes. The site-specific values can be obtained from historical AVC or truck count data (*2*).

2.1.7 Operational speed

There is no default value, but the speed limit depends on functional class, terrain, the percentage of trucks, etc. The value is independent of truck classes.

2.1.8 Lateral Wander

Lateral wander value is constant for all truck classes and does not change over time. A default value of 10 inches is recommended. Limited data are available from AASHO Road Test and a few limited studies (*2*). These values can be obtained from site surveys.

2.1.9 Monthly adjustment factor (MAF)

The monthly distribution factors convey the seasonal variations in AADTT by assigning a normalized weight factor to each month of the year. The default data in the Pavement-ME assumes a seasonally independent value of ‘1’ for each of the 12 MAFs. Consequently, months with higher AADTT than others will receive a weight factor greater than 1 while months having lower AADTT will be assigned a weight factor less than 1. Other studies (*1*, *3-5*) which evaluated MDFs, found different distributions. TMG suggests that two traffic patterns exist, consisting of a “flat urban” which is seasonally independent, and a “rural summer peak” in which the summer months experience higher AADTT than the winter (*5*). The MEPDG Design Guide states that pavements may be sensitive to MAFs and are influenced by factors such as adjacent land use, the location of industries in the area, and whether the site is rural or urban (*1*).

2.1.10 Hourly distribution factor (HDF)

HDFs establish the percentage AADTT that travels on the roadway for each of the 24 hours within a day. As most can relate to the increase of cars on the roadway during rush hour, or peak hour, trucks also exhibit time-dependent behavior. Most hourly distribution factors exhibit a trend of having a peak period between the hours of 10:00 am and 5:00 pm (*6*, *7*). The TMG cites a study (*5*) in which trucking patterns were found to exhibit two types of patterns. The first one being an almost constant percentage of trucks each hour throughout the day and the other having a single-humped peak, typically during the morning. The constant percentage trucks throughout the day signified a greater presence of long-haul through trucks whereas the peaked distribution was found to be consistent with local trucks (*5*). The default HDFs in the Pavement-ME are shown in Figure 2-1 and the actual values by hours are shown in Table 2-2.

Table 2-2 The Pavement-ME default hourly distribution factors

Hour	HDF	Hour	HDF
0	2.3	12	5.9
1	2.3	13	5.9
2	2.3	14	5.9
3	2.3	15	5.9
4	2.3	16	4.6
5	2.3	17	4.6
6	2.3	18	4.6
7	5	19	4.6
8	5	20	3.1
9	5	21	3.1
10	5	22	3.1
11	5.9	23	3.1

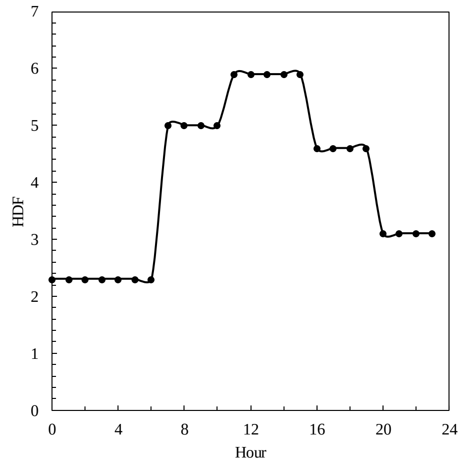


Figure 2-1 Default HDFs in the MEPDG

2.1.11 Vehicle class distribution (VCD)

The FHWA separates all traffic into 13 vehicle classes (classes 1 through 13) as shown in Table 2-3. VCD represents the percentage of each truck class (classes 4 through 13) within the AADTT for the base year. The sum of the percent AADTT of all truck classes should be 100. The MEPDG manual (*1*) reveals that VC 5 and VC 9 vehicles dominate the truck traffic distribution, with varying percentages of other truck classes. Vehicle class distributions is estimated from short duration counts such as WIM and AVC sites, urban traffic centers, toll facilities, etc.

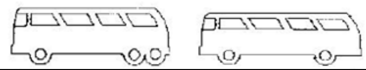
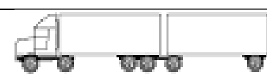
2.1.12 Axle load spectra (ALS)

The Pavement-ME establishes an axle load spectra for each axle configuration within each vehicle class. The percentage of axles is distributed into the following load bins for each axle configuration and vehicle class.

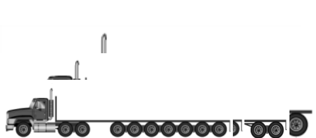
- Single: 3000-41000, in 1000 lb increments (39 bins)
- Tandem: 6000-82000 in 2000 lb increments (39 bins)
- Tridem: 12000-102000 in 3000 lb increments (31 bins)
- Quad: 12000-102000 in 3000 lb increments (31 bins)

ALS are dependent on seasons but independent with time (the values do not change over the analysis period; year-to-year). Many sites located on the interstate and primary roadways have axle load spectra that are not likely to be dependent on season.

Table 2-3 FHWA Vehicle Classes

FHWA Vehicle Class	Description	Example Vehicle Configuration
4	Two-Axle 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	

NOTE: In reporting information on trucks the following criteria should be used:
- Truck tractor units traveling without a trailer will be considered single-unit trucks.
- A truck tractor unit pulling other such units in a "saddle mount" configuration will be considered one single-unit truck and will be defined only by the axles on the pulling unit.
- Vehicles are defined by the number of axles in contact with the road. Therefore, "floating" axles are counted only when in the down position.
- The term "trailer" includes both semi- and full trailers.



2.2 A REVIEW OF PREVIOUS STUDIES

Several research studies in the recent times focused on the following areas:

- Analyzing Weigh-in-Motion (WIM), Automated Vehicle Classifier (AVC), and automated traffic recorder (ATR) data with appropriate quality checks to develop traffic inputs for the Pavement-ME.
- Evaluating the effect of traffic inputs on the Pavement-ME distress predictions and final pavement design thickness (sensitivity analysis).
- Applying statistical models and techniques such as cluster analysis in identifying homogenous traffic patterns.
- Reviewing current traffic collection infrastructure and practices to meet the traffic input requirements of the Pavement-ME.

The research team has found various guidelines, statistical models, and techniques used to obtain the Levels 2 and 3 inputs for use in the Pavement-ME. Therefore, a review of these studies has been conducted to study the application of different approaches in traffic characterization. A summary of the review is presented below.

2.2.1 National Studies

Results of the research studies related to loading inputs (ALS) for use in the ME design procedure are discussed in this section.

2.2.1.1 NCHRP 1-37A Study

The NCHRP 1-37A final report provides guidelines for truck traffic data collection for both axle weights and truck volumes (*8*). These guidelines are based on the allowable error and permissible bias for each data element in establishing the normalized truck volume distribution and normalized axle load spectra (NALS). Truck traffic classification (TTC) groups were developed based on the analysis of national WIM and AVC data collected through the LTPP program. These TTC groups are used to characterize truck volume by vehicle class rather than by vehicle weight. Each TTC group represents a traffic stream with unique truck traffic characteristics (see Table 2-4). For example, TTC 1 describes a traffic stream that is heavily populated with single-trailer trucks and TTC 17 contains more buses. A standardized set of TTC groups that best describes the traffic stream for the different road functional classes is presented in Table 2-5. Table 2-6 presents the recommended data collection frequency for determining the TTC groups.

Table 2-4 NCHRP 1-37A Truck traffic classification (TTC) groups (*8*)

TTC group	TTC description	Vehicle/Truck class distribution (%)									
		4	5	6	7	8	9	10	11	12	13
1	Major single-trailer truck route (Type I)	1.3	8.5	2.8	0.3	7.6	74.0	1.2	3.4	0.6	0.3
2	Major single-trailer truck route (Type II)	2.4	14.1	4.5	0.7	7.9	66.3	1.4	2.2	0.3	0.2
3	Major single- and multi- trailer truck route (Type I)	0.9	11.6	3.6	0.2	6.7	62.0	4.8	2.6	1.4	6.2
4	Major single-trailer truck route (Type III)	2.4	22.7	5.7	1.4	8.1	55.5	1.7	2.2	0.2	0.4
5	Major single- and multi- trailer truck route (Type II)	0.9	14.2	3.5	0.6	6.9	54.0	5.0	2.7	1.2	11.0
6	Intermediate light and single-trailer truck route (I)	2.8	31.0	7.3	0.8	9.3	44.8	2.3	1.0	0.4	0.3
7	Major mixed truck route (Type I)	1.0	23.8	4.2	0.5	10.2	42.2	5.8	2.6	1.3	8.4
8	Major multi-trailer truck route (Type I)	1.7	19.3	4.6	0.9	6.7	44.8	6.0	2.6	1.6	11.8
9	Intermediate light and single-trailer truck route (II)	3.3	34.0	11.7	1.6	9.9	36.2	1.0	1.8	0.2	0.3
10	Major mixed truck route (Type II)	0.8	30.8	6.9	0.1	7.8	37.5	3.7	1.2	4.5	6.7
11	Major multi-trailer truck route (Type II)	1.8	24.6	7.6	0.5	5.0	31.3	9.8	0.8	3.3	15.3
12	Intermediate light and single-trailer truck route (III)	3.9	40.8	11.7	1.5	12.2	25.0	2.7	0.6	0.3	1.3
13	Major mixed truck route (Type III)	0.8	33.6	6.2	0.1	7.9	26.0	10.5	1.4	3.2	10.3
14	Major light truck route (Type I)	2.9	56.9	10.4	3.7	9.2	15.3	0.6	0.3	0.4	0.3
15	Major light truck route (Type II)	1.8	56.5	8.5	1.8	6.2	14.1	5.4	0.0	0.0	5.7
16	Major light and multi-trailer truck route	1.3	48.4	10.8	1.9	6.7	13.4	4.3	0.5	0.1	12.6
17	Major bus route	36.2	14.6	13.4	0.5	14.6	17.8	0.5	0.8	0.1	1.5

Table 2-5 NCHRP 1-37A guide for selecting appropriate TTC groups (*8*)

Highway functional classification descriptions	Applicable TTC group number
Principal Arterials – Interstate and Defense Routes	1,2,3,4,5,8,11,13
Principal Arterials – Intrastate Routes, including Freeways and Expressways	1,2,3,4,6,7,8,9,10,11,12,14,16
Minor Arterials	4,6,8,9,10,11,12,15,16,17
Major Collectors	6,9,12,14,15,17
Minor Collectors	9,12,14,17
Local Routes and Streets	9,12,14,17

Table 2-6 Minimum number of data collection days per season to estimate TTC (*1*)

Expected error (± %)	Confidence level (%)				
	80	90	95	97.5	99
20	1	1	1	2	2
10	1	2	3	5	6
5	3	8	12	17	24
2	20	45	74	105	148
1	78	180	295	—	—

For axle loading inputs, only one set of ALS for each truck class was determined and included in the software as none of the ALS for the different roadway functional classes were found to be significantly different in terms of the predicted distress. One reason for the insignificance is that most of the WIM sites were located along rural interstates and/or primary arterials where local truck traffic may have a lesser impact on the ALS. Table 2-7 provides the frequency of truck weight data collection recommended for establishing the NALS (*1*, *2*).

Table 2-7 Minimum number of data collection days per season to estimate ALS (*1*)

Expected error (± %)	Confidence level (%)				
	80	90	95	97.5	99
20	1	1	1	1	1
10	1	1	2	2	3
5	2	3	5	7	10
2	8	19	30	43	61
1	32	74	122	172	242

2.2.1.2 Federal Traffic Monitoring Guidelines

The 2016 FHWA Traffic Monitoring Guide (TMG) (*5*) provides recommendations and best practices for highway traffic monitoring, including monitoring of truck loading. The TMG recommends a relatively small truck weight program, primarily due to the cost of weight data collection and the limitations of available equipment. The following recommendations can be inferred from the TMG:

- Collecting a representative sample of traffic loading data using truck weight roadway groups
- Making sure that the roadway groups should have similar vehicle types and similar truck axle weight distributions for all roads within that group.
- Collecting weight data by using permanently installed WIM sites or at least permanently installed in-pavement WIM sensors to achieve accurate data.
- Calibrating WIM equipment against systematic errors is critical to WIM data collection.
- Obtaining data such that it accounts for the day-of-week and seasonal changes in vehicle weights that occur within each group.

The truck traffic may vary significantly within a state depending on the road and land use. The roadway system could be divided into roadway groups such that each road within a group experiences similar truck-loading patterns. These groups may be defined based on different methods, such as statistical analysis, a professional judgment based on local knowledge of loading characteristics, or a combination of both. Characteristics of the freight moved on the roads, including the type of commodities carried, the vehicles used, and the freight movement could be used for dividing the roadway system (*5*). The developed roadway groups should be simple enough and logical in discriminating roads that are likely to have different traffic loading patterns.

The developed roadway groups should be periodically reviewed as more traffic data within the state becomes available over time. The accuracy of these road groups depends on the accuracy and precision of the collected weight data. Also, the more data collection sites within a roadway groups, the higher will be the confidence level in the traffic inputs generated. A minimum of six WIM sites with permanently installed WIM sensors per truck weight group is recommended (*5*).

2.2.1.3 NCHRP 1-39 Guidelines

The NCHRP 1-39 report (*9*) contains guidelines for collecting traffic data to be used in mechanistic-empirical pavement design. Three levels of axle-load distribution (or “load spectra”) data are needed for the Pavement-ME: (a) site-specific, (b) TWRG, and (c) statewide averages. Site-specific data requires an adequately calibrated WIM system and near the roadway segment to be constructed or rehabilitated. If the WIM system is unavailable or not properly calibrated (according to the ASTM requirements), Level 2 design inputs should be used to characterize traffic for design.

TWRG axle-loading data are needed because most States do not have sufficient site-specific WIM data for the majority of pavements they design each year. The TWRGs are likely to be state-specific, but multiple states can create “regional” axle load distribution values if these States have similar truck weight laws and enforcement programs. The intent is to group roads by their trucking characteristics so that the load spectra on all the roads in a group are similar. The challenge is to determine the roads (and directions of travel, in some cases) to choose for grouping. The grouping process requires analysis of a State’s available weight data and trucking patterns, possibly for different truck classes, and it results in the creation of appropriate TWRGs. Roadways with similar truck classes may carry different loads. For example, a single road could have loaded trucks in one direction and unloaded trucks in the other direction resulting in two TWRGs needed to characterize axle load distributions for that road.

Also, it was reported that the simple averages of the load distribution at all sites in a TWRG produced better results than weighted averages. It is attributed to a significant positive correlation between the volume of trucks in a particular vehicle class operating at a site and the average loads of these trucks. Because of this correlation, weighted averages produced higher estimates of average pavement load per vehicle than simple averages.

It was also recommended that the statewide axle-load distribution should be used only when a highway agency has little knowledge of the loads that trucks will carry on the roadway being designed. This means that the agency has little confidence in its ability to predict the TWRG for the pavement section. Statewide load distributions are obtained (for each vehicle class) by combining the data collected from all WIM sites in a State. These distributions then serve to represent "average conditions" that can be used whenever better data is unavailable (*2, 9*).

2.2.1.4 LTPP Traffic Pooled-Fund Study

The LTPP TPF-5(004) study has generated high-quality traffic loading information for 26 LTPP Special Pavement Study (SPS) sites located in 23 different states representing moderate and high volume rural principal arterial interstate and non-interstate highways. LTPP defines research-quality traffic data as at least 210 days of data (in a year) collected at a calibrated WIM site conforming to the LTPP's WIM performance requirements (tolerance defined as the percent error computed using 95% confidence limit of error) for single axles, axle groups, gross vehicle weight, vehicle length (bumper-to-bumper), vehicle speed, and axle spacing, as detailed in Table 2-8 (*10*).

Table 2-8 LTPP WIM system performance requirements

Pooled-fund site factors	95 Percent confidence limit of error (tolerance for % error)
Loaded Single Axles	+/-20 percent
Loaded Axle Groups	+/-15 percent
Gross Vehicle Weights	+/-10 percent
Vehicle Length	greater of +/-1.5 ft or +/-3 percent
Vehicle Speed	+/-1 mph
Axle Spacing Length	+/- 0.5 ft [150 mm]

The WIM data from the LTPP TPF 5(004) study were used to develop a two-tier ALS default in a new FHWA study (*10*):

- Tier 1 Global defaults representing average loading
- Tier 2 Defaults representing different loading patterns (clusters)

The methodology for developing LTPP Tier 1 NALS defaults is very similar to the process used to create the original NCHRP 1-37A defaults. However, data used to develop LTPP defaults are of higher quality but of lesser quantity (fewer WIM sites) than the original NCHRP 1-37A defaults.

Tier 2 defaults were developed based on hierarchical clustering of axle load data from multiple sites. Sites that had similar loading conditions were clustered together. Clusters were differentiated based on the differences that load spectra representing each cluster are likely to have on the Pavement-ME outcomes. The Pavement-ME thickness and design life predictions were used to determine what constitutes practical significance in pavement design outcomes to different load spectra clusters. As a result, clustering of load spectra was weighted greatly by the presence of heavy loads. Several alternative default axle loading categories were identified for each vehicle class and axle group and default normalized axle load spectra (NALS) were developed to represent these loading patterns. The definitions of different default traffic loading clusters for ALS and their attributes are provided in Table 2-9 (*2, 10*).

Table 2-9 Summary of NALS categories by weight for different axle group types

Axle loading category by weight	Average RPPIF per cluster	Percent of single axles >= 15 kip	Percent of tandem axles >=26 kip	Percent of tridem axles >=39 kip	Percent of quad axles >=54 kip
Very Light (VL)	<0.05	<3%	0%	n/a	n/a
Light (L)	0.05-0.15	<10%	<10%	n/a	n/a
Moderate (M)	0.15-0.30	10-30%	10-30%	n/a	n/a
Heavy (H)*	0.30-0.50	>30%	30-50%	<50%	<30%
Very Heavy (VH)	>0.50	n/a	>50%	>50%	>30%

*For roads with high percentage of Class 9 vehicles, "Heavy" loading category was further subdivided to "Heavy 1" and "Heavy 2" based on observed high sensitivity of MEPDG outcomes to Class 9 tandem axle load spectra. "Heavy 1" category has RPPIF of 0.3-0.4 and percentage of heavy tandem axles between 30 and 40 percent. "Heavy 2" category has RPPIF of 0.4-0.5 and percentage of heavy tandem axles between 40 and 50 percent. RPPIF = Relative Pavement Performance Impact Factor; summary statistic developed for the study to identify and group load spectra that likely to have similar effect on pavement design outcomes use global MEPDG pavement performance prediction models.

In addition to the defaults, guidelines for State highway agencies were developed showing how to apply the methodology from the LTPP study to develop State-specific traffic loading defaults for the pavement design use.

The newly computed ALS defaults had fewer very light and heavy loads compared to the original defaults. This is likely due to the fact that the new defaults were collected with more consistently calibrated and precise WIM equipment than the data set used for the development of the original NALS defaults under the NCHRP 1-37A project. The better calibration of the WIM scales used to develop the new defaults could result in fewer very light loads (caused by under calibrated scales observing light loads) and fewer very heavy loads (caused by over calibrated scales observing heavy loads) are observed in the new default database. Assuming that the new LTPP defaults are more accurate, a conclusion could be drawn that pavement designs using the new defaults will be thinner than the designs using the original Pavement-ME defaults. However, from a practical perspective, the difference in the design thickness was significant only for a limited number of pavement scenarios tested (*2*).

2.2.2 Other States

Many other state highway agencies (SHAs) have completed studies to determine the truck traffic weight and volume defaults to be used with the Pavement-ME. Some of these agencies include Arizona, Alabama, Arkansas, Colorado, Georgia, Idaho, Missouri, Montana, North Carolina, and Wyoming. Most studies have found that the axle load spectra deviate from the global default values currently included in the Pavement-ME software, especially for local and secondary routes. Thus, the axle load spectra or distributions can depend on the roadway use and/or geographical location.

2.2.2.1 Arizona

A research study (*11*) sponsored by the Arizona Department of Transportation (ADOT) addressed the collection, preparation, and use of traffic data required for pavement design. Procedures to collect Level 1 traffic inputs were documented. Levels 2 and 3 recommended inputs and defaults are provided based on the best historical data available to date using multivariate hierarchical statistical cluster analyses (using correlation coefficient (R^2) method)(*11*). Although determining the optimum number of clusters within a dataset is a subjective decision, five diagnostic statistics were used for determining the optimum number of clusters. Those were (a) Cubic clustering criterion (CCC), (b) Cumulative and partial squared multiple correlations (R^2), (c) Eigenvalue and associated variance (VAR), (d) Pseudo F (PSF) and (e) Pseudo t^2 (PST2). Based on the clustering and sensitivity analyses, two clusters for vehicle class distribution, two clusters for hourly distribution factors, one cluster for monthly distribution factor, three clusters for axle load distribution, and one cluster for axles per truck were recommended. The selection criteria of clusters are based on the highway functional classes (*11*).

2.2.2.2 Alabama

A study (*12*) was conducted in the State of Alabama to develop traffic data clusters for use as inputs in the Pavement-ME. While the Pavement-ME requires only three input levels, the second level inputs were further split into two subcategories in this study. The levels considered were: (a) Level 1 – Site and direction specific data, (b) Level 2A – Cluster or WIM group data, (c) Level 2B – Statewide data and (d) Level 3 – Nationwide data. Thirteen types of traffic inputs were identified based on the Michigan study (*13*) and clusters were developed for those inputs. Those 13 inputs are: 1 HDF, 1 VCD, 4 AGPV (single, tandem, tridem and quad), 3 MDF (single unit, tractor trailer and multi-trailer) and 4 ALS (single, tandem, tridem and quad).

It was noted in the study that hierarchical cluster analysis was the most popular clustering technique. Citing the disadvantages of using Euclidean distance, which is state of the practice, the researchers used Pearson's correlation coefficient (r_{jk}) for clustering purposes. Also, a correlation-based clustering that combines Pearson's correlation distance measure (to evaluate similarity) with unweighted pair group method using arithmetic averages (UPGMA) (to cluster WIM sites) was developed in this study. Once the clusters were developed, sensitivity analyses were conducted to quantify the differences in required pavement thickness between different traffic inputs levels. Geographical patterns were defined to assist in selecting the appropriate clusters for new pavement design (*12*).

2.2.2.3 Arkansas

Another study conducted in the State of Arkansas analyzed WIM data by using cluster analysis methodologies to identify groups of WIM sites with similar traffic characteristics based on the required traffic attributes (*14*). The research team normalized the traffic data attributes on an annual basis. Ten WIM sites located in Arkansas which passed the truck weigh data quality check process have been used in the analyses. Ward's minimum-variance method was used. A dissimilarity coefficient matrix based on the Euclidean distance for each pair of objects was computed for the 10 WIM sites. Three clusters were identified when distribution of gross weight of Class 9 truck was used as the attribute. Two other clustering approaches, K-mean and fuzzy cluster analyses were also applied to the data for comparison purposes. The classifications of clusters had little differences among these three approaches used indicating the patterns of the traffic stream were consistent regardless of cluster methodologies. The clusters for vehicle class distribution factors (VCDs), hourly distribution factors (HDFs), and monthly adjustment factors (MAFs) were identified by using the K-means clustering procedure. Three clusters for vehicle class distributions and monthly adjustment factors, and two clusters for hourly distribution factors were observed. Grouping based on a combination of known geographic, industrial, agricultural, and commercial patterns was done using the Fisher's Exact Test (*15*) for developing the loading groups. Categorical statistical models (multi-category logit [ML] models) were developed to assign a new pavement design project to a cluster (*14*).

2.2.2.4 Colorado

A study was conducted in Colorado with the main objectives being (1) determine how representative available traffic data are for pavement design in Colorado using the Pavement-ME, (2) detect natural groupings or clusters within the available traffic data, and (3) develop defaults for Levels 2 and 3 traffic inputs for pavement design (*16*). Statistical analysis to determine natural clusters within the traffic and the optimum number of clusters was conducted. Natural clusters within the large Colorado traffic data assembled were determined using statistical multivariate hierarchical cluster analysis similar to the analysis done in the State of Arizona (*11*). Clusters were formed for vehicle class distribution, hourly truck volume distribution, monthly adjustment factors, axles per truck class factors, axle load distribution.

2.2.2.5 North Carolina

North Carolina Department of Transportation (NCDOT) sponsored a study for the implementation of the Pavement-ME in the State of North Carolina (*17*). The study included developing the need for resources, procedures, and guidelines for NCDOT traffic data needed for the Pavement-ME. Clustering analyses was performed to develop the required traffic inputs. Initial clustering analysis of 42 WIM sites based on VCD for different months resulted in three major clusters or factor groups. Each factor group includes WIM sites that tend to remain in same cluster over the year (from January to December).

Even though the cluster analyses led to different clusters, the pavement performance was found to be insensitive to hourly distribution factors and monthly adjustment factors. Hence state wide averages were recommended for use. Multi-dimensional clustering was used to determine the Level 2 inputs for axle load spectra. Multi-dimensional clustering tests the similarity among WIM data based on several attributes, where one dimensional clustering does it based on one attribute at a time. One dimensional analysis provides clusters which are distinct by one axle type, but they are difficult to interpret or relate to a definite traffic pattern. Therefore, the cluster representing single axles may not contain the characteristics of roadways where tandem axles are predominant. Moreover, Class 5 (two single axles) and Class 9 (one single axle and two tandem axles) are the predominant truck classes in North Carolina. Class 5 and 9 represented single and tandem axles better, respectively (*18*). Thus, the implementation of multi-dimensional (two-dimensional clustering using Ward's method) clustering may improve the results, because it considers the relationship of multiple attributes simultaneously and processes well-explained clusters. For new pavement projects, 48-hour site specific classification counts were used to derive the traffic parameters (*17*).

2.2.2.6 New York

A study was performed to characterize the traffic inputs (VCD, MDF, HDF, AGPV, and axle load spectra) for the State of New York. Data were obtained from vehicle classification and WIM sites in New York during years 2007 to 2011. Cluster analysis was performed only for VCD, MDF, and HDF due to the unavailability of data for a sufficient number of WIM sites. The MEPDG analyses were executed to study the effect on predicted pavement performance using site-specific, regional (clusters), statewide average and the MEPDG default values on predicted performance measures for conventional new flexible and rigid pavement structures. Ward's method of cluster analysis was adopted. Semi-partial R-squared (SPR) values were used to determine the number of clusters to be selected for further analyses.

Four clusters were formed for the vehicle classification distribution (VCD). Those are differentiated based on proportions of Class 5 and Class 9 vehicles. The direction of travel has little impact on the VCD. The results of cluster analysis are consistent for all the years. Multi-dimensional clustering was adopted for monthly distribution factors considering Class 5 and 9 vehicles simultaneously. Four clusters were formed for 2007, 2008 and 2010. However, three and five clusters were formed for 2009 and 2010 respectively. Four clusters are found for hourly distribution factors for each of the years. The results of cluster analysis are almost consistent over the years. HDF does not show any impact on the performances of pavement. The study recommends statewide average values for VCD, MDF, AGPV, and ALS.

2.2.2.7 Georgia

A study was conducted to make recommendations for establishing Georgia Department of Transportation (GDOT) traffic load spectra program and the WIM data collection plan to support the implementation of the Pavement-ME analysis and design (*2*). There are very few permanent WIM sites in the State of Georgia, and the data obtained from the portable WIM sites were considered inadequate as a Level 1 input. It was mainly due to the limitation of equipment accuracy and challenges with field calibration of the portable WIM system. GDOT's vehicle classification data from automated vehicle classification (AVC) sites were also reviewed and categorized by the MEPDG truck traffic classification (TTC) groups by the researchers. Not all default MEPDG TTCs were observed in Georgia. The study recommended that NALS defaults developed as part of the FHWA study (*10*) be used until more Georgia permanent WIM data become available to compute Georgia-specific loading defaults. This recommendation was based on similarities in loading characteristics and the Pavement-ME outcomes using Georgia WIM data and LTPP defaults. For new alignments, it was recommended that the new NALS be based on the type of traffic loading condition expected based on aggregated road functional classes, GA freight route designation, and expected AADTT and percent of class 9 vehicles A decision tree based on these factors was developed to assist the pavement designers.

2.2.2.8 Idaho

Site-specific traffic inputs were developed based on the analyses of traffic data from 12 out of 25 WIM sites in Idaho as part of the States' MEPDG implementation effort. Statewide axle load spectra and an average number of axles per truck were established. The significance of the MEPDG predicted performance in relation to axle load spectra, vehicle class distribution, monthly adjustment factors and an average number of axle per truck was also investigated. The results showed an average directional distribution, and lane distribution factors agree quite well with the MEPDG recommended default values. Also, in general, Class 9 followed by Class 5 trucks represented the majority of the trucks traveling on Idaho roads. The vehicle class distribution factors at 5 out of 12 investigated WIM sites did not match any of the MEPDG recommended TTC groups. The developed MAF ranged between 0 and 4 indicating that truck volumes vary from month to month. The peak locations of the developed statewide and the MEPDG default ALS were fairly similar for the majority of the truck classes and axle types. However, the percentages of axles within these peaks were different, especially for the tridem and quad axles(*19*). The number of single, tandem and tridem axles per truck for all truck classes based on Idaho data was found quite similar to the MEPDG default values. Idaho data showed few percentages of quad axles for truck classes 7, 10, 11, and 13 compared to the MEPDG default values which are all zero.

The developed statewide axle load spectra yielded significantly higher longitudinal and alligator cracking compared to the MEPDG default spectra. No significant differences were observed for predicted AC rutting, total rutting, and IRI based on statewide and the MEPDG default spectra. High prediction errors were found for longitudinal cracking when statewide/national (Level 3) axle load spectra, vehicle class distribution, or monthly adjustment factors were used instead of site-specific (Level 1) data. Large prediction errors in alligator cracking were only found when the statewide default axle load spectra were used compared to site-specific spectra. Moderate errors were found when the MEPDG typical default monthly adjustment factors or vehicle class distribution were used instead of the site-specific values. The input level of the axle load spectra, monthly adjustment factors, vehicle class distribution, and number of axles per truck had very low impact on predicted AC rutting and negligible impact on total rutting and IRI. The input level of the number of axles per truck had negligible influence on the MEPDG predicted performance. (*19*)

2.3 REVIEW OF EXISTING PRACTICES IN MICHIGAN

The final report "*Characterization of Truck Traffic in Michigan for the New Mechanistic-Empirical Pavement Design Guide"* was reviewed to determine if the clustering methodology used in the 2009 study is still the "best" way for MDOT to develop Levels 2 and 3 inputs for the Pavement-ME use. Another goal of the review was to determine if the current methodology could be improved or simplified to address the needs and constraints faced by MDOT traffic data personnel. In making this determination, techniques used by other SHAs to accomplish similar task were considered.

Several statistical techniques were used in the 2009 study to develop and test traffic clusters and default values. Also, the MEPDG sensitivity analyses were conducted to test the clusters and recommendations on the use of Level 2 (cluster-based) and Level 3 (statewide) defaults were included. Implementation of this approach could be further improved in several areas, as described below.

2.3.1 Potential Areas of Improvement in the Current Practices

Several areas were identified during the review that would benefit from revisions and would lead to the development of the improved road groupings or clusters for the determining more representative Level 2 and Level 3 traffic defaults. The following potential improvements are proposed in the current methodology:

1. Level 3 defaults represent statewide traffic conditions, as such the data from traffic sites used to develop these defaults should be representative of all the State roads that may be designed using the Pavement-ME. Having sample skewed towards a specific road type (that has a disproportionately higher representation in the sample) may bias the statewide defaults. Traffic characteristics on interstate roads and high heavy truck volume primary arterial non-interstate roads typically differ from those observed on non-interstate low heavy truck volume roads. It may be beneficial to have two statewide defaults: one for interstate and high heavy truck volume roads (i.e., designated state freight routes) and another for all other roads. Such strategy would also reduce bias towards a particular road type and account for potential future changes in traffic characteristics or pavement design requirements for these types of roads.
2. In the 2009 study, the term TTC was used both to define cluster groups and as a name of vehicle class distribution input. While TTC is an appropriate name for road clusters that show specific truck traffic characteristics (hence, TTC term), the term 'VCD' could be used to refer to the Pavement-ME vehicle class distribution input.
3. The three VCD clusters developed were not clearly defined in terms of available non-vehicle classification parameters such as road class (i.e., freeway and non-freeway). This poses some challenges for assigning a particular cluster default to a site without site-specific data.
4. An alternative approach to clustering could be used to study similarities in VCD and AADTT levels within road functional classes and then develop clusters based on aggregated functional classes, using AADTT as a secondary qualifier. Clusters or groups based on this approach would allow easy assignment of TTC defaults, as well

as easy updates of Level 2 defaults in the future. Effect of this simplified approach could be further evaluated using the Pavement-ME sensitivity results.

5. When developing monthly distribution factors, vehicle classes were divided into three groups based on body type: VC 4-7, VC 8-10, and VC 11-13 (i.e., single-unit, tractor-trailer combination, and multi-trailer combination). Insignificant seasonal variations were observed in the data. This could be due to the fact that vehicles that serve unlike purposes were combined in the same group (local service trucks or resource-extraction industry trucks were combine with long-haul trucks). Therefore, there is a need to determine Level 2 inputs based on the most observed VCs in Michigan (i.e., VC5 and VC9).
6. The 2009 report identified differences in single, tandem, tridem, and quad axles per vehicle group (AGPV) values. AGPVs are typically stable between the roads unless some unusual truck fleets are using these roads. AGPV is a function of the truck fleet, not road or location. Significant deviations in AGPV could be a sign of vehicle misclassification. The reason is attributed to misclassification of vehicles by Trafload software. It is expected that no difference in AGPV should be observed with the PrepME.
7. In the 2009 study, the single axle load spectra were grouped into three clusters. The clustering was based on VC5 and VC9 percentages and was not based on axle weight differences on the truck-level. Differences in axle weights should be used for individual truck classes. When axle load spectrum is based on all classes combined, then proportion of light weight vehicle classes to heavy weight vehicle classes (i.e. the proportion of VC5 and VC9 vehicles) matters more than truck weight characteristics of a given vehicle class. Since another parameter - VCD parameter is already being used by the MEPDG method to account for proportion of different vehicle classes, there is no need to account for that again in clustering of axle load spectra. Instead, it would be of an advantage to figure out which roads have high percentage of light or heavily loaded trucks for individual vehicle classes that are dominant on Michigan roads (i.e., focus on identifying roads that has a lot of empty or fully loaded freight trucks or empty/loaded service trucks, or empty/loaded resource extraction trucks).
8. The tandem axle load spectra were developed based on all vehicle classes combined. These spectra exhibited five distinct clusters. Clusters 1-3 showed the presence of lighter axles as compared to Clusters 4 and 5. Dominant truck classes with tandem axles (typically VC8 and VC9) should be focused on for developing Level 2 inputs.
9. In tandem clusters, the loaded peak was reported in 30-35 kips range. With a legal load limit of 34 kip, 35 kip peak seems to be a sign of low precision or calibration drift. Data quality issues should be further investigated using new data. Information about calibration frequency, procedures, and documented accuracy are essential in concluding about data accuracy and precision.
10. The study indicated peak values for the quad axle load spectra occur at 104 kips. This is an unexpected and unreasonable number that needs further investigation. Perhaps these numbers manifest a catch-all function for penta+ (five or more) axles in the TrafLoad software. If proven to be true, this would make sense. Penta+ axles should be accounted for but not combined with quad axle load spectra. The PrepME should be able to identify such axle configurations.

11. While the methodology used to develop clusters is well described, no step-by-step procedures are provided in the report that could be used by MDOT to implement this methodology. If clustering methodology was implemented in the PrepME software, software algorithm should be documented in detail.
12. Review of the tandem, tridem, and quad loading defaults indicates potential data anomalies, deviation from typical values, or issues with equipment precision and bias. WIM calibration dates and calibration results should be used in WIM data QC process to draw sound conclusions about data accuracy/reasonableness.
13. At least three years of data per vehicle class per site should be used to avoid mistaking natural variations in truck volume (due to low volumes in some vehicle classes) and identify repeatable and stable seasonal truck volume variations to develop sound conclusions and defaults. Multiple years of WIM data will help to reduce bias in measurements, effects of calibration drifts, as well as variations in traffic.
14. In addition to the continuous data, data from short-term counts should be used to the extent possible. Site-specific or site-related (same road, different location) 48-hour vehicle classification count is better than Level 2 or 3 defaults, or at least it could be used to guide the selection of the appropriate default. Such count could be obtained inexpensively using pneumatic road tubes. It is likely that a significant amount of this data is already available at MDOT and being collected annually as part of FHWA HPMS data submission requirement.
15. For each road segment with site-specific traffic data, the available truck classification and WIM data should be analyzed to identify "design lane" as a lane with the most substantial number of heavy axle load applications. This information should be stored in a database table for future use.

2.3.2 Recommended Improvements

Based on the review of other States' ME implementation efforts and considering the Pavement-ME requirements for traffic data characterization, several recommendations for selecting, developing, or enhancing the existing methodology were developed, as presented below.

1. The methodology should take into account pavement performance and pavement design criteria used by MDOT. The number of traffic defaults should be determined based on the differences in pavement design outcomes observed for a range of traffic conditions identified from MDOT traffic data. If the differences in pavement design outcomes are insignificant for the observed traffic conditions, one statewide default would be sufficient. However, if pavement designs are sensitive to changes in the traffic input parameters computed based the MDOT traffic data, then multiple traffic defaults should be developed to represent each traffic loading condition that results in different pavement design outcomes.
2. The methodology should be applicable for the roads that will be designed using the Pavement-ME methodology, i.e., if multiple defaults are used, they should be applicable to specific types of roads and pavements.

3. The methodology for the development of the defaults and the procedures for updating the defaults or selecting defaults for specific pavement designs will be based on the data that are readily available for MDOT personnel.
4. The methodology for axle load characterization and Level 2 grouping of roads should focus on accurate characterization of loads that matter most for pavement designs (i.e., heavy axle loads and dominant heavy truck classes).
5. The methodology for the development of the defaults and the procedures for updating the defaults or selecting defaults for specific pavement designs should be well documented and easy to follow. In other words, step-by-step instructions and examples should be developed showing how to update the defaults, as well as how to select and use the defaults in the pavement design.
6. The procedures for development, updating, and/or using defaults should be supported by the tools available or developed for MDOT personnel.
7. The Pavement-ME Level 2 traffic inputs should be developed considering the limitations of MDOT traffic data collection program. This primarily refers to the limited number of continuous monitoring WIM and vehicle classification sites that may not provide representative coverage of the roads in MI that will be designed using the Pavement-ME. Also, due to unavailability of freight data for some routes.
8. Enhance WIM data QC checks from 2009 study to focus on the accuracy of heavy loads and proper vehicle classification to compute site-specific parameters.
9. Use available MDOT traffic data to identify ranges of values for different traffic input parameters, for different road functional classes:

    - Rural Interstates
    - Urban Interstates
    - Urban Freeway/Expressway and Non-Interstate Principal Arterials
    - Rural Non-Interstate Principal Arterials
    - All Minor Arterials and Collectors

10. Evaluate the practical significance of the findings, i.e., identify traffic parameters where the use of multiple defaults would likely cause significant differences in pavement design outcomes using criteria provided by MDOT (such as 3 or 4 years difference in 20-year service life) using pavement ME locally-calibrated models. Develop a list of parameters requiring Level 2 clusters.
11. Use functional road class, AADTT, and VCD information to see if these parameters could be used to assign mathematical clustering results, i.e., find parameters that could serve as cluster differentiators. If needed, introduce additional parameters that are available to MDOT such as road type, the direction of travel, proximity, and size of metropolitan areas, and freight route designation.
12. Once parameters that could characterize mathematical clusters are identified, develop procedures showing how MDOT could use available information/parameters to identify what cluster default to be used for the design. Develop decision trees or automated procedures for MDOT to use in the cluster default selection process.
13. Develop procedures how cluster defaults could be updated in the future using available cluster differentiators. In other words, use differentiators to identify and assign available data for each “cluster” or group and compute average values for each

"cluster" to be used as new "cluster" defaults (no mathematical modeling should be needed for this step).

14. Store computed site-specific Pavement-ME traffic inputs, Level 2 and 3 defaults in a database, along with the information about traffic sites used to develop these defaults, including information about site location, road inventory information, data collection period, data availability (number of days with data), WIM calibration dates and performance parameters (accuracy of measurements). Develop documentation explaining database table designs, data upload, and data retrieval procedures.
15. Develop step-by-step instructions for MDOT pavement engineers for obtaining Level 2 traffic inputs for pavement design projects.

2.4 METHODOLGIES FOR DEVELOPING TRAFFIC INPUTS IN MICHIGAN

Based on the above review, the following approaches are proposed for developing traffic inputs in Michigan:

1. Improved existing methodology
2. Alternative simplified methodology

The following sections describe the summary of each proposed approach.

2.4.1 Improved Existing Methodology

Based on the review, several improvements are recommended to enhance the existing methodology to characterize the traffic inputs based on the new (2011 to 2015) WIM and classification data. Several areas were identified during the review that would lead to the improved road groupings or clusters for more representative Level 2 and Level 3 defaults. The following potential improvements are proposed in the current methodology:

1. Level 3 statewide defaults – Based on the distribution of PTR locations, it may be beneficial to have 2 statewide defaults: one for interstates and roads with high volume of heavy trucks (i.e. designated state freight routes) and one for all other roads.
2. Level 2 MAF groups/clusters – In the previous study, vehicle classes were divided into three groups based on body type: VC 4-7, VC 8-10, and VC 11-13 (i.e., single-unit, tractor-trailer combination, and multi-trailer combination). Very little seasonal variations were observed. This could be due to the fact that different truck classes were combined in the same group (i.e., local service trucks or resource-extraction industry trucks were grouped with long-haul trucks). Analysis of individual vehicle classes may help to better identify seasonal trends. This would be most applicable to the vehicle classes that are frequently observed on MI roads (typically classes 5 and 9).
3. An easy to follow step-by-step procedure will be developed for future use by MDOT personnel.
4. The current methodology uses freight data and discriminant analysis for assigning a site to a cluster for significant traffic inputs. However, some routes do not have

freight data available. In such cases, there is a need to develop alternative approaches to establish Level 2 traffic inputs for a particular project. For example, decision trees based on the data availability can be developed and used for cluster assignments.

2.4.2 Alternative Simplified Methodology

The alternative simplified methodology will include the following steps:

1. Use available MDOT traffic data (AADTT, VCD information, and road inventory/GIS information) to identify ranges of values for different traffic input parameters for different road functional class groups, e.g.:
    - Rural interstates
    - Urban interstates
    - Urban freeway/expressway and non-interstate principal arterials
    - Rural non-interstate principal arterials
    - All minor arterials and collectors
2. If needed, introduce additional parameters that are available to MDOT such as road type or designation (Interstate, US, State, county, etc.), direction of travel, proximity and size of metropolitan areas, and freight route designation.
3. Once the groups are identified, establish the traffic inputs based on the averages of sites in each individual group. Averages with these groups should be updated when a PTR site is removed or added or new traffic data become available (see recommendations in Chapter 6).

2.5 SUMMARY

This chapter presents a review of literature and state-of-the-practice related to traffic inputs in the Pavement-ME. The Pavement-ME uses hierarchical input levels and provides flexibility to the designer in obtaining the design inputs based on the project importance. Three different input levels can be used in this hierarchical system ranging from site-specific input values to "best-estimate" or default values as classified below:

1. Level 1 – These inputs provide the highest level of accuracy because they are site/project specific and are measured directly,
2. Level 2 – These inputs provide an intermediate level of accuracy and are used when Level 1 inputs are unavailable. Correlation or regression equations are used to estimate these inputs.
3. Level 3 – These inputs are based on global or regional averages and provide the least amount of knowledge regarding the input parameters.

Most of these inputs can be obtained through weigh-in-motion (WIM), automatic vehicle classification (AVC), and vehicle counts, etc. Each of these traffic inputs were briefly described in this chapter. Several guidelines used to obtain the Levels 2 and 3 inputs for use in the Pavement-ME are documented. The NCHRP 1-37A final report (*8*) provides guidelines for truck traffic data based on the allowable error and permissible bias for each data element in establishing the truck volume distribution and axle load spectra. Also, one set of ALS for each truck class was determined and included in the software as defaults. The 2016 FHWA Traffic Monitoring Guide (TMG) (*5*) provides recommendations and best practices for highway traffic monitoring, including monitoring of truck loading. It is recommended that the roadway system be divided into groups using clustering or traditional approaches such that each road within a group experiences similar truck-loading patterns. The NCHRP 1-39 report (*9*) also contains guidelines for collecting traffic data to be used in the MEPDG. The LTPP TPF-5(004) study has generated high-quality traffic loading information for 26 LTPP Special Pavement Study (SPS) sites located in 23 different States representing moderate and high volume rural principal arterial interstate and non-interstate highways. The WIM data from the LTPP TPF 5(004) study were used to develop a two-tier ALS defaults (*10*): (a) Tier 1 Global defaults representing average loading, and (b) Tier 2 Defaults representing different loading patterns (clusters). Tier 2 defaults were developed based on hierarchical clustering of axle load data from multiple sites. The newly computed ALS defaults had fewer very light and heavy loads compared to the original defaults. This is likely due to the fact that the new defaults were collected with more consistently calibrated and precise WIM equipment than the data set used for the development of the original NALS defaults under the NCHRP 1-37A project.

Many other state highway agencies (SHAs) have determined the truck traffic weight and volume defaults to be used with the Pavement-ME. It was found that that the local axle load spectra for different axle configurations deviate from the global default values currently included in the Pavement-ME software, especially for local and secondary routes. Therefore, the development of regional or statewide traffic defaults is necessary to implement the Pavement-ME design approach. Various approaches have been used to obtain the Levels 2 and 3 inputs for use in the Pavement-ME. A review of these techniques used by other States is provided in Table 2-10.

Table 2-10 Summary of clustering methodologies used to generate level 2 inputs

State	Level 2 inputs	Methodology	Clusters assignment
Arizona	Yes	Hierarchical clustering method using correlation coefficient	Traffic patterns for each of the clusters were defined using highway functional classification.
Alabama	Yes	Hierarchical clustering method using Pearson's correlation coefficient	Traffic patterns for each of the clusters were defined geographically.
Arkansas	Yes	Hierarchical clustering method-Wards method and Euclidean distance. Also K-means and Fuzzy methods were used.	Multi-category logit [ML] models were developed to assign the probabilities that a site belongs to a cluster.
Colorado	Yes	Hierarchical clustering method	Uses statewide defaults for all inputs except VCD. The assignment for VCD is based on functional classification of highways.
Georgia	No	Road groups with similarities in traffic loading patterns were identified	Assigned LTPP defaults to GA roads based on truck volume, vehicle classification and road type criteria. 48-hour site specific classification counts for VCD and AADTT recommended plus portable WIM for ALS default selection.
Michigan	Yes	Hierarchical clustering method-Wards and squared Euclidean distance.	Assignment using discriminant analyses.
North Carolina	Yes	Hierarchical Clustering using Wards method and Euclidean distance.	48-hour site specific classification counts for VCD and ALS. Statewide average values for all other inputs are recommended.
New York	Yes	Hierarchical Clustering using Wards method and Euclidean distance.	Statewide average values for all inputs are recommended.

The final report "*Characterization of Truck Traffic in Michigan for the New Mechanistic-Empirical Pavement Design Guide"* was reviewed to determine if the clustering methodology used in the 2009 study is still the "best" way for MDOT to develop Levels 2 and 3 inputs for the Pavement-ME use. Several areas were identified during the review that would benefit from revisions and would lead to the development of the improved road groupings or clusters for the determining more representative Level 2 and Level 3 traffic defaults. Potential areas of improvement in the current practices are presented in this chapter.

Table 3-2 List of PTR sites with WIM and classification data

PTR Site	Route	Sensor Type	Latitude	Longitude
037319	I-196	Quartz	42.437	-86.248
096429	I-75	Quartz	43.629	-83.960
117189	I-94	Quartz	41.769	-86.738
127269	I-69	Quartz	41.849	-84.996
137159	I-94	Quartz	42.298	-85.039
137169	I-94	Quartz	42.283	-84.873
195019	US-127	Quartz	43.024	-84.546
211459	US-2	Quartz	45.728	-87.231
212229	US-2	Quartz	45.921	-86.992
221199	M-95	Quartz	46.029	-88.060
238869	I-69	Quartz	42.534	-84.821
256119	I-75	Quartz	43.210	-83.770
256449	I-69	Quartz	42.967	-83.782
271009	US-2	Load Cell	46.466	-90.192
308129	US-12	Quartz	41.990	-84.647
338029	US-127	Quartz	42.538	-84.443
345299	I-96	Quartz	42.879	-85.057
387029	I-94	Quartz	42.285	-84.284
387049	US-127	Quartz	42.174	-84.365
403069	US-131	Quartz	44.823	-85.136
419759	M-6	Quartz	42.850	-85.607
478049	I-96	Quartz	42.646	-84.085
478219	I-96	Quartz	42.563	-83.834
492029	US-2	Quartz	46.003	-84.998
588729	US-23	Quartz	41.784	-83.696
615289	US-31	Quartz	43.224	-86.205
694049	I-75	Quartz	45.144	-84.670
705059	I-196	Quartz	42.866	-85.802
705099	I-96	Quartz	43.053	-85.937
724129	US-127	Quartz	44.264	-84.803
724149	I-75	Quartz	44.317	-84.451
752199	M-28	Quartz	46.345	-85.983
776369	I-69	Quartz	42.978	-82.803
776469	I-94	Quartz	42.940	-82.507
787119	US-131	Quartz	41.842	-85.677
807219	I-94	Quartz	42.220	-85.821
818239	US-23	Quartz	42.414	-83.765
828839	I-94	Quartz	42.220	-83.466
829189	I-275	Piezo BL	42.180	-83.388
829209	I-275	Quartz	42.309	-83.442
829699	I-75	Quartz	42.110	-83.241

The PrepME (*1*) was used for analyzing the raw traffic data from PTR sites and developing the Level 1 traffic inputs. MDOT provided the final PrepME database (January 2011 to December 2015) after quality checks (availability of at least one week of data in each month, front and gross vehicle weights). The research team extracted the Level 1 data for traffic inputs through PrepME.

Table 3-3 Number of sites with available WIM and classification data

Type of Data	Available	QC Passed
Weight and Classification	43	41
Weight Only	0	0
Classification Only	19	18
Total	62	59

3.2 GENERATION OF TRAFFIC INPUTS

Site-specific traffic inputs (Level 1) were generated for each of the 41 WIM sites using the PrepME after extensive QC checks (see Chapter 5 for the PrepME QC). Development of regional inputs (Level 2) is crucial when site-specific data are not available. The averages from nearby sites (regional) with similar traffic characteristics (groups or clusters) can be used as Level 2 data (*2*). The average of all the sites (statewide average) can be used as Level 3 data. As discussed in Chapter 2, Level 3 data are further split into Levels 3A, and 3B, where 3A represents average of freeways and non-freeways, and 3B represents overall statewide average for traffic inputs.

The Federal Highway Administration (FHWA) Traffic Monitoring Guide recommends the following two approaches for developing Level 2 inputs (*3*).

(a) Cluster Analyses (Improved existing approach)
(b) Traditional Approaches (Simplified methodology)

These two approaches are explained in more detail below:

3.2.1 Cluster Analyses

Cluster analysis is a data mining technique that identifies homogeneous subsets of data (also known as clusters) within a dataset using only the information found in the data. It uses mathematical similarity of two data objects to group them. The steps involved in a typical cluster analyses include (a) obtaining the data for cluster analyses, (b) identifying the significant attributes of the data, (c) choosing a distance measure, (d) selecting a clustering technique, (e) deciding on the number of clusters, and (f) interpreting the results (*4*). A dataset used for cluster analyses often contains a collection of data objects. Each data object has some attributes that capture the object's fundamental characteristics. The primary aim of cluster analyses is to separate the dataset into subsets such that objects within a subset are *similar* to one another and are *different* from those in other subsets. The word 'Clustering' commonly refers to an entire collection of clusters. A multivariate $m \times n$ data matrix, D, usually represents the data used for cluster analyses as shown below. Each row contains a data object, and the columns contain the attribute values describing each object in the dataset.

$$D = \begin{pmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{mn} \end{pmatrix} \tag{1}$$

where:

d_{ij} = value of the j^{th} attribute of object i.

Attributes of the data objects in the matrix may either be continuous, or ordinal or a mixture of both. Some attributes of an object might not define it very well and might be irrelevant. Such attributes should be excluded if possible, or weights could be added to the essential attributes in the data matrix (*4*). Most clustering techniques convert the data matrix into a $m \times m$ 'distance matrix' of inter-object similarities or dissimilarities. The similarity/dissimilarity between two objects with attributes on a continuous scale is a numerical measure of the degree to which they are alike. Two objects are said to be close to each other when the dissimilarity is small. Several similarity measures can express likeness between a pair of objects. In general, two categories broadly define these measures: (a) distance, and (b) correlation-type. 'Euclidean Distance' is the most commonly used distance measure which is the straight line distance between two objects. It is calculated using Equation (2).

$$d_{o_i,o_j} = \left[\sum_{k=1}^{p} (o_{ik} - o_{jk})^2 \right]^{1/2} \qquad (2)$$

where;

o_{ik}, o_{jk} = k^{th} component of the *p*-dimensional objects o_i, o_j

To illustrate, consider six two dimensional points (or objects) with *x* and *y* coordinates as follows (*5*): (a) P1 (0.40, 0.53), (b) P2 (0.22,0.38), (c) P3 (0.35,0.32), and (d) P4 (0.26,0.19), (e) P5 (0.08, 0.41), and P6 (0.45, 0.30).The distance calculation between P_1 and P_2 is as follows:

$$dist(1,2) = \sqrt{(0.40-0.22)^2 + (0.53-0.38)^2} = 0.234 \qquad (3)$$

Likewise, the distances between all possible pairs of objects can be computed and expressed in the form of a 'distance matrix.' The non-diagonal elements in this matrix represent the distances between pairs of objects and the diagonal elements represent the distance from each object to itself (hence, they are always zero) as seen in Equation (4) (*6*). The objects used in this example has only two dimensions (attributes), but distances for objects with more than two attributes can be computed (e.g., Monthly adjustment factors would have twelve attributes, i.e., one for each month).

$$dist-matrix = \begin{array}{c} \\ P_1 \\ P_2 \\ P_3 \\ P_4 \\ P_5 \\ P_6 \end{array}\begin{pmatrix} P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\ 0 & 0.23 & 0.22 & 0.37 & 0.34 & 0.24 \\ 0.23 & 0 & 0.14 & 0.19 & 0.14 & 0.24 \\ 0.22 & 0.14 & 0 & 0.16 & 0.28 & 0.10 \\ 0.37 & 0.19 & 0.16 & 0 & 0.28 & 0.22 \\ 0.34 & 0.14 & 0.28 & 0.28 & 0 & 0.39 \\ 0.24 & 0.24 & 0.10 & 0.22 & 0.39 & 0 \end{pmatrix} \qquad (4)$$

Mikowski distance is a more generalized form of the Euclidean distance as seen in Equation (5). When *r* is equal to 1, it is called 'Manhattan' or 'City block' distance which is the distance between two points measured at right angles along the axes.

$$d(x,y) = \left(\sum_{k=1}^{n} | x_k - y_k |^r \right)^{1/r} \qquad (5)$$

The other commonly used similarity measure is the 'Mahalanobis' distance as shown in Equation (6). It is a generalization of the Euclidean distance and could be used when the attributes of the data objects are correlated or have different ranges of values.

$$\text{Mahalanobis}(x,y) = (x-y)\sum^{-1}(x-y)^T \qquad (6)$$

where:

$\sum$ = covariance matrix whose ij^th^ entry is the covariance of the i^th^ and j^th^ attribute

$\sum^{-1}$ = inverse of the covariance matrix

Correlation measures are the other category of similarity measures. The most widely used correlation measure is the Pearson correlation coefficient (*7*). The correlation between two data objects is a measure of the linear relationship between their attributes. A correlation value of '1' indicates a strong relationship, and a value of '-1' indicates a fragile relationship between the data objects and is calculated using Equation (7).

$$corr(x,y) = \frac{\text{covariance}(x,y)}{stdev(x) \times stdev(y)} = \frac{\sigma_{xy}}{\sigma_x \times \sigma_y} \qquad (7)$$

A number of similarity/dissimilarity measures exist, which makes choosing a measure for cluster analyses a challenge. Earlier research studies have come up with categorizations of the similarity or dissimilarity measures based on the critical properties of the data (e.g., scale of data, metric, and Euclidean properties of similarity matrices). However, the properties are not very conclusive for choosing between the measures (*7-11*). The general observation is that the nature of the data should strongly influence the choice of the similarity measure. Sometimes, a similarity measure may already have been used previously and thus may have answered the choice of the similarity measure. Occasionally, the clustering technique might limit the choices of the similarity measures that could be used. Different similarity measures can be used to see which ones produce more realistic results. However, for continuous data, distance measures should be used when the magnitude of the data is essential. Assuming that the attributes of a data object (e.g., the traffic volume in January does not affect the traffic volume in February) are not correlated, the Euclidean distance was chosen as the similarity measure in this study as it can be easily interpreted. More information on the choice of similarity or dissimilarity measure and a decision-making table that may help choose the similarity measure can be found in the literature (*5*, *10*).

Clustering techniques divide data into a set of clusters commonly referred to as 'clusterings.' While the clusterings can be described in many ways, the commonly used distinction between different types of clusterings is whether it is partitional or hierarchical. A partitional clustering is merely a division of the set of data objects into nonoverlapping subsets (clusters) such that each data object is precisely in one subset. If these clusters are permitted to have sub-clusters, then a hierarchical clustering is obtained. The most commonly used clustering techniques (*5*) are discussed below.

3.2.1.1 K-means

It is a partitional clustering technique that divides the dataset into a predetermined number of clusters. The algorithm includes choosing 'K' initial centroids (which equals the desired number of clusters). Each data object is assigned to the closest centroid, and each collection of data objects assigned to a centroid forms a cluster. After each iteration, the centroid of each cluster is updated based on the data objects assigned to that cluster. The iterations stop when no objects change clusters, or equivalently, the centroids remain the same. Only a few times, K-means reaches a state in which no objects are shifting from one cluster to another. Usually, a rule is set to stop the iterations after reaching a steady state (e.g., only less than 1% of the objects are changing the clusters) (*5*). Like every clustering technique, K-means needs a similarity measure to assign the object to a centroid. As discussed before, several options exist, but the most often used measure is the Euclidean distance. Given two sets of clusters from different K-means runs, the overall sum of squared error (SSE) often decides the better cluster as shown below (*5*).

$$SSE = \sum_{i=1}^{K} \sum_{x \in C_i} dist(c_i, x)^2 \tag{8}$$

where:

$K =$ number of clusters

$C_i =$ cluster C_i

$c_i =$ centroid of cluster c_i

$x =$ data object in cluster C_i

The mean of a cluster is always the best centroid for minimizing the SSE of a cluster and is shown below. By minimizing the SSE of cluster K and solving for its centroid,

$$\frac{\delta}{\delta c_k} SSE = \frac{\delta}{\delta c_k} \sum_{i=1}^{K} \sum_{x \in C_i} (c_i - x)^2$$

$$= \sum_{i=1}^{K} \sum_{x \in C_i} \frac{\delta}{\delta c_k} (c_i - x)^2$$

$$= \sum_{x \in C_i} 2 \times (c_i - x) = 0$$

$$\sum_{x \in C_k}^{K} 2 \times (c_k - x_k) = 0 \Rightarrow m_k c_k = \sum_{x \in C_k}^{K} x_k \Rightarrow c_k = \frac{1}{m_k} \sum_{x \in C_k}^{K} x_k$$

where:

$m_k =$ number of objects in the cluster K

$x_k =$ data object in cluster C_k

While K-means is a very general algorithm that can be used with different data types, it has various limitations. One of them is choosing the initial centroids. Randomly choosing the initial centroids often results in poor clusters and sometimes in empty clusters. While there are remedies, it is often an exhaustive procedure to find the optimum initial centroids. One procedure would be to run K-means multiple times with random initial centroids and use the one with the least SEE. Another procedure is to use the hierarchical clustering at first to find the clusters and their centroids and then rerun the K-means. Also, the number of clusters required is an input into the K-means algorithm, which can be difficult to determine before the clustering. For these reasons, K-means technique will not be used in the cluster analyses of traffic data.

3.2.1.2 Hierarchical Clustering

Hierarchical clustering techniques are another prominent category of clustering methods. There are two approaches for generating hierarchical clusterings (a) divisive, and (b) agglomerative. In divisive clustering approach, all the objects in the dataset are considered as a single cluster at the beginning and are divided it into two clusters at each stage until all the clusters have only a single object. In the first step of the clustering, all the possible partitions of the dataset need to be considered which equals to $2^{n-1} - 1$ combinations (where *n* is the number of data objects). The large number of combinations makes divisive clustering difficult to implement. Agglomerative approach performs clustering in an opposite manner as compared to divisive approach. Agglomerative clustering technique considers each object in the dataset as an individual cluster and merges them one at a time in a series of sequential steps (*12*). The number of clusters during the first step equals the number of objects in the dataset. At each subsequent step, the clusters that are ‘closest’ (or most similar) to each other are merged to form a new cluster. The final step merges all the objects in the dataset into one single cluster. The objects that are merged to form clusters at each step cannot be reassigned to different clusters at a later stage. Agglomerative hierarchical clustering technique is characterized by two choices: (a) the measurement of similarity between two objects in a dataset, and (b) the type of linkage between clusters (*5*, *13*). The clusters formed using the hierarchical techniques can be represented using a two-dimensional diagram known as a ‘dendrogram.' A dendrogram illustrates the clusters formed at each stage of the clustering process. Figure 3-1 shows an example of a dendrogram. Two clusters are merged at each step of the process at a distance, or the height represented by the *y*-axis. The clustering technique (or the 'linkage type') needs to be established after choosing the distance or similarity measure (*6*). Discussed below are the most commonly used methods.

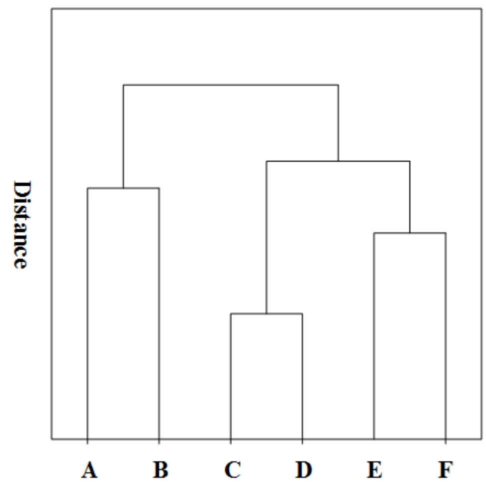


Figure 3-1 An example of the dendrogram

Single Linkage Method

This method is also called the nearest neighbor or minimum method. The similarity between two clusters is the minimum of the distance between any two objects in two different clusters (*12*). Consider the six two dimensional points and the distance matrix discussed above [see Equation (4)]. In the first step of this clustering technique, points '3' and '6' are merged into a cluster (see Figure 3-2a) because they have the smallest distance of 0.102 between them.

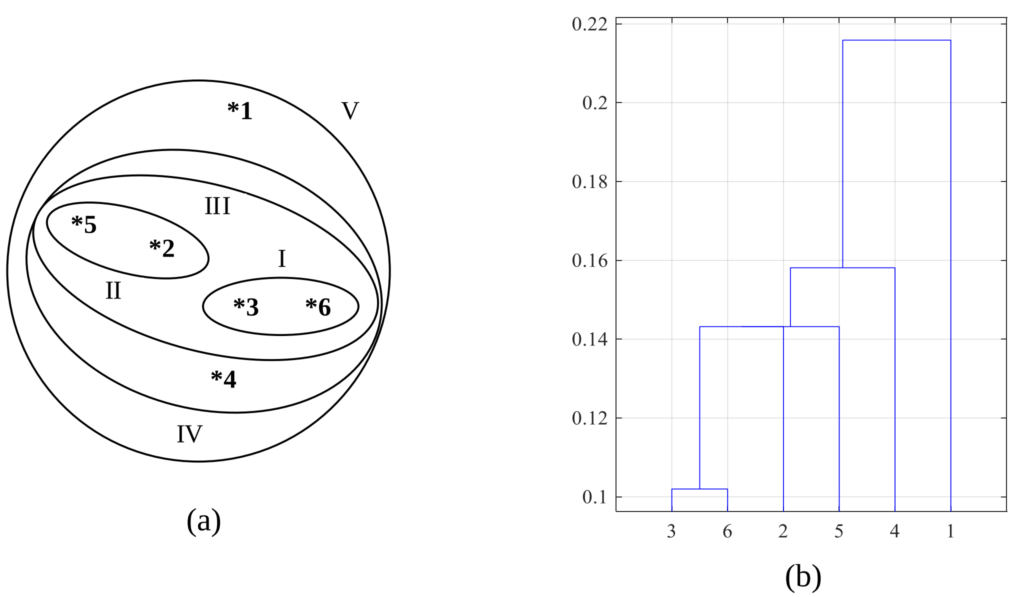


Figure 3-2 Single linkage clustering

As seen in Figure 3-2b (dendrogram), that is the height at which they are merged into a single cluster. In the second step, points ‘2’ and ‘5’ are merged into a cluster. The distances between the newly formed clusters in step 3 are calculated as follows:

$$\begin{aligned} dist(\{3,6\},\{2,5\}) &= \min(dist(3,2), dist(6,2), dist(3,5), dist(6,5)) \\ &= \min(0.143, 0.244, 0.285, 0.386) = 0.143 \\ dist(\{3,6\},\{4\}) &= \min(dist(3,4), dist(6,4),) \\ &= \min(0.158, 0.220) = 0.158 \end{aligned}$$

In the third step, the clusters $\{3,6\},\{2,5\}$ are combined to form a third cluster at the height of 0.143 as seen in the dendrogram. This process goes on until all the points are combined into one single cluster at the height of approximately 0.22.

Complete Linkage Method

This method is also called the furthest neighbor or maximum method. The similarity of two clusters is defined as the maximum of the distance between any two points in two clusters. As with the single linkage method, clusters $\{3,6\}$ and $\{2,5\}$ are formed first (See Figure 3-3a and 3-3b).

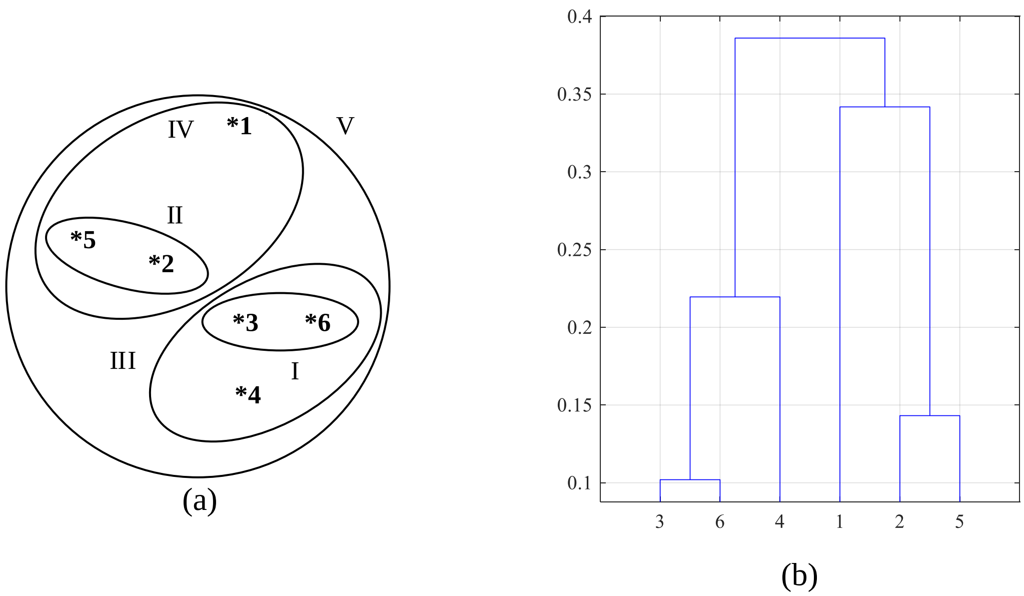


Figure 3-3 Complete linkage clustering

In the third step, instead of $\{3,6\}$ and $\{2,5\}$ merging next, $\{3,6\}$ is merged with $\{4\}$ because the procedure takes into account the least maximum distance between clusters.

$$
\begin{aligned}
dist(\{3,6\},\{2,5\}) &= \max(dist(3,2), dist(6,2), dist(3,5), dist(6,5)) \\
&= \max(0.143, 0.244, 0.285, 0.386) = 0.386 \\
dist(\{3,6\},\{4\}) &= \max(dist(3,4), dist(6,4)) \\
&= \max(0.158, 0.220) = 0.220 \\
dist(\{3,6\},\{1\}) &= \max(dist(3,1), dist(6,1)) \\
&= \max(0.216, 0.235) = 0.235
\end{aligned}
$$

Group Average Method

For the group average version of hierarchical clustering, the similarity of two clusters is the average of pairwise similarity among all pairs of points in the different clusters. Group average method is an intermediate approach to the single, and complete link approaches. Figure 3-4 shows the dendrogram for this method.

The similarity between two clusters A and B of sizes n_A and n_B is calculated using Equation (9).

$$
proximity(A,B) = \frac{\sum_{a \in A} \sum_{b \in B} dist(a,b)}{n_A * n_B} \tag{9}
$$

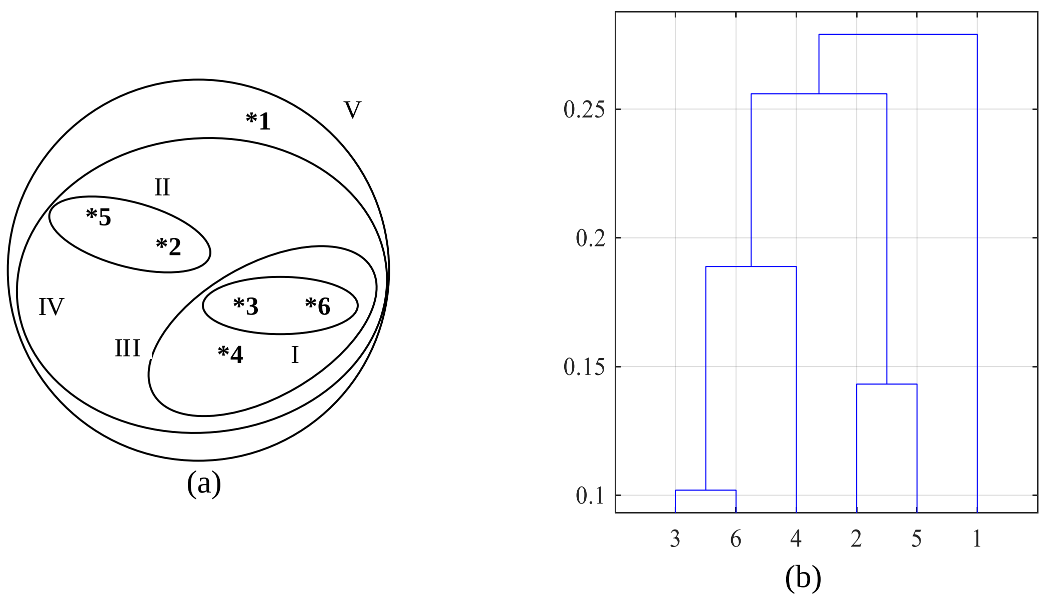


Figure 3-4 Group average clustering

An illustration of group average method is given below.

$$dist(\{3,6,4\},\{1\}) = \frac{dist(3,1)+dist(6,1), dist(4,1)}{(3\times1)} = 0.273$$

$$dist(\{2,5\},\{1\}) = \frac{dist(2,1)+dist(5,1)}{(2\times1)} = 0.288$$

$$dist(\{3,6,4\},\{2,5\}) = \frac{dist(3,2)+dist(3,5)+dist(6,2)+dist(6,5)+dist(4,2)+dist(4,5)}{(3\times2)} = 0.256$$

Because $dist(\{3,6,4\},\{2,5\})$ is smaller than $dist(\{3,6,4\},\{1\})$ and $dist(\{2,5\},\{1\})$, clusters $\{3,6,4\}$ and $\{2,5\}$ are merged in the fourth step.

Ward's Method

Ward's method is another general agglomerative hierarchical clustering technique. The similarity of two clusters depends on an objective functions' optimal value. The most widely used objective function is the error sum of squares or within-cluster variance. Clusters with the least increase in the overall within-cluster variance when combined are merged at each step. Figures 3-5a and 3-5b show the dendrogram for this method.

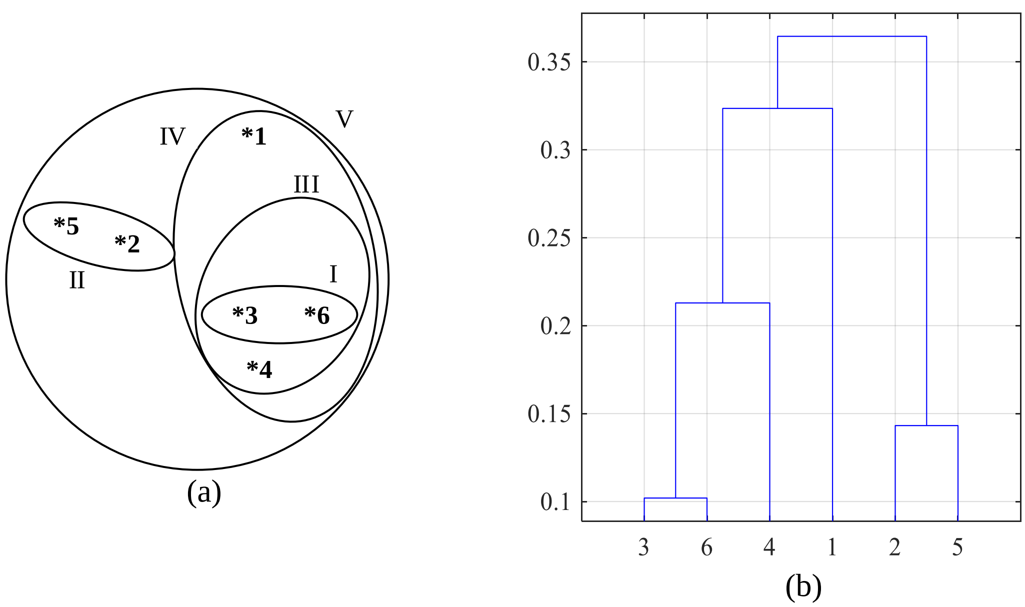


Figure 3-5 Ward's method of clustering

The similarity between two clusters A and B of sizes n_A and n_B can be calculated by using Equation (10), where C_A and C_B are the centroids of clusters A and B.

$$proximity(A,B) = \sqrt{\frac{2\times n_A \times n_B}{n_A + n_B}} \times dist(C_A, C_B) \qquad (10)$$

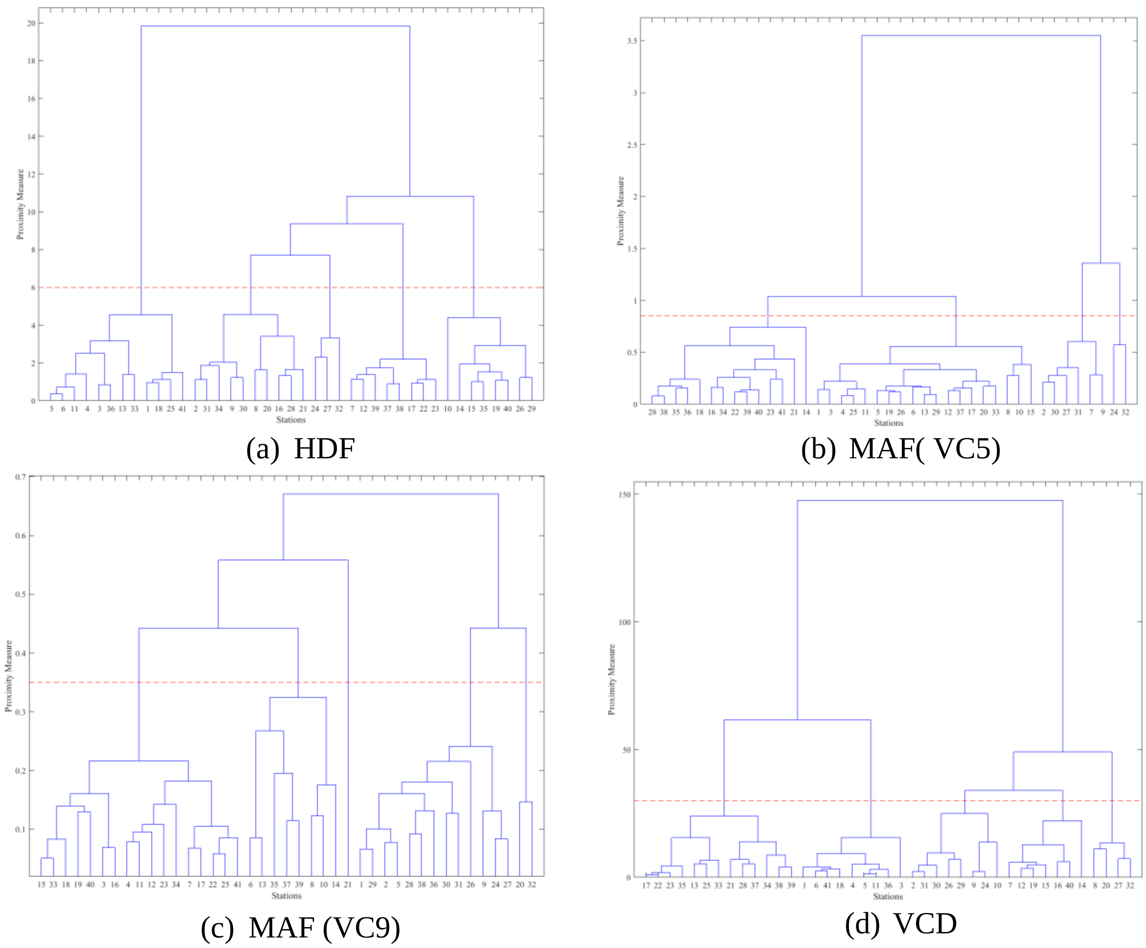
In the first two steps, $\{3,6\}$ and $\{2,5\}$ are combined separately because of the least increase in the sum of squares when combined. The third step is illustrated below.

$$dist(\{3,6\},\{4\}) \quad = \sqrt{\frac{2\times 2\times 1}{(2+1)}}\times dist(\{3,6\},\{4\}) = 0.213$$
$$dist(\{3,6\},\{1\}) \quad = \sqrt{\frac{2\times 2\times 1}{(2+1)}}\times dist(\{3,6\},\{1\}) = 0.254$$
$$dist(\{3,6\},\{2,5\}) \quad = \sqrt{\frac{2\times 2\times 2}{(2+2)}}\times dist(\{3,6\},\{2,5\}) = 0.373$$

The third step combines clusters $\{3,6\}$ and $\{4\}$ since the increase in the sum of squares is minimum among other combinations.

The different linkage methods discussed above define the distance between the pair of clusters in a certain way. Each of these linkage algorithms can yield entirely different results when used on the same dataset. The single linkage method tends to produce one large cluster with other clusters containing very few objects because several clusters may be joined together (called 'chaining effect') merely because one of their objects is within proximity of an object from a separate cluster. This problem is specific to single linkage because only the minimum distance between objects is used. As mentioned before, the objects that are merged to form clusters at one step cannot be reassigned to different clusters at a later stage, and therefore the chaining effect could lead to abnormal clusters. However, single linkage method can be used to detect the outliers, as these will always be merged during the final step of the clustering process (*6, 12*). Complete linkage method solves the problem of chaining. However, they tend to produce large globular clusters. Outliers can profoundly influence the outcome of the clusters as this clustering technique uses the maximum distance between the objects. The average link method is a compromise between the single and complete linkage methods as it takes into account the average distances between the objects. This method is relatively robust compared to the single and complete linkage methods as it takes into account the cluster structure (*7*). Ward's method is sensitive to outliers and tends to find same size and spherical clusters. The average linkage and Ward's method are the most frequently used methods. There are no guidelines on choosing the right linkage method. However, some studies found that Ward's method performed better than the average linkage method (*14*). Therefore, Ward's method was used for cluster analyses of the traffic data.

The advantages of cluster analyses are that the groups are formed objectively (based on a mathematical function) and not subjected to bias or subjective decisions. The other advantage is that it finds patterns in the data that are not intuitively obvious therefore providing new insights into traffic patterns in a region. One main disadvantage is the lack of guidelines on establishing the optimal number of clusters. While various techniques were developed to identify the optimal number of clusters, none of them are perfect and have their drawbacks. The other disadvantage is that, since clustering is purely a mathematical technique, the objects in a cluster might not have the same identifiable attributes making the assignment of data from a new location to the existing clusters difficult. However, the advantages outweigh the disadvantages and hence cluster analyses was used to develop clusters for different input levels in the State of Michigan. The Euclidean distance and Ward's method was used as the similarity measure and the linkage method, respectively. The clusters formed from here on will be designated as 'Level 2A' inputs. Figures 3-6 and 3-7 show the dendrograms of all the traffic inputs using Euclidean distance and Wards method.



(a) HDF

(b) MAF(VC5)

(c) MAF (VC9)

(d) VCD

Figure 3-6 Cluster dendrograms for various traffic inputs — Michigan PTR sites

3.2.1.3 Choosing the Optimal Number of Clusters

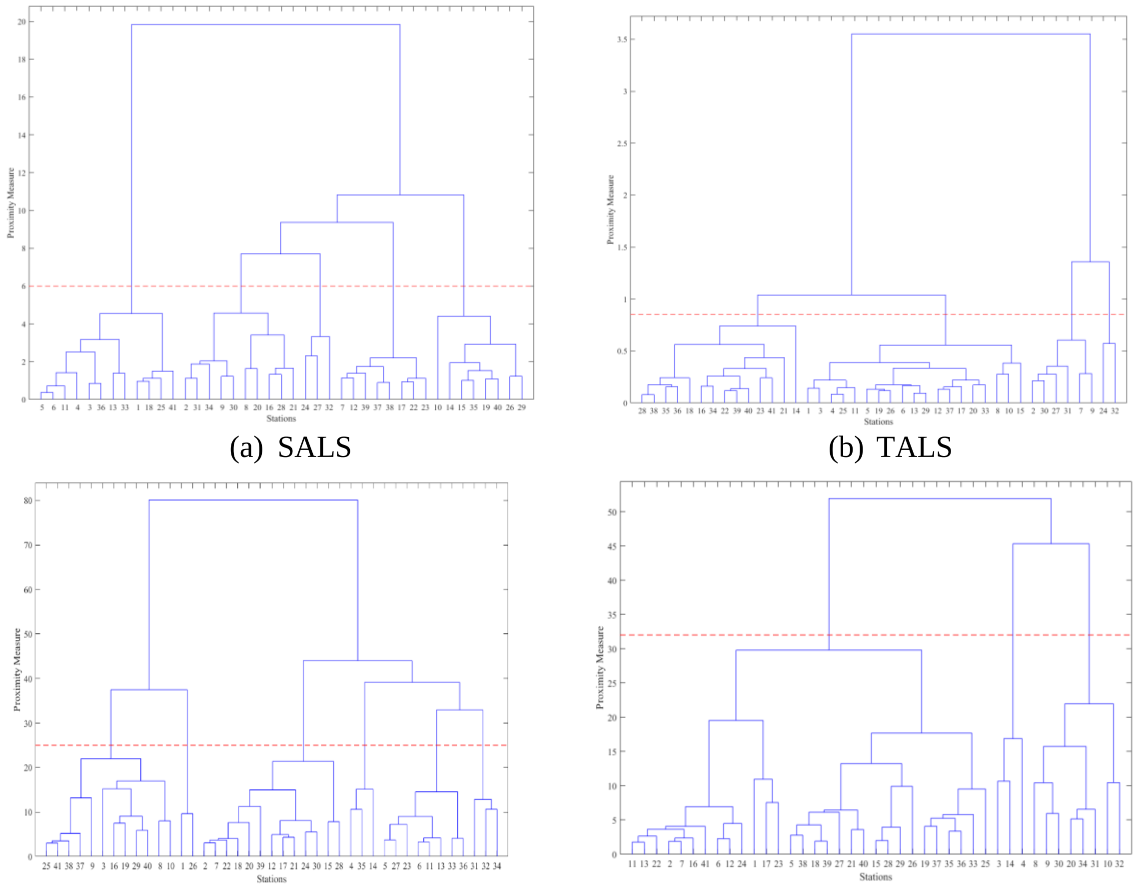
Hierarchical clustering provides limited guidance on the number of clusters to be retained from the data. Several criteria are used to find the optimal number of clusters in the dataset. A research study (*15*) evaluated over 30 such criteria and ranked 'Calinski-Harabasz Criterion' as the top performing criteria. The Calinski-Harabasz criterion is also called the variance ratio criterion (VRC). The Calinski-Harabasz index is defined as (*16*)

$$VRC_K = \frac{SS_B}{SS_W} \times \frac{(N-k)}{(k-1)} \tag{11}$$

where:

SS_B = overall variance between clusters

SS_w = overall variance within clusters
K = number of clusters
N = number of observations



(a) SALS (b) TALS

(c) TRALS (d) QALS

Figure 3-7 Cluster dendrograms for various traffic inputs — Michigan PTR sites

A dataset that has distinct clusters should have a large between-cluster variance (SS_B) and a small within-cluster variance (SS_W). The larger the VRC_K ratio, the better the data partition. VRC_K value is the highest for the optimal number of clusters. It should also be noted that the 'Calinski-Harbasz Criterion' is best suited for K-means clustering (*17*).

Gap criteria is a recently developed method that can be used with virtually any clustering technique (*18*). The gap value is calculated as follows:

$$Gap_n(k) = E_n\{log(W_k)\} - log(W_k) \tag{12}$$

where:

n = sample size
k = number of clusters
W_k = pooled within-cluster variance

$$W_k = \sum_{r=1}^{k} \frac{1}{2n_r} D_r \qquad (13)$$

where:

n_r = number of data points in cluster r

D_r = sum of pairwise distances for all objects in cluster r

The optimal number of clusters has the largest gap value (could be local or global) within a tolerance range. Monte Carlo sampling from a reference (null) distribution is used to determine the expected value $E_n\{log(W_k)\}$. The $log(W_k)$ value is obtained from the sample data. Several other measures are widely used but are not too efficient and often could result in substantial errors *(11)*.

Figure 3-8 shows the 'Calinski-Harbasz Criterion' and 'Gap Criterion' methods applied to the hourly distribution factors (HDF). The results show that five clusters will have the highest VRC_K and gap values. Hence, the HDF dataset was split into five clusters. The 'Calinski-Harbasz Criterion' and 'Gap Criterion' for other traffic inputs can be found in Appendix A.

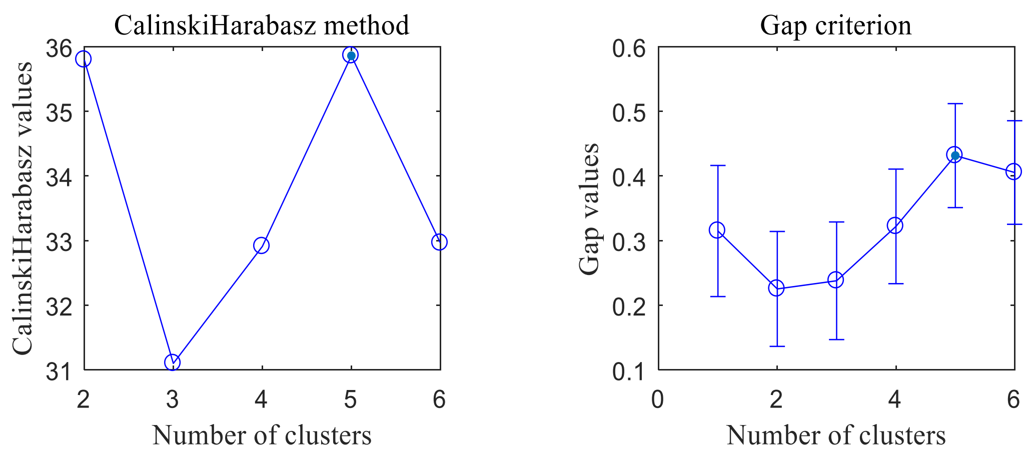


Figure 3-8 Optimum number of clusters for HDF

Using both these criteria, and engineering judgments, the traffic datasets were split into the following number of clusters for each traffic input. Figures 3-9 and 3-10 show the cluster averages of all the traffic inputs mentioned above.

1. Hourly distribution factors (HDF) – 5 clusters

The cluster analysis resulted in five clusters for HDF as shown in Figure 3-9(a). Cluster 1 contains heavier evening proportions of trucks and average AADTT values of less than 500. Cluster 2 has similar percentage of trucks as sites in cluster 1, but on average shifts left by an hour and average AADTT values less than 1000. It is to be noted that the sites in both clusters 1 and 2 are mostly located on US-2 and I-75.

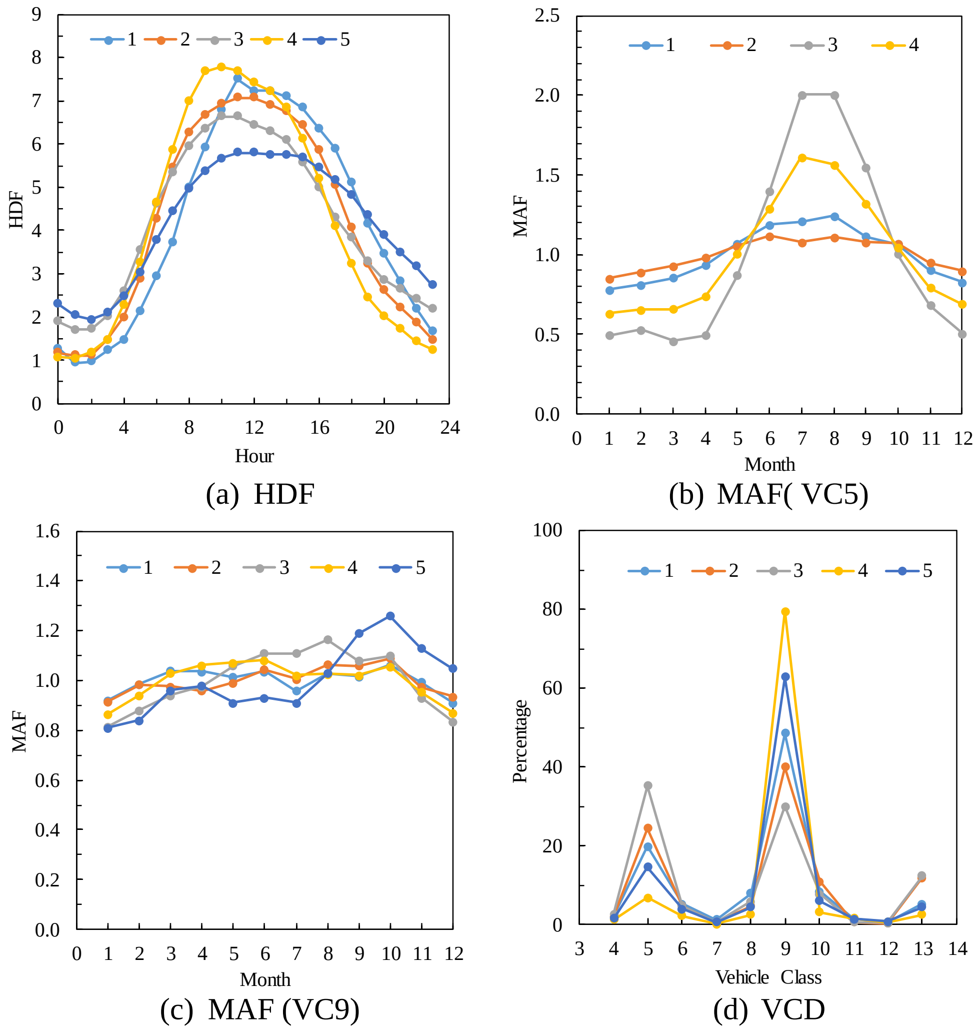


Figure 3-9 Cluster averages (Level 2A) for various traffic inputs

Cluster 3 average has roughly a 1-2% lower truck percentage between the hours of 7:00 am and 4:00 pm than either clusters 1 or 2. Sites in this cluster are located on principal interstates with average AADTT values of more than 2300. Sites in cluster 4 have the highest HDF during 8 am to 12 noon of all clusters. Most of these sites are on US routes with varying traffic levels. Sites in cluster 5 have the flattest curve among all the clusters with all the sites located on I-94, I-69 and I-75 suggesting long haul traffic.

2. Monthly adjustment factors (MAF) based on vehicle class 5 – 4 clusters

Four cluster averages for MAF based on VC5 are shown in Figure 3-9(b). Cluster 1 exhibits slight seasonal variability (MAF > 1) having MAFs close to 1.4 during summer months with lower values in winter. Most of these sites were located in the Lower Peninsula on a variety of roads with varying functional class and AADTT levels. Cluster 2 depicts very little seasonal variability with MAFs close to 1. Major routes, such as I-94, I-96 and I-275 are present in this cluster and most sites are located in the Lower Peninsula. Cluster 3 displays higher MAF in summer and fall, with much lower MAF in winter and spring. However there are only two sites (M-28 and US-2) in this cluster and are located in the Upper Peninsula with low AADTT. Sites in cluster 4 also have higher MAF in summer and fall and are mostly located on north-south routes such as I-75 and US-127.

3. MAF based on vehicle class 9 – 5 clusters

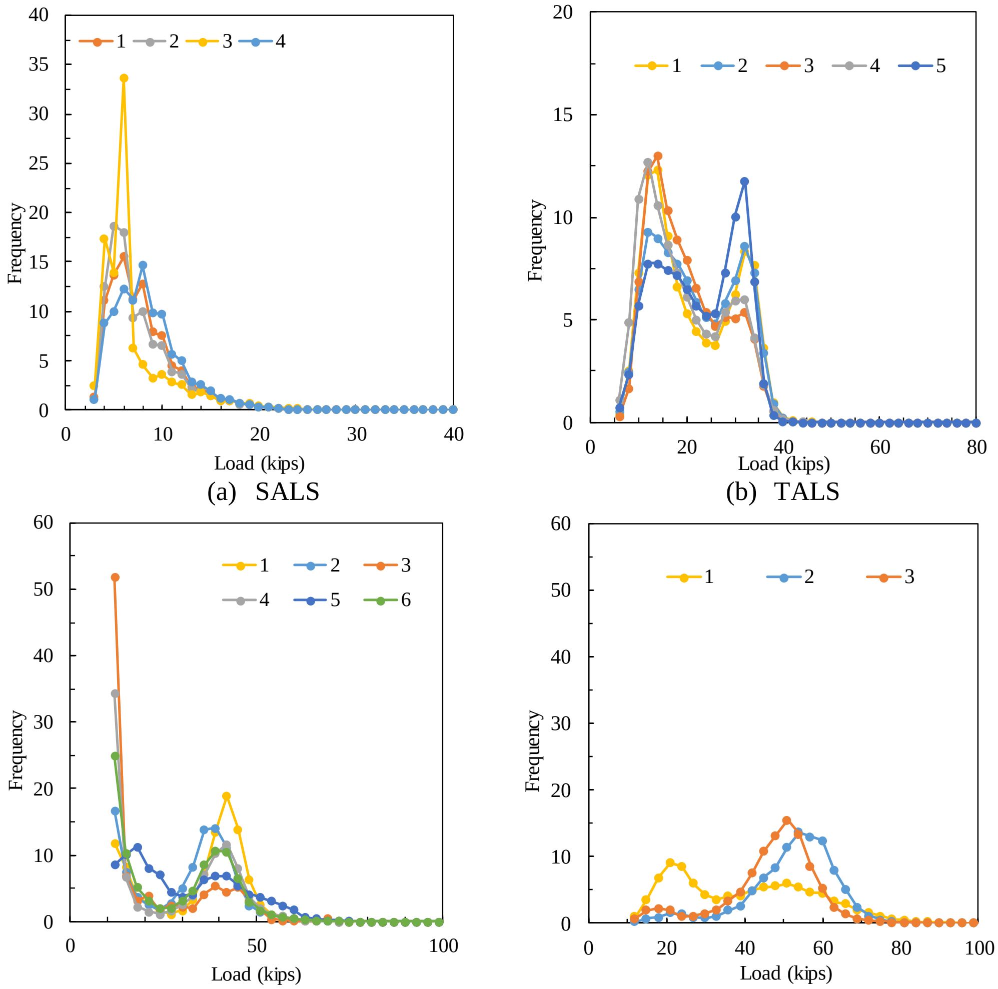
Five cluster averages for MAF based on VC9 are shown in Figure 3-9(c). Almost all the sites in all the clusters have no seasonal variability between months. Since, VC9 trucks are used for long haul throughout the year, a uniform presence of such trucks is expected on all the sites.

4. Vehicle class distribution (VCD) – 5 clusters

Figure 3-9 (d) illustrates the five clusters, each distinguished by the percentage of VC5 and VC9. While four clusters have higher VC9 truck levels than VC5, their proportions are different. Sites in cluster 1 have percentage VC9 trucks in the ranges of 45 to 70 while the VC5 truck percentage was in the range of 15 to 25. Most of these sites were found on state routes such as US-127 and US-2 with one-way AADTT ranging from 700 to 3600. Cluster 2 contained a majority of sites with percentage VC9 trucks less than 45 while the VC5 truck percentage was in the range of 20 to 30. Sites in this cluster are located mostly on rural arterials, such as US-2, US-31, M-95, generally with AADTT of less than 1500. Cluster 3 has sites that have slightly higher percentage of VC5 trucks than VC9 trucks. Most of these sites are on rural arterials with an AADTT of less than 800. Sites in cluster 4 have the highest percentage of VC9 trucks (above 75) with very low percentage of VC5 trucks (below 10). All the sites in this cluster are located on I-94, I-69 and I-75 with AADTT values ranging from 2500 to 8000. Sites in cluster 5 have percentage of VC9 trucks between 55 and 70 with percentage of VC5 trucks between 10 and 20. Most of the sites in this cluster are located on the interstates with a few sites on US-23. The AADTT values ranging from 1200 to 3500.

5. Single axle load spectra (SALS) based on vehicle class 5 – 4 clusters

Single axle load spectra are generally represented by VC5. Therefore, the single axle load spectra data for VC5 trucks were clustered and the cluster averages are shown Figure 3-10 (a). Four clusters were formed and are directly related to the peaks observed in the data. For all the sites in the clusters the first peak occurs at approximately 4 to 6 kips while the second peak occurs at 8 to 10 kips. A review of the individual single axles for all VCs at all sites revealed that the axle load spectra is not influenced so much by the shape of the axle load spectra itself but instead the actual distribution of the truck traffic, particularly the presence of VC5. Cluster 1 has almost equal proportion of axles in the 4-6 kip range and the 8-10 kip range. Cluster 2 has higher proportion of 4-6 kip axles than 8-10 kip axles. The sites located in clusters 1 and 2 are a mixture of interstates and state routes and have varying AADTT levels. Cluster 3 has only one site (US-2) in the Upper Peninsula and the pattern seen in the figure is unique to that site. Cluster 4 has sites with higher proportion of axles in the 8-10 kip range than the 4-6 kip range. All the sites in this cluster are located on I-94, I-96 and I-75 with AADTT levels ranging from 1500 to 8300.



(a) SALS
(b) TALS
(c) TRALS
(d) QALS

Figure 3-10 Cluster averages (Level 2A) for various traffic inputs

6. Tandem axle load spectra (TALS) based on vehicle class 9 – 5 clusters

Tandem axle load spectra are typically represented by VC9. Therefore, the overall tandem axle load spectra data for VC9 were clustered and the cluster averages can be seen in Figure 3-10 (b). Five clusters resulted from the data. The two peaks in the clusters correspond to unloaded (9-14 kips) and loaded (30-33 kips) trucks. Clusters 1, 3 and 4 have more light axles than heavy, whereas Clusters 2 and Cluster 5 have heavier tandem axles. Clusters 1, 3 and 4 consist of mostly secondary arterials and rural freeways scattered throughout the state. All sites have AADTT less than 3500. Nearly all sites in cluster 2 are located on major routes, I-94, I-96, and I-69 in the Lower Peninsula and have AADTT ranging from above 200 to 8000. Cluster 5 has sites mostly located on I-94 and I-96 with AADTT ranging from 400 to 5000.

7. Tridem axle load spectra (TRALS) based on vehicle class 13 – 6 clusters

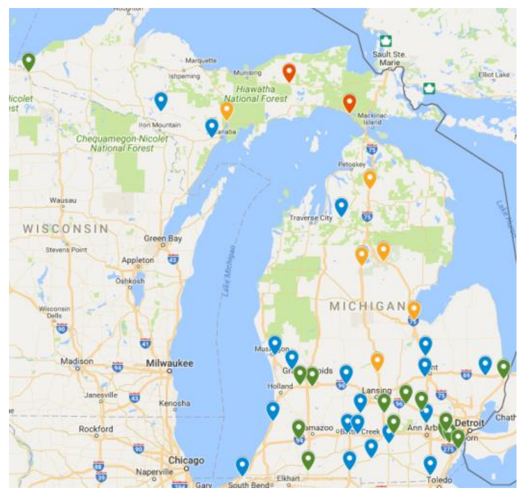
A total of six tridem axle load spectra clusters were generated as shown in Figure 3-10 (c). The general trend of the tridem axle clusters show a large proportion of light axles around 12 kips followed by a peak value around 40-45 kips. Sites found in the first cluster have the least average AADTT and were primarily located on I-75, M-28 and I-94. Sites contained in cluster 2 were also mainly on I-94, I-69 that had AADTT ranging from 400 to 5200. All the sites in the other clusters have varying functional classes and AADTT levels.

8. Quad axle load spectra (QALS) based on vehicle class 13 – 3 clusters

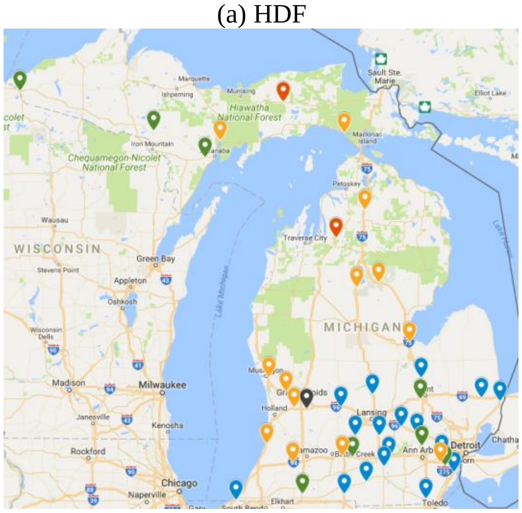
The quad axle load spectra clusters can be seen in Figure 3-10 (d). A total of three clusters were formed. Peak values for the quad axle load spectra occur at the 18-24 kips, 45-60 kip ranges. Dominant characteristics could not be established for the clusters as they have varying functional classifications and AADTT levels.

Figures 3-11 and 3-12 show the geographical distributions of the PTR locations and associated clusters for all traffic inputs.

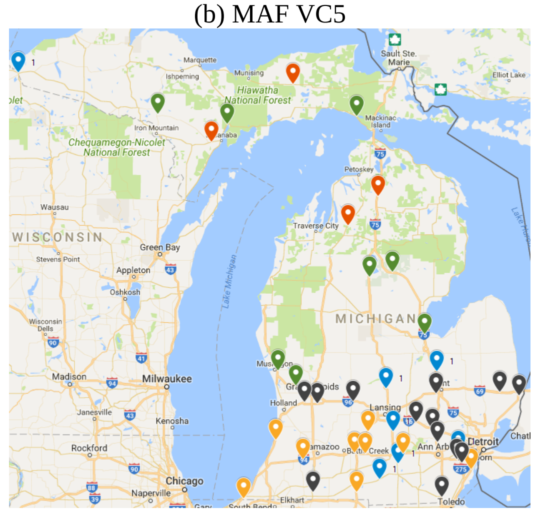
(a) HDF



(b) MAF VC5



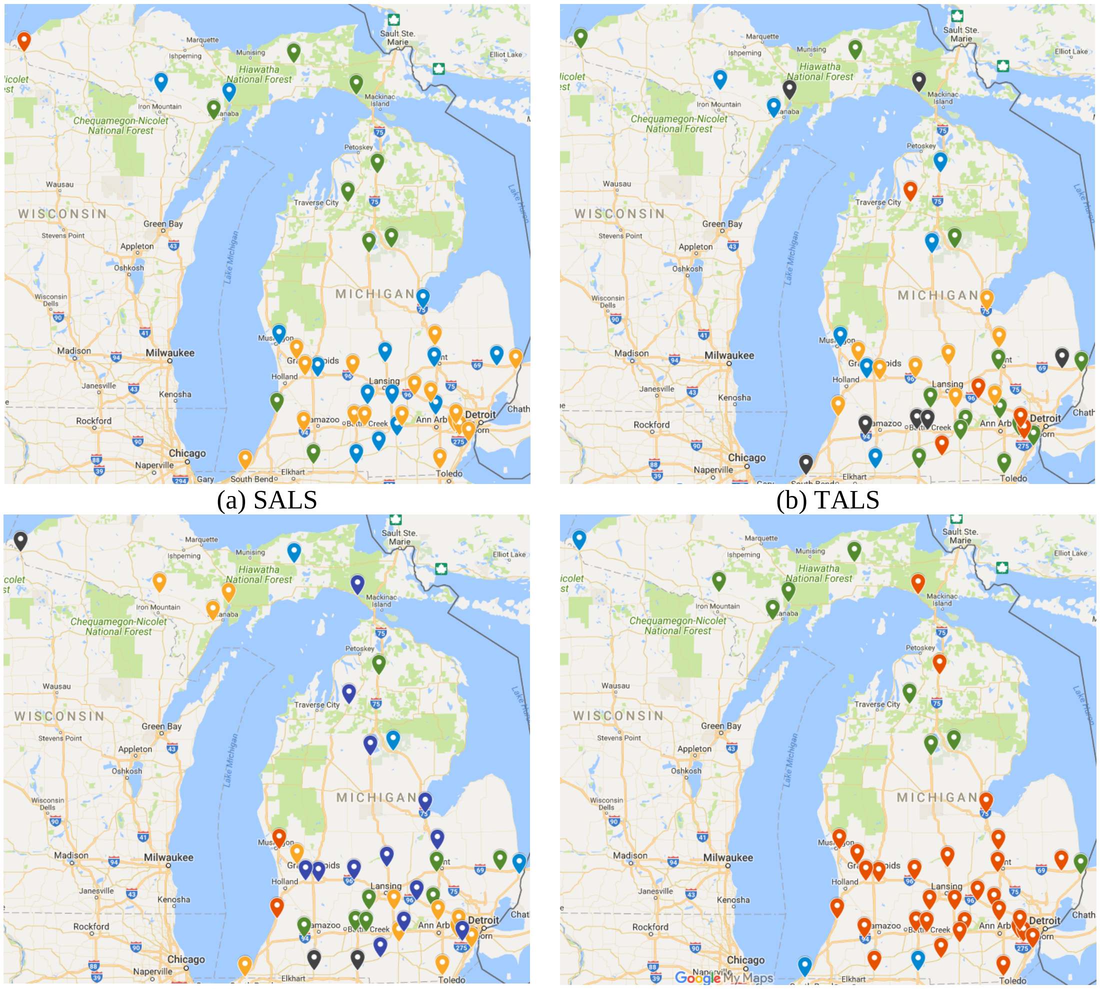
(c) MAF VC9



(d) VCD

Note: blue = cluster 1, green = cluster 2, red = cluster 3, orange = cluster 4, and black = cluster 5

Figure 3-11 Geographical distributions for PTRs by clusters for traffic inputs



Note: blue = cluster 1, green = cluster 2, red = cluster 3, orange = cluster 4, black = cluster 5, dark blue = cluster 6

Figure 3-12 Geographical distributions for PTRs by clusters for all traffic inputs

3.2.2 Traditional Approaches

Traditional approaches are more subjective and involve grouping roads that are expected to behave similarly (i.e., similar traffic patterns). Attributes of the roadways (e.g., road class freeway vs. non-freeway) can be used to identify groups that have similar traffic patterns. Such groups based on these attributes are easy to interpret by the users. The roadways that have unique traffic patterns could consist of the same functional classification. Attributes specific to a State road network could be used to define roads subgroup. Data analyses results and knowledge of specific route information should determine the appropriate number of these groups. The traffic monitoring guide (TMG) recommends a minimum of three to six groups are required, but more groups may be appropriate if significant regional differences exist (*3*). The groups will be referred to as 'Level 2B inputs'. The advantages of this methodology are that the creation of groups is intuitive, and the short-term count from a new site can be used to assign it to an existing group. The drawback of this process is that it is not entirely objective (involves a lot of subjective decisions which may not explain the variability of traffic patterns within a group).

The attributes used to classify groups need not necessarily be the same for all the traffic inputs and instead should depend on the type of traffic input. For monthly adjustment and hourly distribution factors, the primary groups could be based on road class and development type such as (a) rural interstates, (b) rural non-interstates, (c) urban interstates, and (d) urban non-interstates. The TMG recommends adding a fifth group which consists of roadways used by recreational traffic (*3*). Recreational traffic patterns should be identified using local knowledge of specific locations that could generate recreational traffic; they cannot be defined based on functional class or area boundaries. An SHA could further expand these four groups, but more groups may require more data (more WIM and classification sites) which in turn would increase the cost to the agency. The coefficient of variation of monthly patterns in urban areas is usually under 10 percent, while in rural areas it ranges between 10 and 25 percent. Values higher than 25 percent indicate highly variable travel patterns, which reflect recreational patterns but may also be due to reasons other than recreational travel. For MAF and HDF, functional class (freeway or non-freeway), development type (rural or urban), and geographic location within the State have been the typical characteristics for grouping the roadways. Recreational (or geographic) designations can be used for roads that are affected by sizeable recreational traffic generators occasionally (*3*).

For VCD, characteristics of roadways to be considered for groupings should be different. Previous research has found out that functional class of roadways have an inconsistent relationship to truck travel patterns (*19, 20*). The amount of long-distance truck traffic versus the amount of locally oriented truck traffic significantly affect the truck traffic patterns on a route. Also the existence of significant truck traffic generators along a roadway such as agriculture or significant industrial activity can affect these patterns. Functional road classification helps in a limited way to differentiate between roads with heavy through-traffic and those with only local traffic. Typically, interstates and principal arterials have higher through-truck traffic volumes. However, there are roads with several lower functional classifications that are carrying more through-truck volumes than the interstates and principal arterials. Developing these groups also requires an understanding of the freight movements in the State (*19*, *20*). Communication with the staff at the SHA would help in identifying the local and statewide patterns. Cluster analyses could be used to identify the traffic patterns initially, and each cluster could be looked at to gain a fundamental idea of the roadway characteristics of the PTR locations in that cluster.

Based on above discussion, for Level 2B inputs, the challenge lies in identifying a combination of attributes that can be used to group the PTR locations. The traffic patterns at the PTR locations should be similar within a group and should be different between the groups. An automated process was developed to help identify such combinations of attributes. The following attributes from the MDOT's sufficiency database were identified for grouping different PTR locations:

- Functional classification (Freeway vs. Non-Freeway)
- Development type (Urban vs. Rural)
- One-way AADTT levels (1 "<1000", 2 "1000-3000",3 ">3000")
- Corridors of highest significance, COHS (National, Regional, and Statewide)

- Number of lanes (2, 3 and 4)
- Road type (Non-freeway divided, Non-freeway undivided, and Freeway)
- Vehicle class 9 (VC 9) distribution levels (< 45, 45 – 70, >70)

It should be noted that the MDOT sufficiency database itself is no longer being supported, but its data is still available in other platforms and is being updated. Several attributes can be chosen at a time to divide the PTR locations into groups. Tables 3-4, to 3-6 list the possible 2-, 3-, and 4-way combinations of the attributes listed above. Each attribute has sublevels (e.g., functional classification has two sublevels of freeway and non-freeway), and hence a combination of attributes has different sublevel combinations. The Level 1 traffic inputs of PTR sites belonging to a combination of sublevels are averaged. For example, the VCD traffic inputs for the combination of functional class and development type (2-way combination) can be seen in Table 3-7.

Table 3-4 Possible combination of attributes when chosen two at a time

Attribute 1	Attribute 2
Functional Class	Road Type
Functional Class	Number of Lanes
Functional Class	Commercial AADT
Functional Class	COHS
Functional Class	Development Type
Functional Class	VCD Level
Road Type	Number of Lanes
Road Type	Commercial AADT
Road Type	COHS
Road Type	Development Type
Road Type	VCD Level
Number of Lanes	Commercial AADT
Number of Lanes	COHS
Number of Lanes	Development Type
Number of Lanes	VCD Level
Commercial AADT	COHS
Commercial AADT	Development Type
Commercial AADT	VCD Level
COHS	Development Type
COHS	VCD Level
Development Type	VCD Level

Note: There are 21 2-way attribute combinations (based on 7C2=21).

Table 3-5 Possible combination of attributes when chosen three at a time

Attribute 1	Attribute 2	Attribute 3
Functional Class	Road Type	Number of Lanes
Functional Class	Road Type	Commercial AADT
Functional Class	Road Type	COHS
Functional Class	Road Type	Development Type
Functional Class	Road Type	VCD Level
Functional Class	Number of Lanes	Commercial AADT
Functional Class	Number of Lanes	COHS
Functional Class	Number of Lanes	Development Type
Functional Class	Number of Lanes	VCD Level
Functional Class	Commercial AADT	COHS
Functional Class	Commercial AADT	Development Type
Functional Class	Commercial AADT	VCD Level
Functional Class	COHS	Development Type
Functional Class	COHS	VCD Level
Functional Class	Development Type	VCD Level
Road Type	Number of Lanes	Commercial AADT
Road Type	Number of Lanes	COHS
Road Type	Number of Lanes	Development Type
Road Type	Number of Lanes	VCD Level
Road Type	Commercial AADT	COHS
Road Type	Commercial AADT	Development Type
Road Type	Commercial AADT	VCD Level
Road Type	COHS	Development Type
Road Type	COHS	VCD Level
Road Type	Development Type	VCD Level
Number of Lanes	Commercial AADT	COHS
Number of Lanes	Commercial AADT	Development Type
Number of Lanes	Commercial AADT	VCD Level
Number of Lanes	COHS	Development Type
Number of Lanes	COHS	VCD Level
Number of Lanes	Development Type	VCD Level
Commercial AADT	COHS	Development Type
Commercial AADT	COHS	VCD Level
Commercial AADT	Development Type	VCD Level
COHS	Development Type	VCD Level

Note: There are 35 3-way combinations (based on 7C3=35)

Table 3-6 Possible combination of attributes when chosen four at a time

Attribute 1	Attribute 2	Attribute 3	Attribute 4
Functional Class	Road Type	Number of Lanes	Commercial AADT
Functional Class	Road Type	Number of Lanes	COHS
Functional Class	Road Type	Number of Lanes	Development Type
Functional Class	Road Type	Number of Lanes	VCD Level
Functional Class	Road Type	Commercial AADT	COHS
Functional Class	Road Type	Commercial AADT	Development Type
Functional Class	Road Type	Commercial AADT	VCD Level
Functional Class	Road Type	COHS	Development Type
Functional Class	Road Type	COHS	VCD Level
Functional Class	Road Type	Development Type	VCD Level
Functional Class	Number of Lanes	Commercial AADT	COHS

Table 3-6 Possible combination of attributes when chosen four at a time (cont'd…)

Attribute 1	Attribute 2	Attribute 3	Attribute 4
Functional Class	Number of Lanes	Commercial AADT	Development Type
Functional Class	Number of Lanes	Commercial AADT	VCD Level
Functional Class	Number of Lanes	COHS	Development Type
Functional Class	Number of Lanes	COHS	VCD Level
Functional Class	Number of Lanes	Development Type	VCD Level
Functional Class	Commercial AADT	COHS	Development Type
Functional Class	Commercial AADT	COHS	VCD Level
Functional Class	Commercial AADT	Development Type	VCD Level
Functional Class	COHS	Development Type	VCD Level
Road Type	Number of Lanes	Commercial AADT	COHS
Road Type	Number of Lanes	Commercial AADT	Development Type
Road Type	Number of Lanes	Commercial AADT	VCD Level
Road Type	Number of Lanes	COHS	Development Type
Road Type	Number of Lanes	COHS	VCD Level
Road Type	Number of Lanes	Development Type	VCD Level
Road Type	Commercial AADT	COHS	Development Type
Road Type	Commercial AADT	COHS	VCD Level
Road Type	Commercial AADT	Development Type	VCD Level
Road Type	COHS	Development Type	VCD Level
Number of Lanes	Commercial AADT	COHS	Development Type
Number of Lanes	Commercial AADT	COHS	VCD Level
Number of Lanes	Commercial AADT	Development Type	VCD Level
Number of Lanes	COHS	Development Type	VCD Level
Commercial AADT	COHS	Development Type	VCD Level

Note: There are 35 4-way combinations (based on 7C4=35)

Table 3-7 VCD traffic inputs for the combination of functional class and development type

Sublevel	Sublevel	VC4	VC5	VC6	VC7	VC8	VC9	VC10	VC11	VC12	VC13
Freeway	Rural	1.6	14.8	3.5	0.4	4.1	62.4	6.7	1.3	0.6	4.7
Freeway	Urban	1.5	18.4	5.1	0.8	5.4	55.7	6.1	1.3	0.6	5.0
Non-freeway	Rural	2.3	25.0	4.7	0.9	6.1	40.8	7.4	0.8	0.4	11.5
Non-freeway	Urban	0.8	18.8	4.7	0.7	5.1	49.8	11.2	1.8	0.3	6.8

Pairwise Euclidean distances between each sublevel combinations were calculated to identify the combination of attributes that show different traffic patterns. Pairwise distances for the sublevel combinations in Table 3-7 are shown in Table 3-8.

Table 3-8 Pairwise Euclidean distances between the sublevel combinations

Sublevel combination	Freeway_Rural	Freeway_Urban	Non-freeway_Rural	Non-freeway_Urban
Freeway_Rural	**0.0**	8.0	24.9	14.2
Freeway_Urban	8.0	**0.0**	17.6	8.0
Non-freeway_Rural	24.9	17.6	**0.0**	12.6
Non-freeway_Urban	14.2	8.0	12.6	**0.0**

The maximum distance between the sublevel combinations increases with the increase in the number of attributes used for grouping. However, higher the number of attributes used for grouping, lower is the number of PTR locations in each sublevel combinations. For example, in Table 3-9, the total number of sublevel combinations should have been 12 [Road type (4) x VCD Level (3)]; however, due to a limited number of PTR locations, only 7 sublevel combinations exist. When three attributes are chosen (see Table 3-10), only 10 out of a possible 18 sublevel combinations exist. Similarly, when four attributes are chosen (see Table 3-11), only 14 out of a possible 72 sublevel combinations exist and many of them have only one or two PTR locations. Hence it is more appropriate to use only two attribute combinations to form road groups for developing Level 2B inputs.

Table 3-9 Number of PTR locations in each sublevel combination (2-way) for road type/ VCD level combination

Road type	VCD level	Number of PTR locations
'Divided (partial or no access control)'	Low VC9	2
'Freeway (full access control)'	High VC9	10
'Freeway (full access control)'	Low VC9	6
'Freeway (full access control)'	Medium VC9	15
'Two travel lanes with center left turn lane'	Medium VC9	1
'Two-way undivided (any number of lanes)'	Low VC9	4
'Two-way undivided (any number of lanes)'	Medium VC9	3

Table 3-10 Number of PTR locations in each sublevel combination (3-way) for road type/ development type/VCD level combination

Number of lanes	Development type	VCD level	Number of PTR locations
Four	Rural	Medium VC9	1
Three	Rural	High VC9	1
Three	Rural	Medium VC9	2
Three	Urban	High VC9	1
Three	Urban	Medium VC9	2
Two	Rural	High VC9	8
Two	Rural	Low VC9	11
Two	Rural	Medium VC9	11
Two	Urban	Low VC9	1
Two	Urban	Medium VC9	3

The next step is to obtain the pairwise distances between sublevel combinations and identifying the missing ones for each attribute combination. The descriptive statistics for these distances for each two-way combination of attributes (all 7 attributes and 21 combinations), the number of missing sublevel combinations, combinations with only one

PTR site are listed in Table 3-12 for VCD. Similar data for other traffic inputs can be found in Appendix A.

Table 3-11 Number of PTR locations in each sublevel combination (4-way) for road type/number of lanes/ development type/VCD level combination

Road type	Number of lanes	Development type	VCD level	Number of PTR locations
Divided (partial or no access control)	Two	Rural	Low VC9	2
Freeway (full access control)	Four	Rural	Medium VC9	1
Freeway (full access control)	Three	Rural	High VC9	1
Freeway (full access control)	Three	Rural	Medium VC9	2
Freeway (full access control)	Three	Urban	High VC9	1
Freeway (full access control)	Three	Urban	Medium VC9	2
Freeway (full access control)	Two	Rural	High VC9	8
Freeway (full access control)	Two	Rural	Low VC9	5
Freeway (full access control)	Two	Rural	Medium VC9	8
Freeway (full access control)	Two	Urban	Low VC9	1
Freeway (full access control)	Two	Urban	Medium VC9	2
Two travel lanes with center left turn lane	Two	Urban	Medium VC9	1
Two-way undivided (any number of lanes)	Two	Rural	Low VC9	4
Two-way undivided (any number of lanes)	Two	Rural	Medium VC9	3

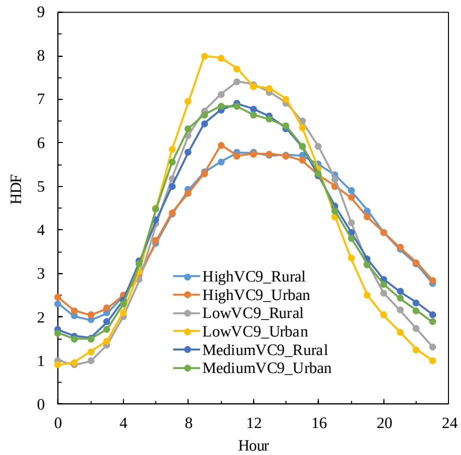
After careful evaluation of the results, the following attribute combinations are chosen based on the availability of the sublevel combinations and the distances between them. The traffic data of all the PTR sites in each of the sublevel combinations (road groups) for the attributes chosen are averaged to obtain the Level 2B inputs. Figure 3-13 shows the averages of road groups for various traffic inputs.

a) Hourly distribution factors: VCD Level and Development Type

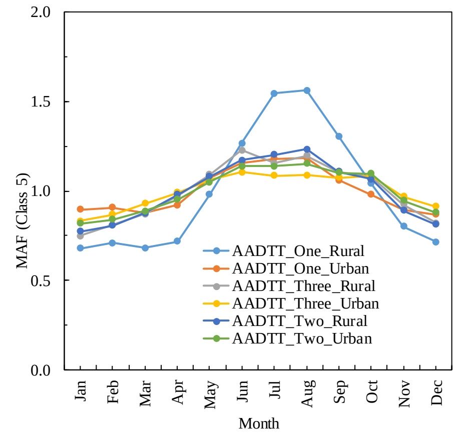
The attributes of VCD level and development type resulted in six groups for HDF as shown in Figure 3-13(a). The sites having low VC9 levels in the urban areas have the highest peak among all other groups between 8:00 am and 4:00 pm suggesting local traffic patterns. The sites in this group are state routes with AADTT of less than 1300. Sites having high VC9 levels have the flattest peaks in both urban and rural areas suggesting long haul traffic patterns. All the sites in high VC9 groups are on interstate routes.

b) Monthly adjustment factors: Commercial AADT and Development Type

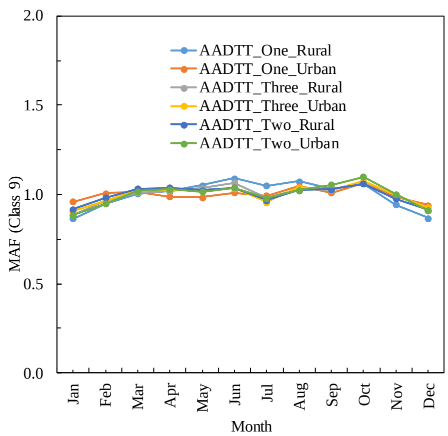
The attributes of commercial AADT and development type resulted in six groups of inputs for MAFs as shown in Figure 3-13(b) & (c). Almost all the groups have similar MAF patterns for VC5 except for sites with low AADTT in the rural areas suggesting seasonal traffic patterns. Almost all the sites in this group are on US-2, US-12, and US-127 with AADTT level less than 1000. No differences in MAFs for VC9 trucks were found between the groups and are always close to 1.



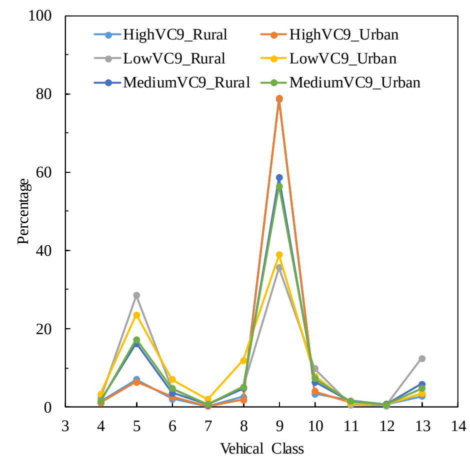
(a) HDF



(b) MAF (VC 5)



(c) MAF (VC 9)



(d) VCD

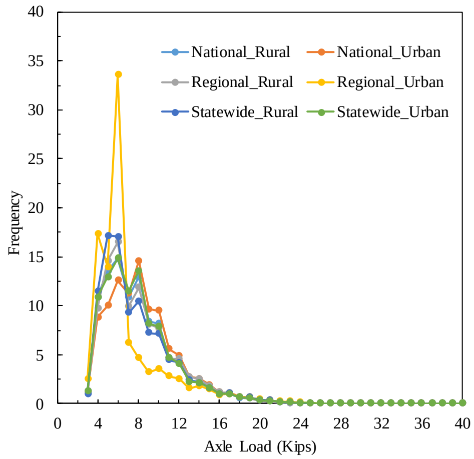
Figure 3-13 Group averages (Level 2B) for various traffic inputs

c) Vehicle class distribution: VCD Level and Development Type

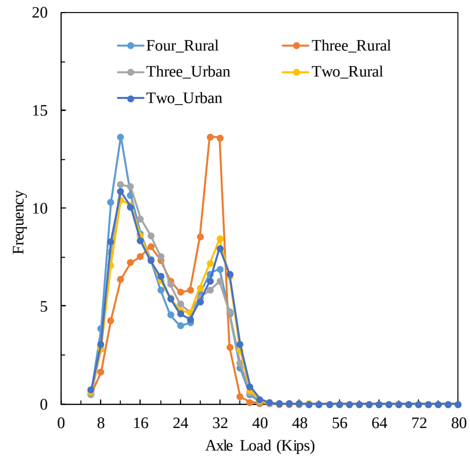
The attributes of VCD level and development type resulted in six groups for VCD as shown in Figure 3-13(d). Since the attribute used is VCD level, three distinct patterns can be seen with varying levels of VC9 irrespective of the development type. All the sites in high VC9 groups are located on the interstates while most of the sites in low VC9 groups are located on state routes. Sites in the medium VC9 groups have a mix of both intestates and state routes in rural and urban areas.

d) Single Axle Load Spectra: COHS and Development Type

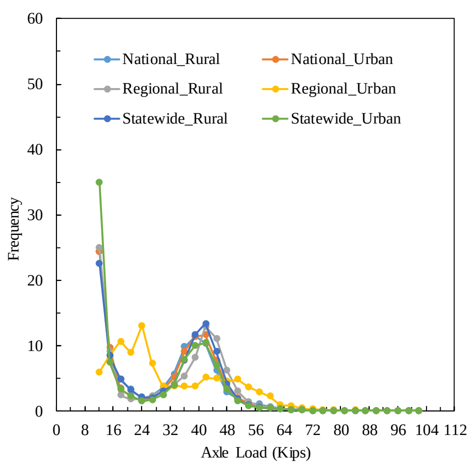
The attributes of COHS and development type resulted in six groups for SALS as shown in Figure 3-14(a). For all the sites in different groups, the first peak occurs at approximately 4-6 kips while the second peak occurs at 8-10 kips. Road groups in the urban areas have almost equal proportion of axles in the 4-6 kip range and the 8-10 kip range while the sites in the rural areas have higher proportion of 4-6 kip axles than 8-10 kip axles. The road group of regional corridor in the urban area has only one site on US-2 with a unique loading pattern.



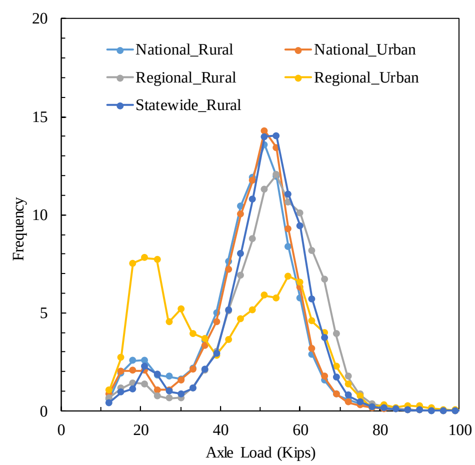
(a) SALS



(b) TALS



(c) TRALS



(d) QALS

Figure 3-14 Group averages (Level 2B) for various traffic inputs

e) Tandem Axle Load Spectra: Number of Lanes and Development Type

The attributes of number of lanes and development type resulted in five groups for TALS as shown in Figure 3-14 (b). The two peaks seem to correspond to unloaded (9-14 kips) and loaded (30-33 kips) tandem axles. Other characteristics could not be established for the groups as they have varying functional classifications and AADTT levels and also due to the fact that some groups only have one site.

f) Tridem Axle Load Spectra: COHS and Development Type

The attributes of COHS and development type resulted in six groups for TRALS as shown in Figure 3-14 (c). The general trend of the tridem axle groups appears to be a large proportion of light axles around 12 kips followed by a peak value around 40-45 kips. All the sites in the national corridors are located on interstates while the sites on regional and statewide corridors are on state routes with varying AADTT levels irrespective of the development type.

g) Quad Axle Load Spectra: COHS and Development Type

The attributes of COHS and development type resulted in six groups for QALS as shown in Figure 3-14 (d). Again, all the sites in national corridors are on the interstates while the sites on regional and statewide corridors are on state routes with varying AADTT levels irrespective of the development type.

Table 3-12 Descriptive Statistics of the pairwise distances between the sublevel combinations for various attribute combinations (VCD)

Attribute 1	Attribute 2	Pairwise Euclidean distances between the sublevel combinations					Sublevel combinations			
		Max	Min	Avg.	Std.	Range	Total	Available	With only one PTR location	Missing
VCD Level	**Development Type**	**50.0**	**1.5**	**26.5**	**15.1**	**48.5**	**6**	**6**	**0**	**0**
Commercial AADT	Development Type	46.8	1.9	21.3	11.9	44.9	6	6	0	0
COHS	Development Type	28.3	2.9	18.0	7.1	25.4	6	6	1	0
Road Type	Development Type	27.7	4.8	17.6	6.8	22.9	6	6	3	0
Functional Class	Development Type	25.9	4.8	17.2	7.4	21.1	4	4	0	0
Functional Class	VCD Level	50.4	6.7	25.5	14.4	43.7	6	5	0	1
Number of Lanes	Development Type	41.6	4.3	19.0	16.1	37.3	6	5	2	1
Functional Class	Commercial AADT	40.2	5.4	21.1	11.5	34.8	6	5	0	1
Functional Class	COHS	28.7	8.0	15.9	6.7	20.7	6	5	0	1
COHS	VCD Level	54.5	2.5	23.0	13.2	52.1	9	7	1	2
Commercial AADT	VCD Level	50.3	1.9	24.3	14.3	48.4	9	7	0	2
Commercial AADT	COHS	42.0	4.2	22.0	11.9	37.9	9	7	1	2
Road Type	COHS	28.7	2.1	16.1	7.7	26.7	9	7	3	2
Functional Class	Number of Lanes	28.0	6.9	15.8	7.8	21.2	6	4	1	2
Road Type	VCD Level	56.1	7.6	25.3	14.0	48.5	9	6	0	3
Number of Lanes	VCD Level	53.2	1.7	23.9	14.7	51.4	9	6	1	3
Road Type	Commercial AADT	42.7	5.4	21.0	10.9	37.3	9	6	0	3
Number of Lanes	Commercial AADT	42.3	1.1	18.1	11.0	41.1	9	6	1	3
Functional Class	Road Type	23.1	9.7	17.8	7.2	13.5	6	3	0	3
Road Type	Number of Lanes	28.8	6.9	16.4	7.5	22.0	9	5	1	4
Number of Lanes	COHS	26.1	5.5	14.9	7.0	20.6	9	5	1	4

Note: Shaded cells indicate the selected attribute combination for generation of Level 2B inputs

3.3 SUMMARY

This chapter discussed the permanent traffic recorder (PTR) data collection and processing for developing traffic input defaults for the Pavement-ME. Site-specific traffic inputs (Level 1) were generated for each of the 41 WIM sites using the PrepME software after applying QC checks. Development of Level 2 inputs is crucial when site-specific data are not available. The averages from clusters or groups with similar traffic characteristics can be used as Level 2 data (*2*). The average of all the sites (statewide average) can be used as Level 3 data. Level 3 data are further divided into Levels 3A, and 3B, where 3A represents average traffic inputs of freeways and non-freeways, and 3B represents overall statewide average for traffic inputs. Two approaches were used to develop Level 2 traffic inputs (a) cluster analyses (i.e., improved existing approach) and (b) traditional approaches (simplified methodology).

The advantages of cluster analyses are that the groups are formed objectively (based on a mathematical function) and not subjected to bias or subjective decisions. In addition, it finds patterns in the data that are not intuitively obvious therefore providing new insights into traffic patterns in a region. One main disadvantage is the lack of guidelines on establishing the optimal number of clusters. While various techniques were developed to identify the optimal number of clusters, none of them are perfect and have their drawbacks. The other disadvantage is that, since clustering is purely a mathematical technique, the sites in a cluster might not have the same identifiable attributes making the assignment of data from a new location to the existing clusters difficult. The Euclidean distance and Ward's method were used as the similarity measure and the linkage method, respectively to cluster the traffic data. 'Calinski-Harbasz Criterion' and 'Gap Criterion' methods , and engineering judgements were used to determine the optimal number of clusters for each traffic input. The inputs developed using this methodology are identified as 'Level 2A' inputs in this report.

Traditional approaches are more subjective and involve grouping roads that are expected to behave similarly (i.e., similar traffic patterns). Attributes of the roadways (e.g., road class freeway vs. non-freeway) can be used to identify groups that have similar traffic patterns. Such groups based on these attributes are easy to interpret by the users. A minimum of three to six groups are required, but more groups may be appropriate if significant regional differences exist (*3*). The advantages of this methodology are that the creation of groups is intuitive, and the short-term count from a new site can be used to assign it to an existing group. The drawback of this process is that it is not entirely objective (involves a lot of subjective decisions which may not explain the variability of traffic patterns within a group). Also, the challenge lies in identifying a combination of attributes that can be used to group the PTR locations. The traffic patterns at the PTR locations should be similar within a group and should be different between the groups. An automated process was developed to help identify such combinations of attributes. The inputs developed using this methodology are called 'Level 2B' inputs in this report.

The traffic input levels developed in this study are listed below.

a. Level 1 – Site-specific inputs
b. Level 2A – Averages of clusters based on cluster analyses
c. Level 2B – Averages of groups based on roadway characteristics (attributes)
d. Level 3A – Averages of groups based on freeway and non-freeway road class
e. Level 3B – Statewide averages

Table 3-13 lists the number of clusters and road groups formed that could be used as Level 2 traffic inputs.

Table 3-13 Number of clusters and road groups formed for Level 2 inputs

Input	Number of clusters (Level 2A)	Road groups (Level 2B)
Hourly distribution factors (HDF)	5	6
Monthly adjustment factors (MAF) based on VC 5	4	6
MAF based on VC9	5	6
Vehicle class distribution (VCD)	5	6
Single axle load spectra (SALS)	4	6
Tandem axle load spectra (TALS)	5	5
Tridem axle load spectra (TRALS)	6	6
Quad axle load spectra (QALS)	3	6

CHAPTER 4 - SIGNIFICANT TRAFFIC INPUTS

In Chapter 3, the Pavement-ME traffic inputs were generated for Levels 1, 2A, 2B, 3A and 3B. Level 1 inputs should always be used for design purposes wherever possible as it is the actual traffic data specific to the site. When Level 1 inputs are unavailable, Level 2 or Level 3 inputs need to be used. The results of the sensitivity analyses based on statistical significance and maximum life difference should be used to decide on the appropriate traffic input level. The primary purpose of sensitivity analyses is to identify if the traffic defaults developed based on clustering (Level 2A inputs) or road grouping (Level 2B inputs) techniques would provide significantly different pavement life predictions. The statewide defaults (Level 3A or 3B inputs) would suffice for some of the traffic inputs for which the Level 2 inputs do not have a significant impact on pavement design outcomes. The steps involved in sensitivity analyses include establishing base designs, performance criteria and other input parameters in the Pavement-ME and then evaluating the impact of Levels 2 and 3 traffic inputs.

The impact of Level 2 inputs on pavement designs can be evaluated in two ways:

Option 1: Changing one input at a time to Level 2 and keeping all other inputs at Level 1, this sensitivity analyses is referred to as Option 1.
Option 2: Changing one input at a time to Level 2 and keeping all other inputs at Level 3, this sensitivity analyses is referred to as Option 2.

In Option 1, the impact of input Level 2 is relative to site-specific traffic characteristics (i.e., Level 1). On the other hand, in Option 2 the effect of Level 2 is relative to the statewide traffic characteristics (i.e., Level 3). Option 2 will isolate the impact of a single traffic input because only one traffic input was changed to Level 2 and all other inputs were kept at Level 3. Option 1 is more realistic since site-specific traffic data are used except for the Level 2 input for each WIM location. However, Option 2 was included since the most States have adopted such approaches.

4.1 SENSITIVITY ANALYSES – OPTION 1

Table 4-1 contains the baseline flexible pavement design used for the sensitivity analyses. Material inputs used in these designs were as per MDOT guidance. The Pavement-ME Version 2.3 was used for the sensitivity analysis. For both the flexible and rigid pavements, locally calibrated performance models were used with only one climate station in Lansing (*1*, *2*) (see Appendix B). The pavement design life was assumed 20 years with 95% design reliability. For each of the 41 WIM locations, the HMA surface layer thickness was designed to achieve a 20-year design life for bottom-up fatigue cracking threshold of 20% for flexible pavements since it typically controls the designs. Level 1 inputs were used in this process. For these designs, the rut depth values at the end of 20 years were also recorded. Table 4-2 presents the baseline rigid pavement design used for the sensitivity analyses. For each of the 41 WIM locations, the slab thickness was designed to achieve a 20-year design life for IRI threshold of 172 inches/mile since it controls the designs for rigid pavements. Faulting and transverse cracking values were also recorded at the end of 20 years.

For both the flexible and rigid pavement designs, one traffic input was changed at a time to appropriate cluster or road groups for the site of the PTR. (Levels 2A and 2B) to determine the effect of that input on the design life. Levels 3A and 3B inputs for each design (one input at a time) were also tested in the Pavement-ME to determine their impact on the design life. The time for the distress values (for Levels 2 and 3) to reach the threshold values in the Level 1 designs were documented. The differences in design lives between different inputs levels were quantified for further analyses.

Table 4-1 Baseline designs for flexible pavements

Layer/Detail	Elastic Modulus (psi)	Thickness (in)
Asphalt	Estimated by the Pavement-ME	Variable
Aggregate base (A-1-a)	33000	6
Sand subbase-A-1-b	20000	18
Sandy clay subgrade-A4	4400	Semi-Infinite
Climate	Lansing, MI	

Table 4-2 Baseline designs for rigid pavements

Layer/Detail	Elastic Modulus (psi)	Thickness (in)
JPCP	5600 ($f_c^{'}$)	Variable
Open graded base (A-1-a)	33000	6
Sand subbase (A-1-b)	20000	10
Sandy clay roadbed (A-6)	4400	Semi-Infinite
Joint spacing	15 ft.	
Dowel bar diameter	1.25 in (<10in) 1.5in (=>10in)	
Climate	Lansing, MI	

Many statistical analyses can be performed to understand the characteristics of a data set and differences between datasets. Statistical analyses could detect differences in the datasets, but the differences might not have much practical significance or vice versa. Statistically, significant differences can be found even with minimal differences between datasets of considerable size. That is, a statistical significance of the results does not always imply practical consequence. Hence in addition to finding the likelihood of a value (significance value 'α') outside the 95% confidence interval (CI), the maximum life difference (MLD) values between two input levels were also adopted as an indicator of the variability in the data. The MLD is the maximum difference in life between traffic input levels among the PTR locations. Table 4-3 lists the criteria used to determine the impact (sensitivity) of the difference between traffic inputs and correspondingly select the proper input level needed for the design. These designations will be used to measure each traffic characterization performance against site-specific values and to determine its impact on life differences.

Table 4-3 Impact designation on predicted pavement performance

Designation of Impact	Maximum Life Difference (MLD) in years
Significant	MLD > 5
Moderate	2 < MLD < 5
Negligible	MLD < 2

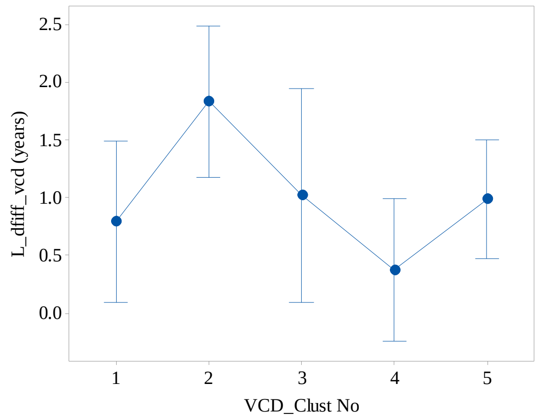
4.1.1 Level 2A Sensitivity Analyses

A one way analysis of variance (ANOVA) can be used when to determine the statistical differences in the means of two or more groups (*3*). If the p-value is less than 0.05 (i.e., 95% confidence level), at least one group is different from the others. Additionaly, multiple comparisons can be made to identify which group means are different from others. One way ANOVA was performed on the absolute life differences ($|\text{Life}_{\text{Level 1}} - \text{Life}_{\text{Level 2A}}|$) to detect the differences between the clusters for each traffic input. Table 4-4 and Figure 4-1 show the results of the ANOVA for Level 2A VCD clusters for flexible pavements. Since the *p*-value is below 0.05, the results indicate that at least two of the cluster averages are statistically different from each other. The multiple compariosn (Tukey's test) results show that clusters 2 and 4 are different from each other and that their use in pavement design would result in statistically different design lives [see Figure 4-1(b)]. More details on the interpretation of ANOVA can be found in the reference (*3*). However, it does not indicate whether the differences are of practical significance. Figure 4-2 presents the differences in predicted performance for flexible pavements with the use of different VCD Level 2A clusters for each WIM location. Each plot is divided into three regions (negligible, moderate and significant) based on the MLD categories presented in Table 4-3. Figure 4-2(a) shows the WIM locations in VCD Cluster 1 and the life differences when Cluster 1 VCD values are used in the Pavement-ME as compared to Level1 VCD inputs for each WIM location. Note that all the other traffic input values are at Level 1. Similar tables and figures for other traffic inputs can be found in Appendix C.

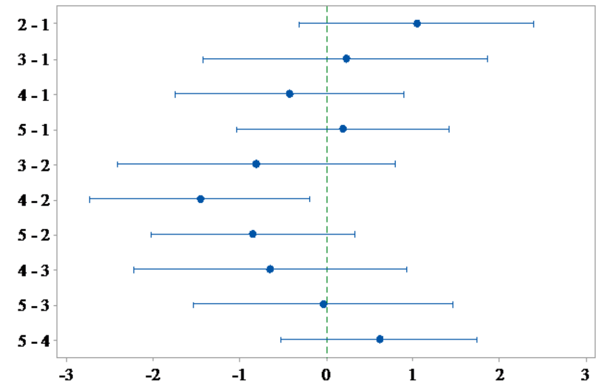
Table 4-4 ANOVA results for Level 2A VCD clusters for flexible pavements
(bottom-up fatigue cracking)

Source	DF	Adj SS	Adj MS	*F*-value	*p*-value
VCD Cluster	4	9.454	2.3634	2.78	0.041
Error	36	30.599	0.85		
Total	40	40.052			
VCD Cluster	N	Mean	StDev	95% CI	
1	7	0.794	0.35	(0.087, 1.501)	
2	8	1.834	1.568	(1.173, 2.495)	
3	4	1.02	1.193	(0.085, 1.955)	
4	9	0.379	0.399	(-0.244, 1.002)	
5	13	0.872	0.77	(0.353, 1.390)	

DF = degrees of freedom, SS = sum of squares, MS = mean square



(a) Mean differences between clusters



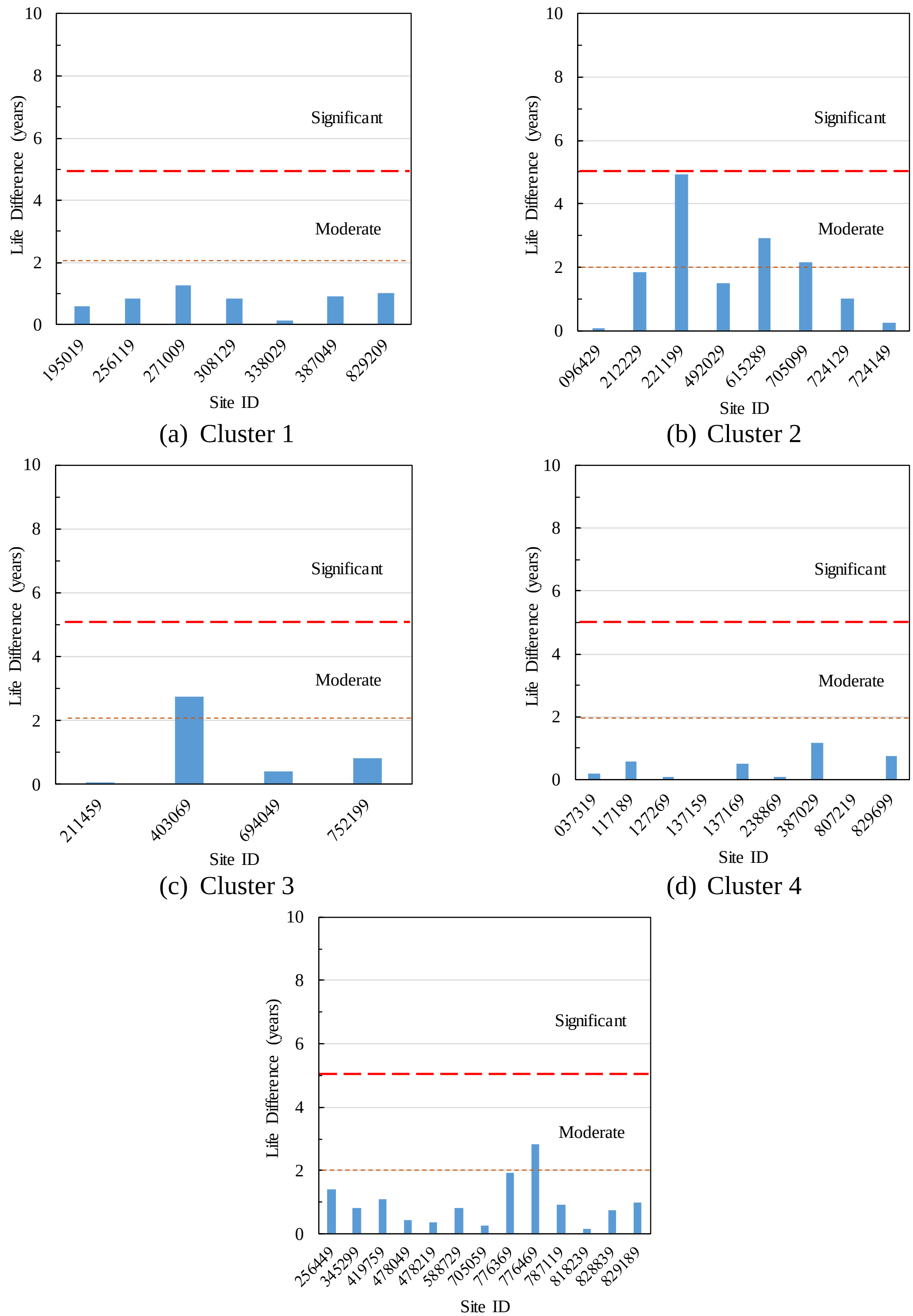
(b) Tukey test results

Figure 4-1 Mean design life comparisons between different for Level 2A VCD clusters for flexible pavements (bottom-up fatigue cracking)

None of the WIM locations in Cluster 1 have 'moderate' or 'significant' life differences. Three VCD clusters result in moderate differences in design life [see Figures 4-2 (b), 4-2 (c), and 4-2 (e)]. If there is at least one WIM location in any cluster with a 'moderate' or 'significant' life difference, then the cluster was considered sensitive. Similar analyses were conducted for other Level 2A inputs and the results can be found in Appendix C. Table 4-5 summarizes the statistical sensitivity of flexible and JPCP pavements to different traffic inputs. The letter 'Y' means that the mean design life for at least one cluster is different from the other clusters (i.e., statistically or practically sensitive depending on the analysis type) whereas an 'N' means insensitive. Table 4-6 summarizes the sensitivity of flexible and JPCP pavements to different traffic inputs that led to moderate practical significances in the Pavement-ME design outcomes.

Table 4-5 Sensitivity of rigid and flexible pavements to statistical significance – Level 2A

Traffic input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom-up Fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	Y	Y	N	Y	Y
HDF	-	-	N	N	Y
MAF	N	N	N	N	Y
SALS	N	N	N	N	N
TALS	N	N	N	N	N
TRALS	N	N	N	N	N
QALS	N	Y	N	N	N



(a) Cluster 1

(b) Cluster 2

(c) Cluster 3

(d) Cluster 4

(e) Cluster 5

Figure 4-2 Differences in flexible pavement life predictions (bottom-up fatigue cracking) for Level 2A VCD clusters

Table 4-6 Sensitivity of rigid and flexible pavements to moderate MLD criteria – Level 2A

Traffic input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	Y	Y	N	Y	Y
HDF	-	-	N	N	Y
MAF	N	N	N	N	N
SALS	Y	Y	N	N	N
TALS	Y	Y	N	N	Y
TRALS	N	N	N	N	N
QALS	N	N	N	N	N

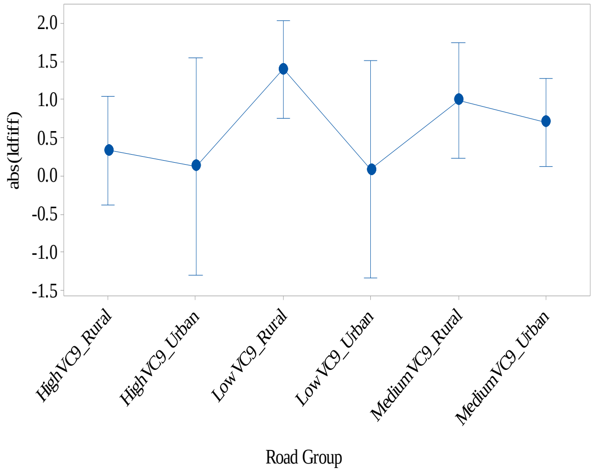
4.1.2 Level 2B Sensitivity Analyses

Similar to the Level 2A sensitivity analyses, one way ANOVA was performed on the absolute life difference data ($|Life_{Level\ 1} - Life_{Level\ 2B}|$) to detect the differences between the road groups for each traffic input. Table 4-7 and Figure 4-3 show the results of the ANOVA for Level 2B VCD as an example. Since the *p*-value is above 0.05, the results indicate that the group averages are not different from each other and that their use in pavement design would not result in statistically different design lives. Table 4-8 summarizes the statistical sensitivity of flexible and JPCP pavements to different traffic inputs. However, the maximum life difference among the groups needs to evaluated for practical significance.

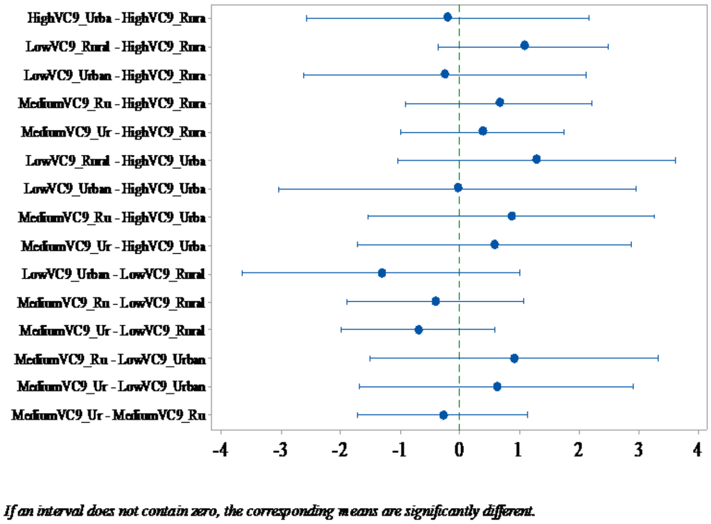
Table 4-7 ANOVA results for Level 2B groups

Source	DF	Adj SS	Adj MS	*F*-value	*p*-value
VCD Groups	5	7.64	1.53	1.54	0.203
Error	35	34.71	0.99		
Total	40	42.35			

VCD Groups	N	Mean	StDev	95% CI
HighVC9_Rural	8	0.334	0.509	(-0.381, 0.049)
HighVC9_Urban	2	0.125	0.063	(-1.305, 1.55)
LowVC9_Rural	10	1.399	1.660	(0.760, 2.038)
LowVC9_Urban	2	0.080	0.000	(-1.349, 1.509)
MediumVC9_Rural	7	0.987	0.536	(0.223, 1.751)
MediumVC9_Rural	10	0.698	0.761	(0.115, 1.282)



(a) Mean differences between clusters



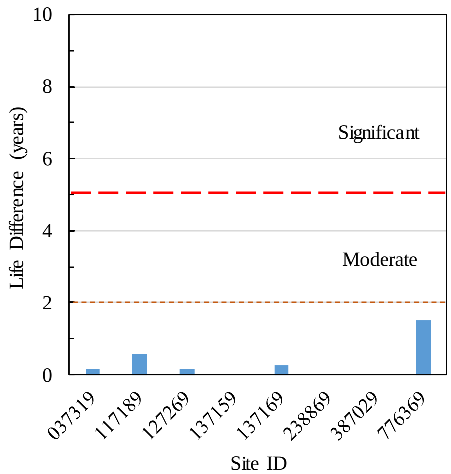
(b) Tukey test results

Figure 4-3 Mean design life comparisons between different clusters for VCD

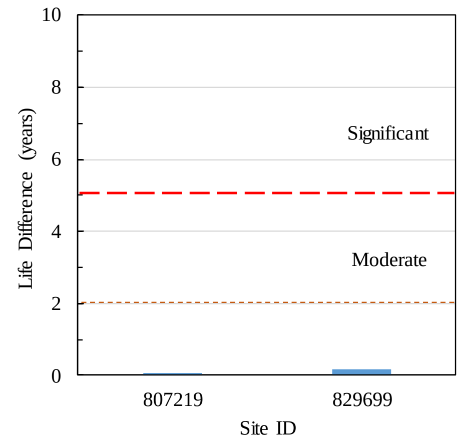
Table 4-8 Sensitivity of rigid and flexible pavements to statistical significance – Level 2B

Traffic input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	N	N	N	N	N
HDF	-	-	Y	N	Y
MAF	N	N	N	N	N
SALS	N	Y	N	Y	N
TALS	N	N	N	N	N
TRALS	N	N	N	N	N
QALS	N	Y	N	N	N

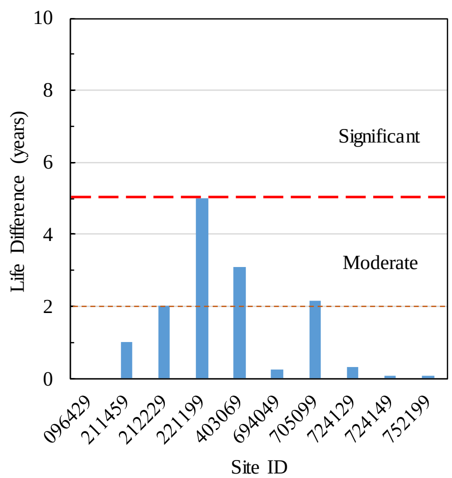
Figure 4-4 presents the differences in predicted performance in flexible pavements with the use of different Level 2B groups for each WIM location. Similar to Figure 4-2, each plot is divided into three regions (negligible, moderate and significant) based on the MLD values in Table 4-3. Figure 4-4(a) shows the WIM locations in the road group with high VC9 levels in a rural area, and the life differences when that road group values are used in the Pavement ME. Note that all the other traffic input values are at Level 1. None of the WIM locations in this road group have 'moderate' or 'significant' life differences. However, three other road groups resulted in moderate to significant differences in design life [see Figures 4-4 (c), 4-4 (e), and 4-4 (f)]. Note that if there is at least one WIM location in any road group with a 'moderate' or 'significant' life difference, then that road group was deemed sensitive. Similar analyses were conducted for other Level 2B inputs, and results are shown in Appendix C. Table 4-9 summarizes the sensitivity to moderate life differences of flexible and JPCP pavements to different traffic inputs.



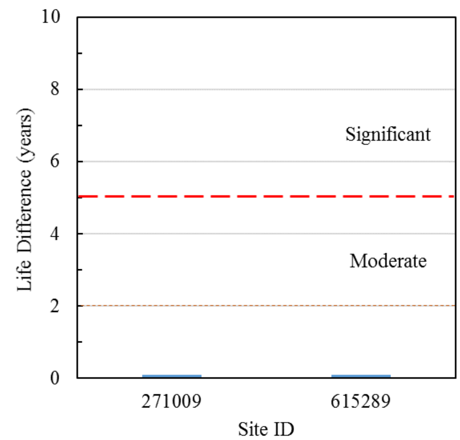
(a) High VC9 and Rural



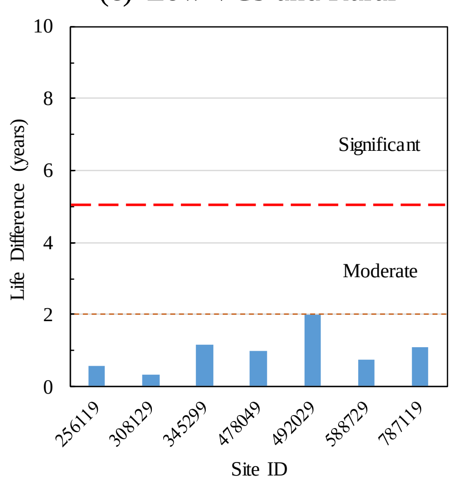
(b) High VC9 and Urban



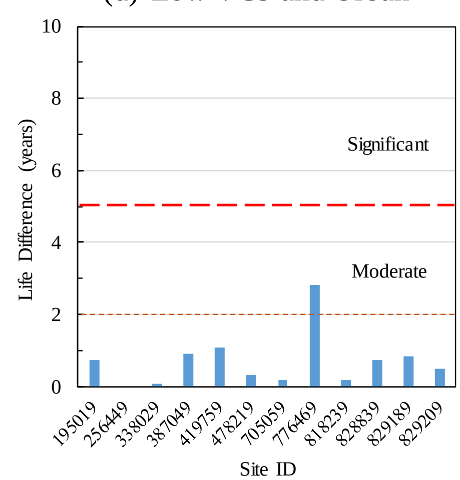
(c) Low VC9 and Rural



(d) Low VC9 and Urban



(e) Medium VC9 and Rural



(f) Medium VC9 and Urban

Figure 4-4 Differences in flexible pavement life predictions (bottom-up fatigue cracking) for Level 2B VCD road groups

Table 4-9 Sensitivity of rigid and flexible pavements to moderate MLD criteria – Level 2B

Traffic input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	Y	Y	N	Y	Y
HDF	-	-	N	N	Y
MAF	N	N	N	N	N
SALS	N	Y	N	N	N
TALS	Y	Y	N	N	Y
TRALS	N	N	N	N	N
QALS	N	N	N	N	N

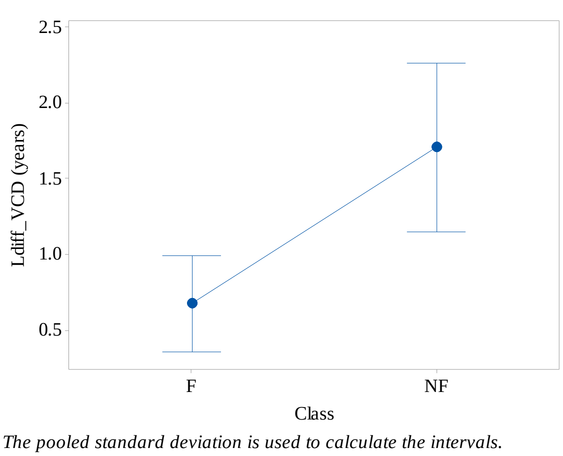
4.1.3 Level 3A Sensitivity Analyses

Level 3A has two road groups for all traffic inputs, i.e., freeways and non-freeways. The procedure used for Level 2A and 2B sensitivity analyses was followed. Since there are only two groups, a one way ANOVA or a two-sample *t*-test could be used to find the differences between the two sets. Table 4-10 and Figure 4-5 show the results of the ANOVA for Level 3A VCD. Since the *p*-value is below 0.05, the results indicate that the group averages are different from each other and that their use in pavement design would result in statistically different design lives.

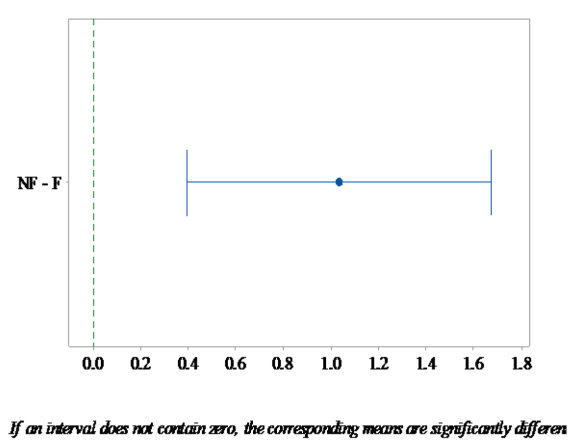
Table 4-10 ANOVA results for Level 3A VCD clusters or groups

Source	DF	Adj SS	Adj MS	*F*-value	*p*-value
Class	1	8.075	8.0753	10.67	0.002
Error	39	29.529	0.7571		
Total	40	37.604			

Class	N	Mean	StDev	95% CI
F	31	0.6735	0.442	(0.3574, 0.9897)
NF	10	1.707	1.622	(1.150, 2.264)



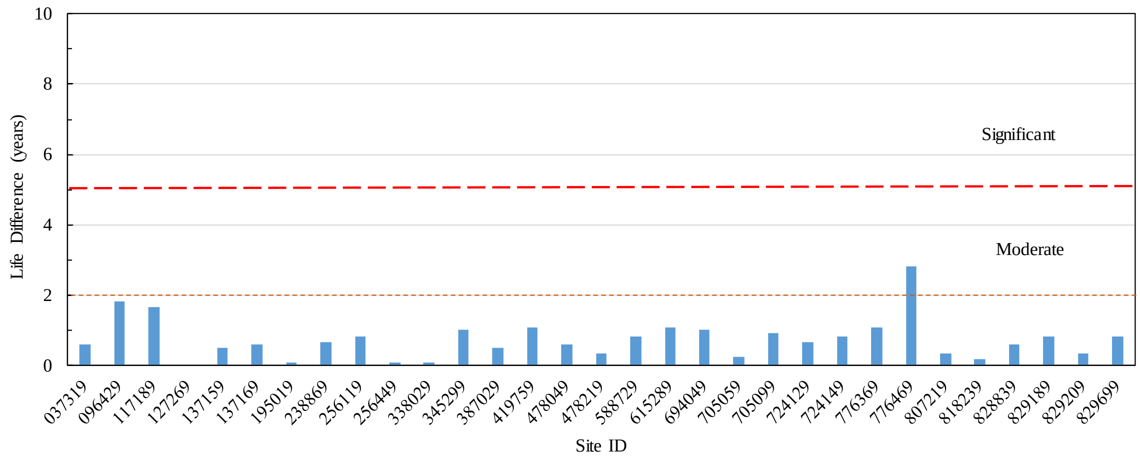
(a) Mean differences between clusters



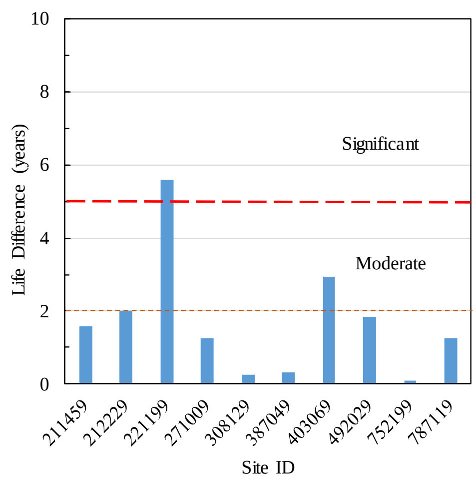
(b) Tukey test results

Figure 4-5 Mean design life comparisons between different clusters for VCD

Figure 4-6 presents the differences in predicted performance in flexible pavements (bottom-up cracking) with the use of different Level 3A groups for each WIM location. Figure 4-6(a) shows the WIM locations in freeway VCD group and the life differences when freeway VCD group values are used in the Pavement-ME. Only one WIM location in the freeway VCD group has ‘moderate’ life difference. Moderate to significant differences can be seen for WIM locations in the non-freeway VCD group [Figure 4-6(b)]. Table 4-11 summarizes the statistical sensitivity of flexible and JPCP pavements to different traffic inputs for Level 3A. Table 4-12 summarizes the sensitivity to maximum life differences of flexible and JPCP pavements to different traffic inputs.



(a) Freeway cluster



(b) Non-freeway cluster

Figure 4-6 Differences in flexible pavement life predictions (bottom-up fatigue cracking) for Level 3A VCD groups

Table 4-11 Sensitivity of rigid and flexible pavements to statistical significance – Level 3A

Traffic Input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom-up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	Y	Y	N	N	N
HDF	-	-	N	N	N
MAF	N	N	N	N	Y
SALS	N	Y	N	N	N
TALS	N	Y	N	Y	N
TRALS	N	Y	N	N	N
QALS	N	N	N	N	N

Table 4-12 Sensitivity of rigid and flexible pavements to MLD criteria – Level 3A

Traffic Input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom-up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	Y	Y	N	Y	Y
HDF	-	-	N	N	Y
MAF	N	N	N	N	Y
SALS	N	Y	N	N	Y
TALS	Y	N	N	N	Y
TRALS	N	N	N	N	N
QALS	N	N	N	N	N

4.1.4 Choosing the Appropriate Traffic Input Level

As mentioned before, Level 1 traffic inputs should always be used for pavement design if available. In the absence of Level 1 inputs, use either Level 2 or Level 3 inputs. The results of the sensitivity analyses based on statistical significance and maximum life difference should be used to decide on the appropriate traffic input level. The criteria used in this evaluation is that the traffic input levels are sensitive if the life difference is moderate (> 2 years). The recommendations for each traffic input are as follows:

4.1.4.1 Vehicle class distribution

The statistical sensitivity analyses show that the use of different VCD clusters (Level 2A) would result in statistically different design lives for both flexible and rigid pavements (see Table 4-5). This observation is also valid for MLD sensitivity analyses. The results indicate the existence of localized traffic patterns that would yield different pavement thicknesses in the design process. While the statistical analyses do not show that Level 2B inputs would result in statistically different design lives for both flexible and rigid pavements, the MLD criteria indicate that the use of Level 2B inputs would result in moderate life differences. Hence, for VCD, either Level 2A or 2B inputs could be used in the absence of Level 1 inputs. The next step is to identify if there are any statistical differences between Levels 2A and 2B. If there are no differences between the two levels, then Level 2B can be used since it will simplify the VCD input selection process. A paired *t*-test was used to verify if there are significant differences between the values of ($|Life_{Level\ 1}$ - $Life_{Level\ 2A}|$) and ($|Life_{Level\ 1}$ - $Life_{Level\ 2B}|$). Table 4-13 shows the results based on the paired *t*-test for various traffic inputs. It can be seen from the table that there is a statistical difference between Levels 2A and 2B for rut depth in flexible pavements.

However, the differences in design lives for flexible pavements in terms of rutting between the Levels 2A and 2B are practically insignificant (mean difference) although statistically significant as shown in Table 4-14. Further, the number of times the pavement sections are overdesigned or under designed when using Levels 2A and 2B were calculated. Figure 4-7 shows the number of under designed are higher for Level 2A compared to Level 2B. The descriptive statitistics for design differences for all traffic inputs can be seen in Appendix D. A pavement at a WIM location will be overdesigned when the difference is design lives ($Life_{Level\ 1}$ - $Life_{Level\ x}$) is positive and under designed when the difference ($Life_{Level\ 1}$ - $Life_{Level\ x}$) is negative. While a positive life difference would suggest increasing the thicknesses making the project overdesigned, a negative life difference will force to reduce the thicknesses making the project under-designed relative to Level 1.

Table 4-13 Summary of statistical significance – Levels 2A vs. 2B

Traffic input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	Y	N	N	N	N
HDF	-	-	Y	N	Y
MAF	N	N	N	N	N
SALS	N	N	N	N	N
TALS	N	N	Y	Y	N
TRALS	N	N	N	N	N
QALS	N	N	N	N	N

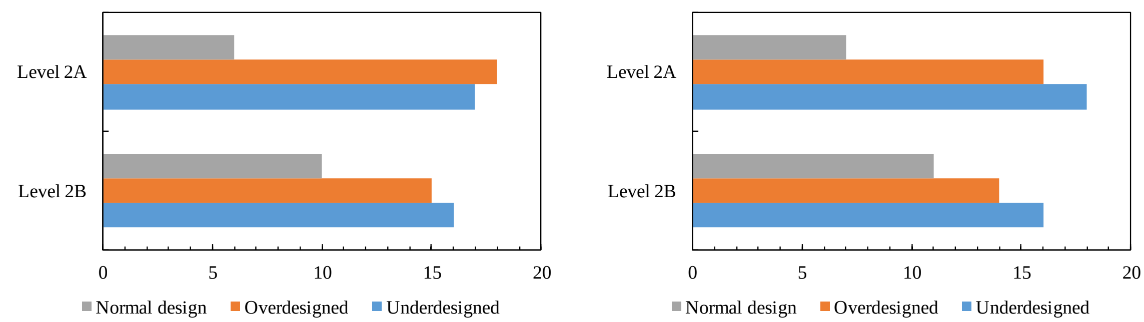
Table 4-15 and 4-16 show the results of the sensitivity analyses between Levels 2A and 3A, 2B and 3A, respectively based on the paired *t*-test for various traffic inputs. It can be seen from Table 4-16 that there are statistical differences between Levels 2B and 3A. Therefore, Level 2B inputs are recommended for VCD for both flexible and rigid pavements.

Table 4-14 Paired t-test results between Levels 2A and 2B for rutting

Sample	N	Mean	StDev	SE Mean
Ldiff_Rut_2B	41	0.929	1.134	0.177
Ldiff_Rut_2A	41	1.179	1.08	0.169

Mean	StDev	SE Mean	95% CI
-0.25	0.762	0.119	(-0.491, -0.009)

t-value	*p*-value
-2.1	0.042



(a) Rutting (b) Fatigue cracking

Figure 4-7 Number of over and under-designed PTR locations — Levels 2A and 2B (VCD)

Table 4-15 Summary of statistical significance – Levels 2A vs. 3A

Traffic input	Flexible Pavements		Rigid Pavements		
	Rut depth (in)	Bottom-up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	N	N	Y	Y	Y
HDF	-	-	N	N	Y
MAF	N	N	N	N	N
SALS	N	N	N	N	N
TALS	Y	Y	Y	Y	Y
TRALS	N	N	N	N	N
QALS	N	N	Y	Y	N

Table 4-16 Summary of statistical significance – Levels 2B vs. 3A

Traffic input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom-up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	Y	Y	Y	Y	Y
HDF	-	-	Y	N	Y
MAF	N	N	N	N	N
SALS	N	N	N	N	N
TALS	N	N	N	N	N
TRALS	N	N	N	N	N
QALS	N	N	N	N	N

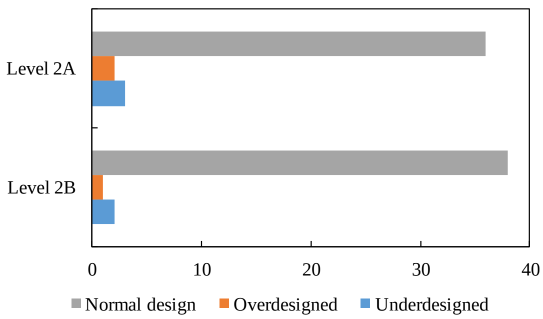
4.1.4.2 Hourly distribution factors

Level 2A HDF inputs have shown to have a statistically significant impact on the design rigid pavement designs compared to Level 2B inputs (see Table 4-13). Note that the HDF inputs are only used in rigid pavement design process. However, the differences in design lives for rigid pavements in terms of IRI and transverse cracking between the Levels 2A and 2B are very insignificant (0.04 and 0.9 years) from a practical standpoint as shown in Table 4-17. Figure 4-8 shows that Level 2A is slightly better with the number of undersigned PTR locations for transverse cracking. However, note that predicted cracking levels are less than

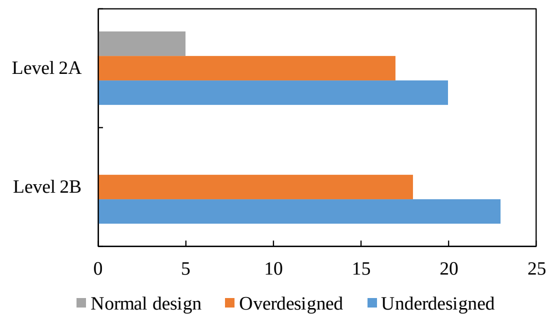
5% at 20 years for all the 41 PTR locations; therefore, the difference of 0.9 years between Levels 2A and 2B may not be of any practical significance. Hence, Level 2B is recommended for HDF.

Table 4-17 Paired *t*-test results between Levels 2A and 2B for HDF (IRI and transverse cracking)

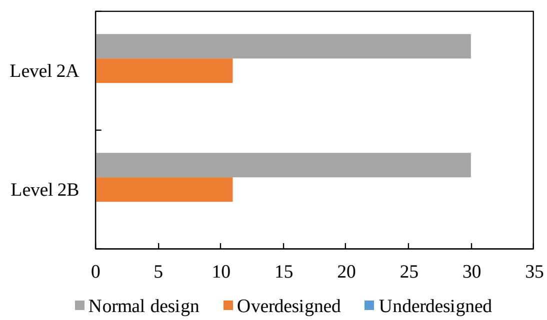
Sample	N	Mean	StDev	SE Mean
Ldiff_IRI_2B	41	0.071	0.0764	0.0119
Ldiff_IRI_2A	41	0.0324	0.0906	0.0142
	Difference	0.04		
Sample	N	Mean	StDev	SE Mean
Ldiff_Crack_2B	41	2.539	1.909	0.298
Ldiff_Crack_2A	41	1.624	1.591	0.248
	Difference	0.9		



(a) IRI



(b) Transverse cracking



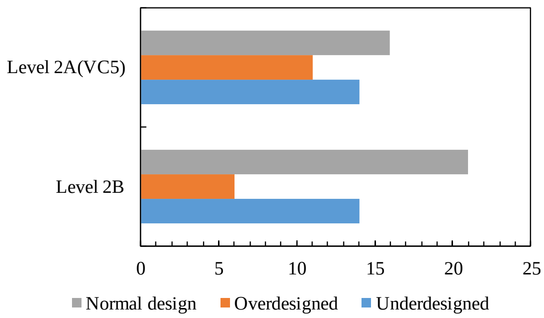
(c) Faulting

Figure 4-8 Number of over and under-designed PTR locations — Levels 2A and 2B (HDF)

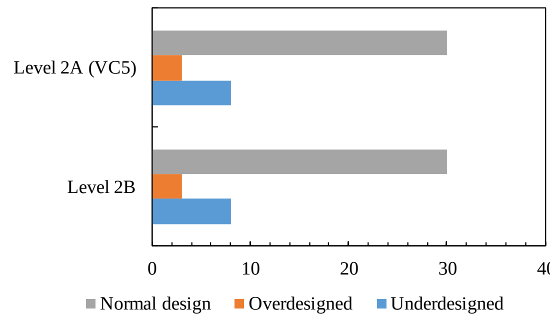
4.1.4.3 Monthly adjustment factors

No statistical differences in design lives between Level 2A clusters or 2B road groups were observed for both flexible and rigid pavements based on sensitivity analyses (see Table 4-13). Based on Figure 4-9, Level 2B should be chosen because of similar number of PTR locations with under designed PTR locations. It can be seen from Table 4-16 that there are no statistically significant differences between Levels 2B and 3A. The next step is to identify if there are any statistical differences between Levels 3A and 3B. If there are no differences between the two levels, then Level 3B can be used because it is more simplified. Table 4-18 shows the results of the sensitivity analyses between Levels 3A and 3B based on the paired *t*-

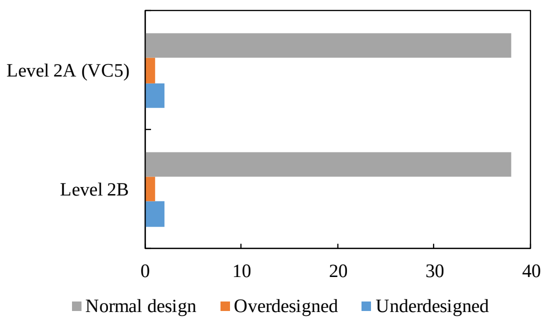
test for various inputs. Since there are statistically significant differences between Levels 3A and 3B, Level 3A inputs are recommended for MAF for both flexible and rigid pavements.



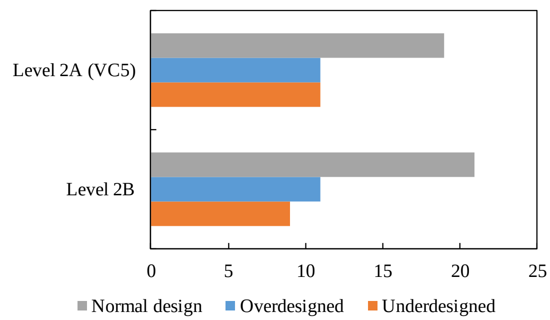
(a) Flexible pavements (rutting)



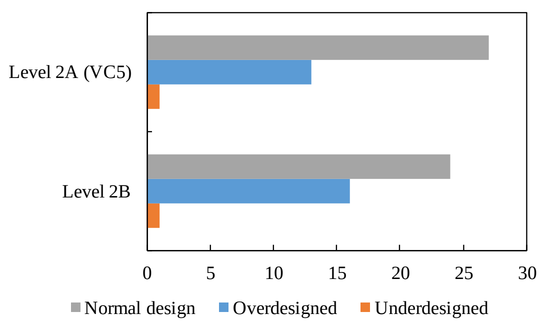
(b) Flexible pavements (fatigue cracking)



(c) Rigid pavement (IRI)



(d) Rigid pavement (transverse cracking)



(e) Rigid pavement (faulting)

Figure 4-9 Number of over and underdesigned PTR locations — Levels 2A and 2B (MAF)

4.1.4.4 Axle load spectra

For single axle load spectra, no differences were observed between Levels 2A and 2B (see Table 4-13) for both flexible and rigid pavements. Based on Figure 4-10, there are almost equal number of under-designed PTR locations for Levels 2A and 2B. Hence, Level 2B inputs should be used because it is more simplified. Also, since there are no differences between Levels 2B and 3A (see Table 4-16), and a difference exists between Levels 3A and 3B (see Table 4-17), Level 3A can be used for single axle load spectra.

Table 4-18 Summary of statistical significance – Levels 3A vs. 3B

Traffic input	Flexible pavements		Rigid pavements		
	Rut depth (in)	Bottom up fatigue cracking (%)	IRI (in/mile)	Faulting (in)	Transverse cracking (%)
VCD	N	N	N	N	N
HDF	-	-	N	N	N
MAF	N	N	N	N	Y
SALS	N	N	N	N	Y
TALS	N	N	N	N	Y
TRALS	N	N	N	N	N
QALS	N	N	Y	Y	N

For tandem axle load spectra, some differences were observed between Levels 2A and 2B (see Table 4-13) for both flexible and rigid pavements. Based on Figure 4-11, Level 2A is slightly better with the number of undersigned PTR locations for IRI and faulting. However, the differences in design lives (see Tables 4-19 4-20) for rigid pavements in terms of IRI and faulting between the Levels 2A and 2B are very insignificant (0.07 and 0.28 years) from a practical standpoint. Hence Level 2B inputs can be chosen over Level 2A inputs because it is more simplified.

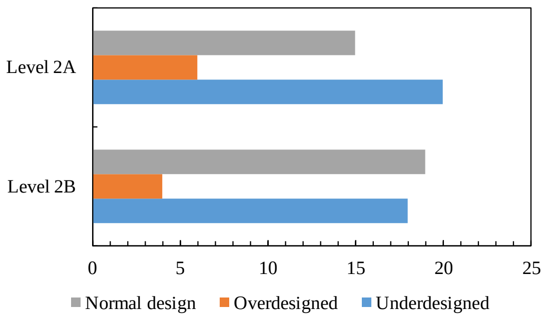
Table 4-19 Paired *t*-test results between Levels 2A and 2B for TALS (IRI)

Sample	N	Mean	StDev	SE Mean
Ldiff_IRI_2B	41	0.1585	0.1356	0.0212
Ldiff_IRI_2A	41	0.0907	0.0919	0.0143
	Difference	0.07		
Mean	StDev	SE Mean	95% CI for	
0.0678	0.1701	0.0266	(0.0141, 0.1215)	
t-value	*p*-value			
2.55	0.015			

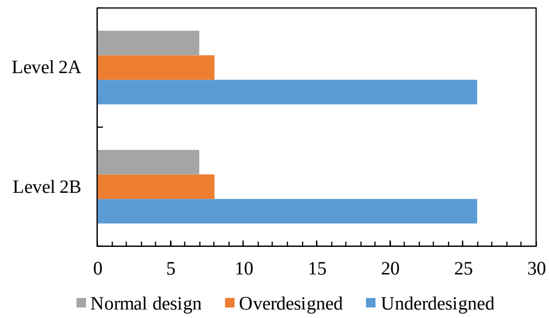
Table 4-20 Paired *t*-test results between Levels 2A and 2B for TALS (Faulting)

Sample	N	Mean	StDev	SE Mean
Ldiff_Fault_2B	41	0.6015	0.4855	0.0758
Ldiff_Fault_2A	41	0.3256	0.2336	0.0365
	Difference	0.28		
Mean	StDev	SE Mean	95% CI	
0.2759	0.5126	0.0801	(0.1140, 0.4377)	
t-value	*p*-value			
3.45	0.001			

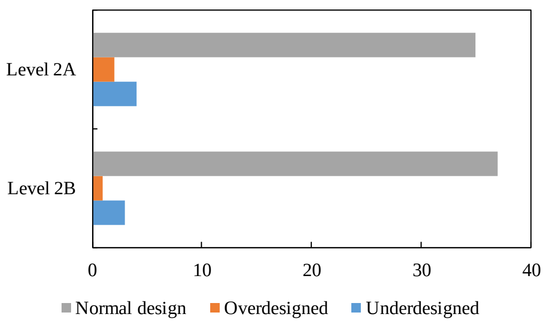
For tridem and quad axle load spectra, no differences were observed between Levels 2A and 2B (see Table 4-13) for both flexible and rigid pavements. In addition, there are no differences between Levels 2B and 3A (See Table 4-16). However, there are difference between Levels 3A and 3B for quad axle load spectra. Therefore, Levels 3A are recommended for both tridem and quad axle load spectra.



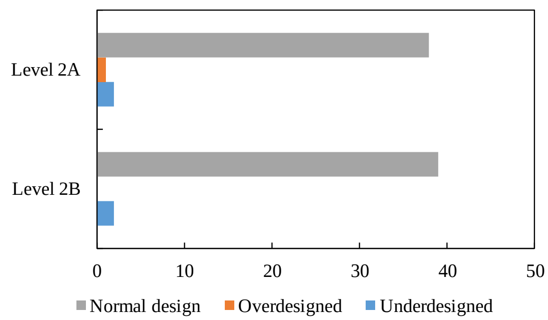
(a) Flexible pavements (rutting)



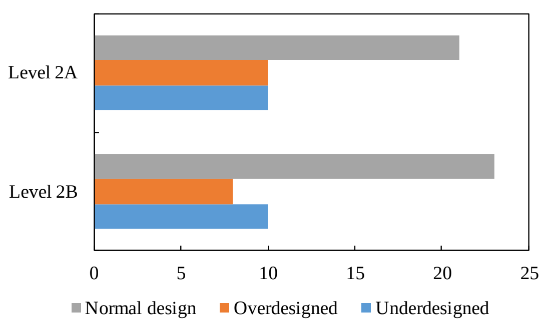
(b) Flexible pavements (fatigue cracking)



(c) Rigid pavement (IRI)

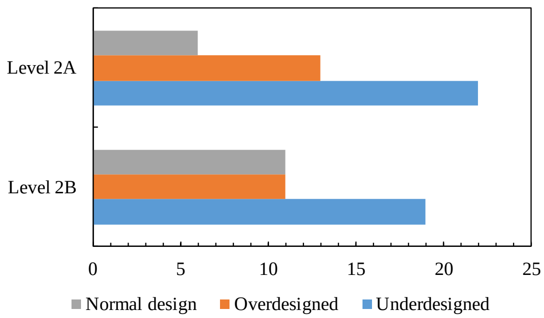


(d) Rigid pavement (transverse cracking)

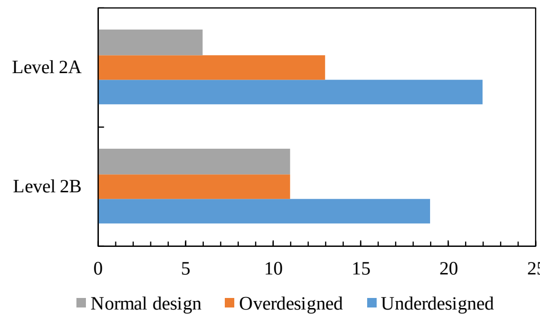


(e) Rigid pavement (faulting)

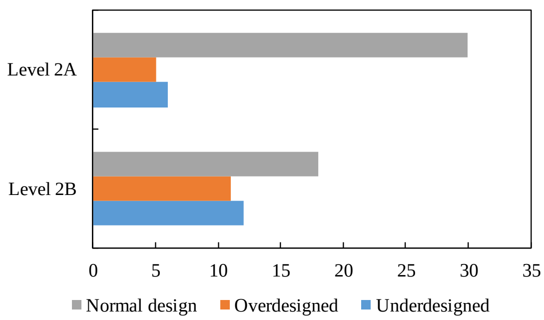
Figure 4-10 Number of over and under-designed PTR locations — Levels 2A and 2B (SALS)



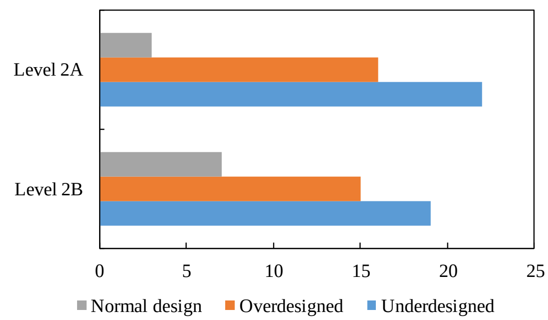
(a) Flexible pavements (rutting)



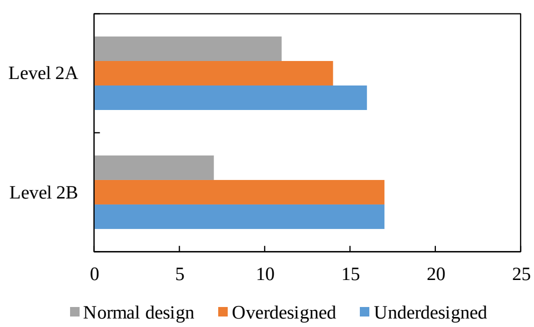
(b) Flexible pavements (fatigue cracking)



(c) Rigid pavement (IRI)



(d) Rigid pavement (transverse cracking)



(e) Rigid pavement (faulting)

Figure 4-11 Number of over and under-designed PTR locations — Levels 2A and 2B (TALS)

4.2 SENSITIVITY ANALYSES – OPTION 2

The sensitivity analysis was performed to evaluate the impact of Level 2 traffic inputs on pavement design lives predicted by the Pavement-ME. The impact of Level 2 inputs were evaluated by changing one input at a time to Level 2 and keeping all other at Level 3A. Since Level 3A inputs are based on freeways and non-freeways, two base designs were used for the sensitivity analyses as shown in Tables 4-21 and 4-22.

Table 4-21 Baseline designs for flexible pavements

Layer	Layer thickness, inches	
	Freeways	Non-Freeways
HMA top course	2	1.5
HMA leveling course	3	2
HMA base course	3.5	3
Non-stabilized GAB	6	6
Sand subbase	18	18
Sandy clay subgrade	Semi-infinite	Semi-infinite

Table 4-22 Baseline designs for rigid pavements

Layer	Layer thickness, inches	
	Freeways	Non-freeways
PCC	11	8
Non-stabilized GAB	6	6
Sand subbase	10	10
Sandy clay subgrade	Semi-infinite	Semi-infinite

For each of the base designs, the AADTT values were changed to achieve a 20-year design life for bottom-up fatigue cracking (20%) for flexible pavements. As a reference, Level 3A inputs were used in this process. Table 4-23 shows the AADTT values that provide a 20-year design in terms of bottom-up fatigue cracking in flexible pavements. Similarly, for rigid pavements, the AADTT values were changed to achieve a 20-year design life for an IRI of 172 inch/mile (see Table 4-24). This normalizes the dataset to the determining threshold for design. The thresholds for design of flexible and rigid pavements were determined based on the criteria most likely to control the design.

Table 4-23 AADTT and predicted distress and IRI at 20-years design life

Pavement type	Design lane AADTT 20-year design life	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)
Freeway-flexible	850	145.6	0.4	0.4	20.0	1269.6	345.7
Non-freeway - flexible	188	139.9	0.3	0.3	20.0	1591.1	349.4

Table 4-24 AADTT and predicted distress and IRI at 20-year design life

Pavement type	Design lane AADTT 20-year design life	IRI (in/mi)	Mean joint faulting (in)	JPCP transverse cracking (percent slabs)
Freeway- rigid	525	172.9	0.1	0.7
Non-freeway - rigid	500	172.4	0.0	2.9

Once the baseline designs are established, one input at a time were changed to Level 2 keeping all the other inputs at Level 3A. The time it takes for the pavement sections to reach the threshold limit of 20 percent bottom-up fatigue cracking for flexible pavements and 172 inch/mile IRI for rigid pavements were determined.

4.2.1 Level 2A Sensitivity Analyses

4.2.1.1 Vehicle Class Distribution

Tables 4-25 and 4-26 demonstrate the results of the sensitivity analysis of five VCD clusters (Level 2A) inputs. Since the percent difference in design life is less than 2 years for both freeways and non-freeways and for all clusters, it can be concluded that VCD clusters have little to no practical effect on the design life and Level 3A inputs will suffice for VCD for flexible and rigid pavement designs.

Table 4-25 Effects of VCD Level 2A inputs on flexible pavements performance

Clusters	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-Flexible-Baseline	20.0	145.60	0.43	0.4	20.0	1,270	345.7	-
Cluster 1	20.7	145.30	0.43	0.4	19.9	1,275	345.7	3%
Cluster 2	18.9	146.10	0.44	0.4	20.4	1,340	345.7	-5%
Cluster 3	20.0	145.30	0.43	0.4	20.0	1,296	345.7	0%
Cluster 4	20.0	145.80	0.43	0.4	20.0	1,240	345.7	0%
Cluster 5	20.1	145.60	0.43	0.4	20.0	1,263	345.7	0%
Non-Freeway - Flexible-Baseline	20.0	139.90	0.34	0.3	20.0	1,591	349.4	-
Cluster 1	21.8	139.40	0.33	0.3	19.6	1,551	349.4	9%
Cluster 2	19.9	140.10	0.34	0.3	20.1	1,621	349.4	0%
Cluster 3	20.9	139.50	0.33	0.3	19.7	1,562	349.4	5%
Cluster 4	20.8	139.90	0.34	0.3	19.9	1,559	349.4	4%
Cluster 5	20.9	139.70	0.33	0.3	19.7	1,559	349.4	5%

Table 4-26 Effects of VCD Level 2A inputs on rigid pavements performance

Clusters	Years to failure	IRI (in/mi)	Mean joint faulting (in)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway- rigid-baseline	20	172.9	0.1	0.7	-
Cluster 1	20.25	171.6	0.1	0.7	1.3%
Cluster 2	20.17	172.0	0.1	0.7	0.9%
Cluster 3	20.67	170.2	0.1	0.7	3.4%
Cluster 4	19.58	174.4	0.1	0.7	-2.1%
Cluster 5	19.92	173.0	0.1	0.7	-0.4%
Non-freeway-rigid-baseline	20	172.4	0.0	2.9	-
Cluster 1	20.08	172.0	0.0	2.6	0.4%
Cluster 2	20	172.6	0.0	3.0	0.0%
Cluster 3	20.25	171.3	0.0	3.0	1.3%
Cluster 4	19.67	173.9	0.0	2.5	-1.6%
Cluster 5	19.83	172.9	0.0	2.5	-0.9%

4.2.1.2 Monthly Adjustment Factors (MAF)

Table 4-27 presents the results of the sensitivity of the Pavement-ME outcomes to MAF clusters. Since the percent difference in design life is less than 10 percent for both freeways and non-freeways, it can be concluded that MAF clusters for Class 5 have little to no practical effect on the design life and Level 3A inputs will suffice for MAF for flexible pavement designs. Note that Level 3A was used in option 2 based on the results of option 1 sensitivity analysis.

Table 4-27 Effect of MAF Level 2A inputs (VC5) on flexible pavements performance

Clusters	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-flexible-baseline	20.0	146	0.43	0.40	20.0	1,270	346	-
Cluster 1	20.0	146	0.43	0.41	20.0	1,271	346	0.0%
Cluster 2	20.1	146	0.43	0.40	20.0	1,269	346	0.4%
Cluster 3	19.1	146	0.44	0.42	20.3	1,289	346	-4.6%
Cluster 4	19.9	146	0.44	0.41	20.1	1,273	346	-0.4%
Non-freeway - flexible-baseline	20.0	140	0.34	0.31	20.0	1,591	349	-
Cluster 1	20.2	140	0.34	0.31	19.9	1,586	349	0.8%
Cluster 2	20.4	140	0.33	0.30	19.9	1,586	349	2.1%
Cluster 3	19.8	140	0.34	0.31	20.2	1,603	349	-1.3%
Cluster 4	20.0	140	0.34	0.31	20.0	1,586	349	0.0%

Similarly, the percent difference in design life is less than 10 percent for both freeways and non-freeways for the five MAF clusters based on VC9 (see Table 4-28). It can be concluded that variation in MAF clusters for Class 9 have little to no practical effect on the design life and Level 3A inputs will suffice for MAF for flexible pavement designs.

Table 4-28 Effect of MAF Level 2A inputs (VC9) on flexible pavements performance

Clusters	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-flexible-baseline	20.0	146	0.43	0.40	20.0	1,270	346	-
Cluster 1	20.1	146	0.43	0.40	20.0	1,269	346	0.4%
Cluster 2	20.0	146	0.43	0.41	20.0	1,275	346	0.0%
Cluster 3	19.2	146	0.44	0.42	20.3	1,292	346	-4.2%
Cluster 4	19.9	146	0.43	0.41	20.1	1,273	346	-0.4%
Cluster 5	20.8	145	0.42	0.40	19.8	1,251	346	4.2%
Non-freeway - flexible-baseline	20.0	140	0.34	0.31	20.0	1,591	349	-
Cluster 1	20.3	140	0.33	0.31	19.9	1,585	349	1.7%
Cluster 2	20.1	140	0.34	0.31	19.9	1,588	349	0.4%
Cluster 3	19.8	140	0.34	0.31	20.2	1,608	349	-0.9%
Cluster 4	20.1	140	0.34	0.31	20.0	1,588	349	0.4%
Cluster 5	21.0	139	0.33	0.30	19.7	1,557	349	5.0%

Similarly, the effect of MAF on predicted rigid pavement performance was evaluated (see Tables 4-29 and 4-30). Based on the analysis results, the percent difference in design life is equal to zero for both freeways and non-freeways for all clusters. It can be concluded that MAF clusters have little to no practical effect on the design life and Level 3A inputs will suffice for MAF for rigid pavement designs.

Table 4-29 Effect of MAF Level 2A inputs (VC5) on rigid pavements performance

Clusters	Years to failure	IRI (in/mi)	Mean joint faulting (in)	JPCP trans. cracking (percent slabs)	% Difference in design life
Freeway- rigid-baseline	20.0	172.9	0.06	0.72	-
Cluster 1	20.0	172.8	0.06	0.72	0%
Cluster 2	20.0	172.9	0.06	0.72	0%
Cluster 3	20.0	172.8	0.06	0.72	0%
Cluster 4	20.0	172.8	0.06	0.72	0%
Non-freeway-rigid-baseline	20.0	172.4	0.04	2.91	-
Cluster 1	20.0	172.4	0.04	2.91	0%
Cluster 2	20.0	172.4	0.04	2.91	0%
Cluster 3	20.0	172.6	0.04	2.96	0%
Cluster 4	20.0	172.5	0.04	2.96	0%

Table 4-30 Effect of MAF Level 2A inputs (VC9) on rigid pavements performance

Clusters	Years to failure	IRI (in/mi)	Mean joint faulting (in)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway- rigid-baseline	20.0	172.9	0.06	0.72	-
Cluster 1	20.0	172.8	0.06	0.72	0.0%
Cluster 2	20.0	172.8	0.06	0.72	0.0%
Cluster 3	20.0	172.9	0.06	0.72	0.0%
Cluster 4	20.0	172.9	0.06	0.72	0.0%
Cluster 5	19.9	173.3	0.06	0.72	-0.4%
Non-freeway-rigid-baseline	20.0	172.4	0.04	2.91	-
Cluster 1	20.0	172.4	0.04	2.91	0.0%
Cluster 2	20.0	172.4	0.04	2.91	0.0%
Cluster 3	20.0	172.6	0.04	2.96	0.0%
Cluster 4	20.0	172.5	0.04	2.96	0.0%
Cluster 5	20.0	172.4	0.04	2.82	0.0%

4.2.1.3 Hourly Distribution Factors (HDF)

The effect of five Level 2 HDF clusters on the Pavement-ME rigid pavement design was investigated. Based on the analysis results, the percent difference in design life is equal to zero (see Table 4-31) for all clusters and for both freeways and non-freeways. It can be concluded that HDF clusters have little to no practical effect on the design life and Level 3A inputs will suffice for HDF for rigid pavement designs.

Table 4-31 Effect of HDF Level 2A inputs on rigid pavements performance

Clusters	Years to failure	IRI (in/mi)	Mean joint faulting (in)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway-rigid-baseline	20.0	172.9	0.06	0.72	-
Cluster 1	20.0	172.9	0.06	0.72	0.0%
Cluster 2	20.0	172.9	0.06	0.72	0.0%
Cluster 3	20.0	172.9	0.06	0.72	0.0%
Cluster 4	20.0	172.9	0.06	0.72	0.0%
Cluster 5	20.0	172.9	0.06	0.96	0.0%
Non-freeway-rigid-baseline	20.0	172.4	0.04	2.91	-
Cluster 1	20.0	172.5	0.04	3.05	0.0%
Cluster 2	20.0	172.5	0.04	2.96	0.0%
Cluster 3	20.0	172.5	0.04	3.05	0.0%
Cluster 4	20.0	172.4	0.04	2.87	0.0%
Cluster 5	20.0	172.6	0.04	3.18	0.0%

4.2.1.4 Axle Load Spectra (ALS)

The effect of Level 2A clusters on pavement performance was evaluated in terms of predicted pavement service life using the baseline designs. Four single and five tandem Level 2A ALS cluster inputs were tested. The results are presented in Table 4-32. Since the percent difference in design life is less than 10 percent for both freeways and non-freeways, it can be concluded that single ALS clusters have little to no practical effect on the design life and Level 3A ALS would suffice for pavement designs.

Table 4-32 Effect of single ALS Level 2A inputs on flexible pavements performance

Clusters	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-flexible-baseline	20.0	146	0.43	0.40	20.0	1,270	346	-
Cluster 1	19.9	146	0.43	0.41	20.0	1,270	346	-0.4%
Cluster 2	19.4	146	0.43	0.41	20.2	1,270	346	-2.9%
Cluster 3	19.8	146	0.43	0.40	20.1	1,270	346	-0.8%
Cluster 4	20.1	146	0.43	0.40	20.0	1,270	346	0.4%
Non-freeway - flexible-baseline	20.0	140	0.34	0.31	20.0	1,591	349	-
Cluster 1	20.9	140	0.34	0.31	19.7	1,591	349	4.6%
Cluster 2	20.4	140	0.34	0.31	19.9	1,591	349	2.1%
Cluster 3	21.0	140	0.33	0.30	19.7	1,591	349	5.0%
Cluster 4	21.1	140	0.34	0.31	19.7	1,591	349	5.4%

Similarly, the percent difference in design life was less than 10 percent for both freeways and non-freeways for the 5 tandem ALS clusters. It can be concluded that tandem ALS clusters have little to no practical effect on the design life and Level 3A ALS defaults would suffice for MDOT (see Table 4-33).

Table 4-33 Effect of tandem ALS Level 2A inputs on flexible pavement performance

Clusters	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-flexible-baseline	20	146	0.43	0.40	20.0	1,270	346	-
Cluster 1	19.8	146	0.44	0.41	20.2	1,281	346	-1.3%
Cluster 2	19.2	146	0.44	0.41	20.3	1,289	346	-4.2%
Cluster 3	21.0	145	0.42	0.40	19.7	1,247	346	5.0%
Cluster 4	21.1	145	0.42	0.40	19.7	1,246	346	5.4%
Cluster 5	19.3	146	0.44	0.41	20.3	1,288	346	-3.8%
Non-freeway -flexible-baseline	20.0	140	0.34	0.31	20.0	1,591	349	-
Cluster 1	20.3	140	0.34	0.31	19.9	1,586	349	1.3%
Cluster 2	19.9	140	0.34	0.31	20.0	1,596	349	-0.4%
Cluster 3	21.3	139	0.33	0.30	19.6	1,551	349	6.3%
Cluster 4	21.8	139	0.33	0.30	19.6	1,542	349	8.8%
Cluster 5	20.1	140	0.34	0.31	20.0	1,590	349	0.4%

Similarly, the effect of single and tandem ALS Level 2A clusters on pavement performance was evaluated for rigid pavements. All pavement scenarios tested failed due to high IRI. However, the effect of loading on IRI deterioration was negligible and factors other than loading (initial IRI, joint spalling, age, freezing conditions, and soil type) were responsible for IRI deterioration. Faulting or cracking predictions were minor. The results are presented in Tables 4-34 and 4-35. Since the percent difference in design life is less than 10 percent for both single and tandem ALS for freeways and non-freeways, it can be concluded that ALS clusters have little to no practical effect on the design life and Level 3A will suffice for single and tandem ALSs for rigid pavements. The tridem and quad axle load spectra did not show any effect on the design life differences and are not presented in the results.

Table 4-34 Effect of single ALS Level 2A inputs on rigid pavement performance

Clusters	Years to failure	IRI (in/mi)	Mean joint faulting (in)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway- rigid-baseline	20	172.9	0.06	0.7	-
Cluster 1	20	172.8	0.06	0.7	0.0%
Cluster 2	20	173.0	0.06	0.7	0.0%
Cluster 3	20.1	172.4	0.06	0.7	0.4%
Cluster 4	20	172.9	0.06	0.7	0.0%
Non-freeway-rigid-baseline	20	172.4	0.04	2.9	-
Cluster 1	20.1	172.1	0.04	2.5	0.4%
Cluster 2	20	172.4	0.04	2.9	0.0%
Cluster 3	20.17	171.8	0.04	2.4	0.9%
Cluster 4	20	172.3	0.04	2.5	0.0%

Table 4-35 Effect of tandem ALS Level 2A inputs on rigid pavement performance

Clusters	Years to failure	IRI (in/mi)	Mean joint faulting (in)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway- rigid-baseline	20	172.9	0.06	0.7	-
Cluster 1	19.92	173.2	0.06	0.7	-0.4%
Cluster 2	19.75	173.7	0.06	0.7	-1.3%
Cluster 3	20.2	172.0	0.06	0.7	0.9%
Cluster 4	20.3	171.6	0.06	0.7	1.6%
Cluster 5	19.67	174.1	0.06	0.7	-1.6%
Non-freeway-rigid-baseline	20	172.4	0.04	2.9	-
Cluster 1	20.0	172.2	0.04	2.9	0.0%
Cluster 2	20	172.5	0.04	2.9	0.0%
Cluster 3	20.17	171.7	0.04	2.8	0.9%
Cluster 4	20.25	171.4	0.04	2.8	1.3%
Cluster 5	19.92	172.6	0.04	2.9	-0.4%

4.2.2 Level 2B Sensitivity Analyses

4.2.2.1 Vehicle Class Distribution

Tables 4-36 and 4-37 show the results of the sensitivity analysis for six VCD Level 2B inputs for flexible and rigid pavements, respectively. Since the percent difference in design life is more than 10 percent for at least one of the groups (low VC9 and urban), it can be concluded that Level 2B VCD inputs have practical effect on the design life and should be used for flexible pavement designs.

Table 4-36 Effect of VCD Level 2B inputs on flexible pavement performance

Groups	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-flexible-baseline	20.0	145.6	0.43	0.4	20.0	1,270	345.7	-
Medium VC9_Rural	19.9	145.7	0.43	0.4	20.1	1,274	345.7	-0.4%
High VC9_Rural	19.9	145.8	0.44	0.4	20.1	1,245	345.7	-0.4%
High VC9_Urban	19.8	145.9	0.44	0.4	20.1	1,258	345.7	-0.9%
Low VC9_Rural	19.2	145.9	0.44	0.4	20.3	1,327	345.7	-4.1%
Low VC9_Urban	21.8	144.6	0.42	0.4	19.5	1,246	345.7	9.1%
Medium VC9_Urban	20.3	145.4	0.43	0.4	19.9	1,271	345.7	1.3%
Non-freeway-flexible-baseline	20.0	139.9	0.34	0.3	20.0	1,591	349.4	-
Medium VC9_Rural	20.8	139.8	0.34	0.3	19.8	1,568	349.4	4.1%
High VC9_Rural	20.8	139.9	0.34	0.3	19.9	1,563	349.4	3.8%
High VC9_Urban	20.2	140.0	0.34	0.3	20.0	1,577	349.4	0.9%
Low VC9_Rural	20.0	140.0	0.34	0.3	20.0	1,603	349.4	0.0%
Low VC9_Urban	23.2	138.8	0.32	0.3	19.1	1,504	349.4	15.9%
Medium VC9_Urban	21.80	139.6	0.33	0.3	19.7	1,559	349.4	9.0%

Table 4-37 Effect of VCD Level 2B inputs on rigid pavement performance

Groups	Years to failure	IRI (in/mi)	Mean joint faulting (in)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway-rigid-baseline	20	172.9	0.1	0.7	-
Medium VC9_Rural	19.8	172.9	0.1	2.0	-1.0%
High VC9_Rural	19.5	174.5	0.1	2.0	-2.5%
High VC9_Urban	19.4	174.6	0.1	2.0	-2.9%
Low VC9_Rural	20.3	171.5	0.1	2.0	1.3%
Low VC9_Urban	20.67	170.0	0.1	2.0	3.4%
Medium VC9_Urban	20	172.4	0.1	2.0	0.0%
Non-freeway-rigid-baseline	20	172.4	0.0	2.9	-
Medium VC9_Rural	19.8	173.3	0.0	5.2	-1.0%
High VC9_Rural	19.6	174.2	0.0	5.0	-2.1%
High VC9_Urban	19.6	174.4	0.0	5.0	-2.1%
Low VC9_Rural	19.9	172.7	0.0	5.8	-0.4%
Low VC9_Urban	20.3	171.1	0.0	4.9	1.6%
Medium VC9_Urban	19.9	172.9	0.0	5.1	-0.4%

4.2.2.2 Monthly Adjustment Factors (MAF)

Table 4-38 presents the results of the sensitivity of the Pavement-ME outcomes to MAF Level 2B inputs. Since the percent difference in design life is less than 10 percent for both freeways and non-freeways, it can be concluded that MAF Level 2B inputs have little to no practical effect on the pavement design life and Level 3A inputs (statewide defaults) will suffice for MAF for flexible pavement designs.

Table 4-38 Effect of MAF Level 2B inputs on flexible pavement performance

Groups	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-flexible-baseline	20.0	146	0.43	0.40	20.0	1,270	346	-
AADTT One_Rural	19.9	146	0.44	0.41	20.1	1,277	346	-0.4%
AADTT One_Urban	20.0	146	0.43	0.41	20.0	1,275	346	0.0%
AADTT Two_Rural	20.1	146	0.43	0.40	20.0	1,267	346	0.4%
AADTT Two_Urban	20.1	146	0.43	0.40	20.0	1,271	346	0.4%
AADTT Three_Rural	20.0	146	0.43	0.40	20.0	1,268	346	0.0%
AADTT Three_Urban	20.1	146	0.43	0.40	20.0	1,271	346	0.4%
Non-freeway-flexible-baseline	20.0	140	0.34	0.31	20.0	1,591	349	-
AADTT One_Rural	20.0	140	0.34	0.31	20.0	1,590	349	0.0%
AADTT One_Urban	20.1	140	0.34	0.31	20.0	1,591	349	0.4%
AADTT Two_Rural	20.5	140	0.33	0.30	19.9	1,583	349	2.5%
AADTT Two_Urban	20.3	140	0.34	0.31	19.9	1,588	349	1.3%
AADTT Three_Rural	20.8	140	0.33	0.30	19.9	1,578	349	3.8%
AADTT Three_Urban	20.2	140	0.34	0.31	20.0	1,591	349	0.9%

Similarly, the effect of MAF on rigid pavement performance was evaluated. Based on the analysis results, the percent difference in design life is less than 1 percent for both freeways and non-freeways for all Level 2B MAF inputs (see Table 4-39). It can be concluded that Level 2B MAF inputs have little to no practical effect on the design life and Level 3A inputs will suffice for MAF for rigid pavement designs.

Table 4-39 Effect of MAF Level 2B inputs on rigid pavement performance

Groups	Years to failure	IRI (in/mile)	Mean Joint faulting (in.)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway-rigid-baseline	20.0	172.9	0.06	0.72	-
AADTT One_Rural	19.9	172.8	0.06	2.03	-0.4%
AADTT One_Urban	19.9	172.7	0.06	2.03	-0.4%
AADTT Two_Rural	19.8	172.9	0.06	2.03	-0.9%
AADTT Two_Urban	19.8	173.0	0.06	2.03	-0.9%
AADTT Three_Rural	19.8	172.9	0.06	2.03	-0.9%
AADTT Three_Urban	19.9	172.9	0.06	2.03	-0.4%
Non-freeway-rigid-baseline	20.0	172.4	0.04	2.91	-
AADTT One_Rural	19.9	172.9	0.04	5.66	-0.4%
AADTT One_Urban	19.9	172.9	0.04	5.66	-0.4%
AADTT Two_Rural	19.9	172.9	0.04	5.66	-0.4%
AADTT Two_Urban	19.9	172.9	0.04	5.66	-0.4%
AADTT Three_Rural	19.9	172.9	0.04	5.62	-0.4%
AADTT Three_Urban	19.8	172.9	0.04	5.66	-0.9%

4.2.2.3 Hourly Distribution Factors (HDF)

The effect of Level 2B HDF inputs on rigid pavement performance was investigated. Based on the analysis results, the percent difference in design life is less than 1 percent for Level 2B

HDF inputs and for both freeways and non-freeways (see Table 4-40). It can be concluded that Level 2B HDF inputs have no practical effect on the design life and Level 3A HDF inputs will suffice for rigid pavement designs.

Table 4-40 Effect of HDF Level 2B inputs on rigid pavement performance

Groups	Years to failure	IRI (in/mile)	Mean Joint faulting (in.)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway-rigid-baseline	20.0	172.9	0.06	0.72	-
High VC9_Rural	19.8	173.0	0.06	2.45	-0.9%
High VC9_Urban	19.8	173.0	0.06	2.45	-0.9%
Low VC9_Rural	19.8	172.9	0.06	2.03	-0.9%
Low VC9_Urban	19.8	172.9	0.06	2.03	-0.9%
Medium VC9_Rural	19.8	172.9	0.06	2.03	-0.9%
Medium VC9_Urban	19.8	172.9	0.06	2.03	-0.9%
Non-freeway-rigid-baseline	20.0	172.4	0.04	2.91	-
High VC9_Rural	19.8	173.1	0.04	6.03	-0.9%
High VC9_Urban	19.8	173.1	0.04	6.03	-0.9%
Low VC9_Rural	19.9	172.9	0.04	5.66	-0.4%
Low VC9_Urban	19.9	172.9	0.04	5.57	-0.4%
Medium VC9_Rural	19.8	173.0	0.04	5.81	-0.9%
Medium VC9_Urban	19.8	173.0	0.04	5.76	-0.9%

4.2.2.4 Axle Load Spectra (ALS)

The effect of Level 2B inputs on pavement performance was evaluated in terms of predicted pavement service lives using the baseline designs. Six single and five tandem Level 2B ALS inputs were tested. The results are presented for flexible pavements in Table 4-41. Since the percent difference in design life is less than 10 percent for both freeways and non-freeways, it can be concluded that single ALS clusters have little to no practical effect on the design life and Level 3A ALS defaults would suffice for pavement designs. Similarly, for the tandem ALS, the percent difference in design life was less than 10 percent (see Table 4-42) for both freeways and non-freeways Level 2B inputs. It can be concluded that tandem ALS Level 2B inputs have little to no practical effect on the design life and Level 3A ALS defaults would suffice for flexible pavement designs.

Table 4-41 Effect of single ALS Level 2B inputs on flexible pavements performance

Groups	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-flexible-baseline	20	146	0.43	0.40	20.0	1,270	346	-
National Rural	20.2	146	0.43	0.40	19.9	1,270	346	0.9%
National Urban	20.0	146	0.43	0.41	20.0	1,270	346	0.0%
Regional Rural	19.2	146	0.43	0.41	20.3	1,270	346	-4.1%
Regional Urban	19.8	146	0.43	0.40	20.1	1,270	346	-0.9%
Statewide Rural	18.9	146	0.44	0.41	20.4	1,270	346	-5.4%
Statewide Urban	20.0	146	0.43	0.41	20.0	1,270	346	0.0%
Non-freeway-flexible-baseline	20.0	140	0.34	0.31	20.0	1,591	349	-
National Rural	21.4	140	0.33	0.31	19.6	1,591	349	7.1%
National Urban	21.0	140	0.34	0.31	19.7	1,591	349	5.0%
Regional Rural	20.0	140	0.34	0.31	20.0	1,591	349	0.0%
Regional Urban	21.0	140	0.33	0.30	19.7	1,591	349	5.0%
Statewide Rural	19.9	140	0.34	0.31	20.1	1,591	349	-0.4%
Statewide Urban	20.0	142	0.34	0.31	20.0	1,613	350	0.0%

Table 4-42 Effect of tandem ALS Level 2B inputs on flexible pavements performance

Groups	Years to failure	IRI (in/mi)	Total rutting (in.)	AC rutting (in.)	Bottom-up fatigue cracking (%)	Top-down fatigue cracking (ft/mile)	AC thermal cracking (ft/mile)	% Difference in design life
Freeway-flexible-baseline	20	146	0.43	0.40	20.0	1,270	346	-
2L Rural	19.9	146	0.43	0.41	20.1	1,277	346	-0.4%
2L Urban	19.9	146	0.43	0.41	20.1	1,277	346	-0.4%
3L Rural	20.1	146	0.43	0.41	20.0	1,268	346	0.4%
3L Urban	20.9	145	0.43	0.40	19.8	1,252	346	4.6%
4L Rural	20.9	145	0.43	0.40	19.8	1,256	346	4.6%
Non-freeway-flexible-baseline	20	140	0.34	0.31	20.0	1,591	349	-
2L Rural	20.7	140	0.34	0.31	19.9	1,581	349	3.4%
2L Urban	20.6	140	0.34	0.31	19.9	1,583	349	2.9%
3L Rural	21.3	140	0.33	0.30	19.6	1,549	349	6.3%
3L Urban	21.3	139	0.33	0.30	19.6	1,552	349	6.3%
4L Rural	21.2	140	0.33	0.30	19.7	1,554	349	5.9%

Similarly, the effect of single and tandem ALS Level 2B inputs on pavement performance was evaluated for rigid pavements. The results are presented in Tables 4-43 and 4-44. Since the percent difference in design life is less than 10 percent for both single and tandem ALS for freeways and non-freeways, it can be concluded that Level 2B inputs have little to no practical effect on the design life and Level 3A inputs (statewide defaults) will suffice for single and tandem ALSs for rigid pavements. The tridem and quad axle load spectra did show any effect on the design life differences and are not presented in the results.

Table 4-43 Effect of single ALS Level 2B inputs on rigid pavements performance

Groups	Years to failure	IRI (in/mi)	Mean joint faulting (in)	JPCP transverse cracking (percent slabs)	% Difference in Design Life
Freeway-rigid-baseline	20	172.9	0.06	0.7	-
National Rural	19.9	172.9	0.06	2.0	-0.4%
National Urban	19.8	173.0	0.06	2.0	-0.9%
Regional Rural	19.9	172.9	0.06	2.0	-0.4%
Regional Urban	20.0	172.5	0.06	2.0	0.0%
Statewide Rural	19.8	173.2	0.06	2.0	-1.3%
Statewide Urban	19.9	172.9	0.06	2.0	-0.4%
Non-freeway-rigid-baseline	20	172.4	0.04	2.9	-
National Rural	20	172.4	0.04	4.9	0.0%
National Urban	19.9	172.6	0.04	5.0	-0.4%
Regional Rural	19.9	172.9	0.04	5.5	-0.4%
Regional Urban	20.1	172.1	0.04	4.9	0.4%
Statewide Rural	19.8	173.2	0.04	5.9	-0.9%
Statewide Urban	19.9	172.6	0.04	5.2	-0.4%

Table 4-44 Effect of tandem ALS Level 2B inputs on rigid pavements performance

Groups	Years to failure	IRI (in/mile)	Mean Joint faulting (in.)	JPCP transverse cracking (percent slabs)	% Difference in design life
Freeway-rigid-baseline	20.0	172.9	0.06	0.72	-
2L Rural	19.8	173.3	0.06	2.03	-1.3%
2L Urban	19.8	173.1	0.06	2.03	-0.9%
3L Rural	19.7	173.8	0.06	2.03	-1.6%
3L Urban	20.0	172.2	0.06	2.03	0.0%
4L Rural	20.1	172.0	0.06	2.03	0.4%
Non-freeway-rigid-baseline	20.0	172.4	0.04	2.91	-
2L Rural	19.9	172.7	0.04	5.62	-0.4%
2L Urban	19.9	172.7	0.04	5.62	-0.4%
3L Rural	20.0	172.5	0.04	5.41	0.0%
3L Urban	20.1	172.2	0.04	5.46	0.4%
4L Rural	20.1	172.1	0.04	5.46	0.4%

4.3 CLUSTER ASSIGNMENT METHODOLOGY

The next step after the generation of clusters and sensitivity analyses is to develop a cluster assignment methodology. Cluster assignment methodology (classification technique) usually involves developing a classification model which assigns new sites to one of the previously developed clusters. Examples of classification techniques include decision tree classifiers, discriminant analysis, neural networks, support vector machines, and naïve Bayes classifiers. The input data for a classification model includes a data array D as shown in Equation (1).

Each row contains a data object, and the columns contain the attribute values and the class label of each data object.

$$D = \begin{Bmatrix} x_{11} & \cdots & x_{1n} & y_1 \\ \vdots & \ddots & \vdots & \vdots \\ x_{m1} & \cdots & x_{mn} & y_m \end{Bmatrix} \tag{1}$$

where:

x_{ij} = value of the j[th] attribute of object i.

y_i = Class label of the object i

The attribute values (e.g., road class and development type) could be either discrete or continuous while the class label (clusters) should always be discrete. All the classification techniques use a learning algorithm to identify a model that best fits the relationship between the attribute set and the class label of the input data. For this study, the attribute set includes various attributes of the PTR locations. The class labels are the pre-defined cluster numbers. The models generated by the learning algorithms should fit the input data well and correctly predict the clusters of a new PTR location it has never seen before. The general approach in developing a model is to have a training set of PTR locations whose cluster numbers are known. This training set is used to develop a classification model. This model is then applied to test set which consists of PTR locations and their clusters numbers not used by the model. Evaluation of any classification model is based on its accurate number predictions of the cluster numbers and can be presented in a tabular form called the confusion matrix (see Table 4-45).

Table 4-45 Confusion matrix for dataset with two class labels (clusters)

Confusion matrix		Predicted Class	
		Cluster = 1	Cluster = 2
Actual class	Cluster = 1	**P_{11}**	P_{12}
	Cluster = 2	P_{21}	**P_{22}**

Each element in the diagonal (bolded) are predicted accurately and the non-diagonal elements are the inaccurate predictions. One could use a performance metric of a model such as accuracy as defined below.

$$\text{Accuracy} = \frac{\text{Number of accurate predictions}}{\text{Total number of predictions}} = \frac{P_{11} + P_{22}}{P_{11} + P_{12} + P_{21} + P_{22}} \tag{2}$$

Consequently, the error rate is

$$\text{Error rate} = \frac{\text{Number of inaccurate predictions}}{\text{Total number of predictions}} = \frac{P_{12} + P_{21}}{P_{11} + P_{12} + P_{21} + P_{22}} \tag{3}$$

The error rate of a classification model can be divide into two categories (a) training error, and (b) testing error. The training error is the misclassification rate of the model on the training records. The testing error is the misclassification rate of the model using the data which it has not seen before. A good classification model should have high accuracy and low error rate.

As previously mentioned, several techniques exist for building a classification model but the research team decided to use the decision tree classifiers for its ease of use. An example of a decision tree can be seen in Figure 4-12. A decision tree has three types of nodes: (a) a root node that has no incoming edges and zero or more outgoing edges (Development type) (b) internal nodes, which have exactly one incoming edge and two or more outgoing edges (Functional Class), and (c) leaf or terminal nodes, which has exactly on incoming edge and no outgoing edges. Each leaf node is assigned the cluster number. Many decision trees can be constructed from a given set of attributes. While some of the trees are more accurate than others, finding the optimal tree is computationally infeasible. Many algorithms can be used to decide on the attribute to be used for partitioning the data but the one most commonly used is the Hunt's algorithm which is the basis of many existing decision tree induction algorithms (*4*).

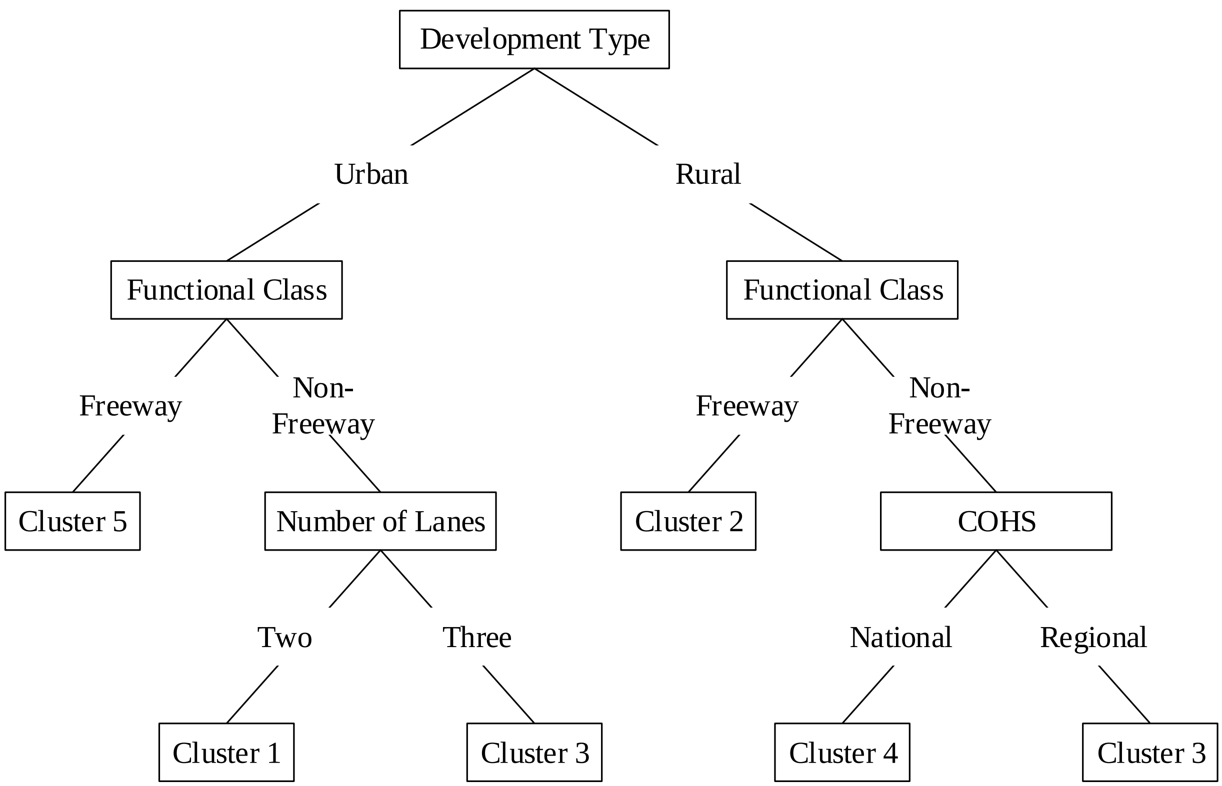


Figure 4-12 Example of a decision tree

The advantages of decision trees are that they are easy to understand and interpret. They can handle both numerical and categorical data input data and can be used to solve problems with multi-class labels (as opposed to certain techniques that can handle only binary class labels).

However, decision tree classifiers can create long and complex trees that tend to over fit the data. A long and complex decision tree (i.e. a tree with more nodes and leaves) have low training errors and high testing errors.

To improve the classification accuracy, multiple classifiers can developed and their predictions can be aggregated. Such techniques are called ensemble methods. Ensemble methods construct multiple classifiers from the training data, predict the class labels and picks the one with the one with most predicted class label. One of such techniques used in this study is called bagging (also known as bootstrap aggregating). This technique repeatedly samples from the data set with replacement. Each sample has the same size as the original data and a model is fit to the data. This process was repeated for 500 times. Tables 4-46 and 4-47 present the training and testing losses for the classification models of HDF and TALS. Single decision tree for HDF can be seen in Figure 4-13 while one of the trees built using random forests can be seen in Figure 4-14. Similarly, a single decision tree for TALS can be seen in Figure 4-15 while one of the trees built using random forests can be seen in Figure 4-16. Note that the data from only 41 WIM sites are used for the models. Although bagging (random forests) techniques are better than a single decision tree, the accuracy cannot be improved unless there are more WIM sites or more data are available that describe these 41 PTR sites better. Only three traffic inputs (VCD, HDF and TALS) need Level 2 inputs based on the sensitivity. For Level 2A, classification models are needed to assign a site to clusters. It is recommended that for design purposes VCD should be estimated based on the short-term counts while classifications trees for HDF and TALS can be used for cluster assignments if Level 2A inputs are needed. Due to relatively high misclassification rates, practically insignificant difference between Levels 2A and 2B, and ease of use, Level 2B inputs can be used for design purposes.

Table 4-46 Training and testing losses for various classification models — HDF

Classification Model	Training Loss	Testing Loss
Single Tree (entire data)	0.15	
Random Forests (entire data)	0.00	
Single Tree (75-25 cross validation)	0.19	0.39
Random Forests (75-25 cross validation)	0.00	0.29

Table 4-47 Training and testing losses for various classification models — TALS

Classification Model	Training Loss	Testing Loss
Single Tree (entire data)	0.22	
Random Forests (entire data)	0.00	
Single Tree (75-25 cross validation)	0.29	0.41
Random Forests (75-25 cross validation)	0.03	0.33

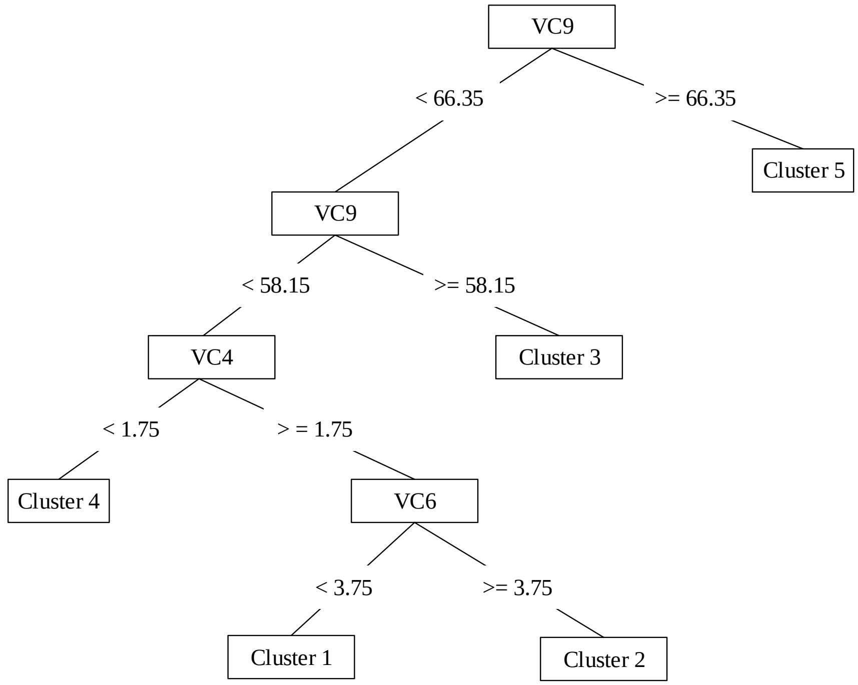


Figure 4-13 Single decision tree for HDF using entire data

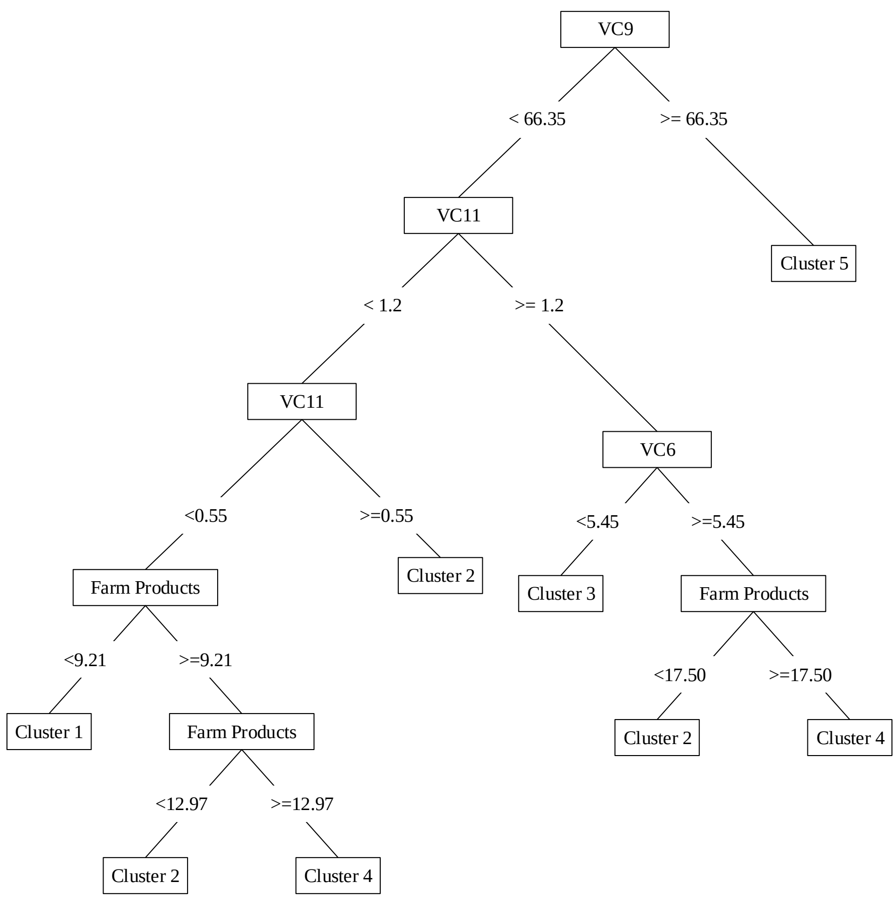


Figure 4-14 Random forests (100^{th}) tree for HDF using entire data

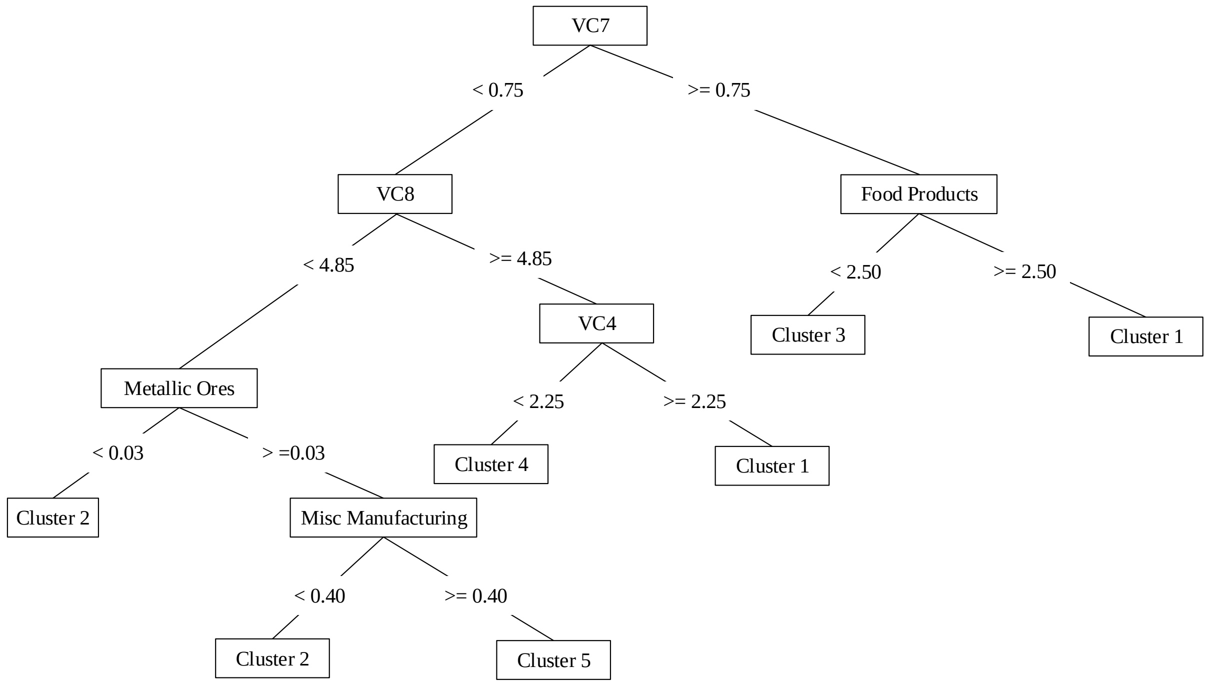


Figure 4-15 Single decision tree for TALS using entire data

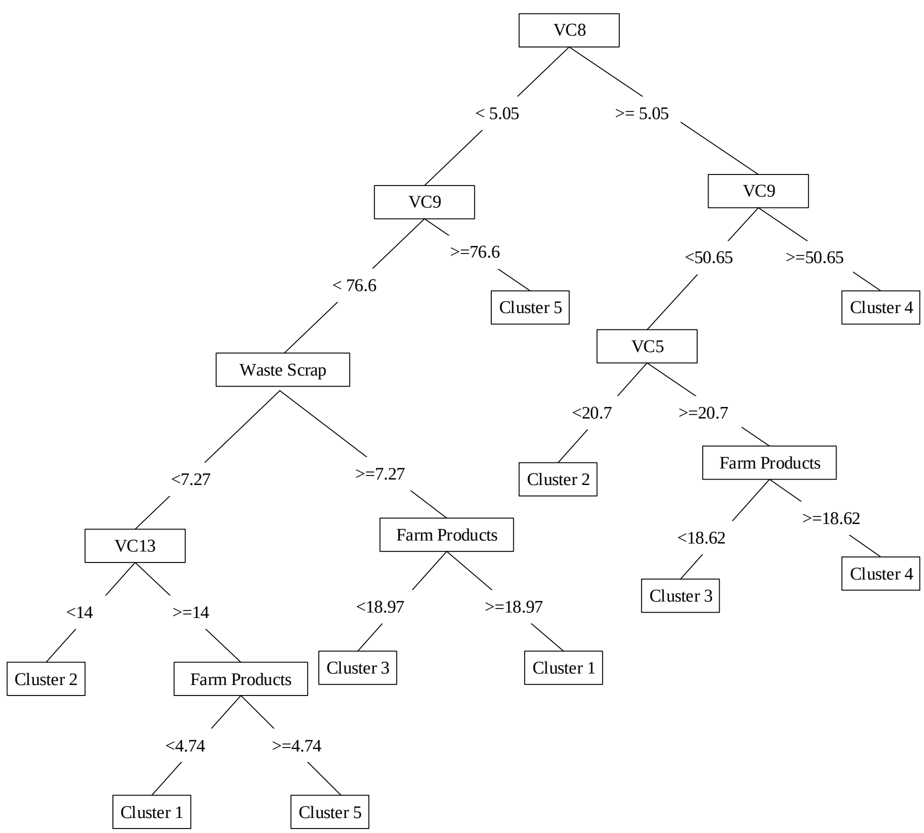


Figure 4-16 Random forests (180[th]) tree for TALS using entire data

4.4 SUMMARY

Five traffic input levels were developed in this study as listed below.

a. Level 1 – Site-specific inputs
b. Level 2A – Averages of clusters based on cluster analyses
c. Level 2B – Averages of groups based on roadway characteristics (attributes)
d. Level 3A – Averages based on freeway and non-freeway road classes
e. Level 3B – Statewide averages

Level 1 inputs should always be used for design purposes wherever possible as it is the actual traffic data specific to the site. When Level 1 traffic inputs are unavailable, either Levels 2 or 3 inputs have to be used for pavement designs. The impact of Level 2 inputs on predicted pavement performance can be evaluated by using sensitivity analyses. If no differences in the predicted performance or pavement lives are observed between Levels 1 and 2 inputs, Level 3 traffic inputs will suffice for pavement design. The steps involved in sensitivity analyses include establishing base designs, performance criteria and other input parameters in the Pavement-ME and then evaluating the impact of Levels 2 and 3 traffic inputs.

For sensitivity analyses, the pavement design life was assumed 20 years with 95% design reliability for flexible and rigid pavements. For each of the 41 WIM locations, the HMA surface layer thickness was designed to achieve a 20-year design life for bottom-up fatigue cracking threshold of 20% for flexible pavements since it is a critical structural distress for pavement design. Level 1 inputs were used in this process. For these designs, the rut depth values at the end of 20 years were also recorded. In addition, for each of the 41 WIM locations, the slab thickness was designed to achieve a 20-year design life for IRI threshold of 172 inches/mile for the rigid pavements because it controls most of the designs. Faulting and transverse cracking values were also recorded at the end of 20 years. For both the flexible and rigid pavement designs, one traffic input was changed at a time to Levels 2A and 2B to determine their effects on the design lives. Levels 3A and 3B inputs for each design (one input at a time) were also used in the Pavement-ME to determine their impact on the design lives. The time for the distress values (for Levels 2 and 3) to reach the threshold values in the Level 1 designs were documented. The differences in design lives between different inputs levels were quantified for further analyses.

Statistical analyses could detect differences between clusters or groups, but the differences might not have much practical significance. Hence, in addition to the statistical significance, the maximum life difference (MLD) values between two input levels were adopted as an indicator of the variability in the data and correspondingly select the proper input level needed for the design. One way ANOVA was performed on the absolute life differences ($|\text{Life}_{\text{Level 1}} - \text{Life}_{\text{Level X}}|$) to detect the differences between the clusters for each traffic input. If the *p*-value is below 0.05, the results indicate that the cluster or group averages are different from each other and that their use in pavement design would result in statistically different design lives. However, it does not indicate whether the differences are of practical significance. The absolute differences in predicted lives were estimated relative to Level 1 design life of 20 years. The cluster or group was considered sensitive or of practical significance if the absolute life differences of at least one WIM location is higher than two years.

Once the sensitivity of inputs at Levels 2 and 3 was determined, the next step was to identify if there are any differences between predicted lives for Levels 2A and 2B. If there are no differences between the Levels 2A and 2B, then Level 2B can be used since it will simplify the input selection process. A paired *t*-test was used to verify if there are significant differences between the values of ($|Life_{Level\ 1} - Life_{Level\ 2A}|$) and ($|Life_{Level\ 1} - Life_{Level\ 2B}|$). Also, the number of under- and over-designed WIM sites due to the use of Levels 2A and 2B inputs were determined. A pavement at a WIM location will be overdesigned when the difference in design lives ($Life_{Level\ 1} - Life_{Level\ x}$) is positive and under-designed when the difference ($Life_{Level\ 1} - Life_{Level\ x}$) is negative. While a positive life difference would suggest increasing the thicknesses making the project over-designed, a negative life difference will force to reduce the thicknesses making the project under-designed relative to Level 1. If there were statistically significant differences, either Level 2A or 2B was selected for that traffic input after careful evaluation of the average design life differences. If there were no differences between Levels 2A and 2B, comparisons were made between Levels 2A and 3A or 2B and 3A to see if Level 3A would suffice for pavement designs. Again, if there are no differences between Levels 2 and 3A, comparisons were made between Levels 3A and 3B to see if Level 3B would suffice for pavement designs. Subsequent to the sensitivity analyses, classifications models (decision trees) were developed for cluster assignment.

The criteria used in this analyses to establish significant traffic inputs are based on engineering judgment and local experience. The statistical analyses may not be reliable alone; practical significance should always support it. Based on the sensitivity analyses of Levels 2A, 2B, 3A, and 3B, it is recommended that for design purposes VCD should be estimated based on the short-term counts while classifications trees for HDF and TALS can be used for cluster assignments if Level 2A inputs are needed. Due to relatively high misclassification rates, practically insignificant difference between Levels 2A and 2B, and ease of use, Level 2B inputs can be used for design purposes. The following input levels are recommended for each traffic input (see Table 4-48).

Table 4-48 Recommended traffic input levels

Traffic input	Recommended traffic input level	
	Flexible pavements	Rigid pavements
VCD	2B	2B
HDF	-	2B
MAF	3A	3A
SALS	3A	3A
TALS	2B	2B
TRALS	3A	3A
QALS	3A	3A

CHAPTER 5 - PREPME EVALUATION

5.1 BACKGROUND

The Pavement-ME design (previously MEPDG/DARWin-ME) is a substantial advancement in pavement design process. Therefore, it requires many more inputs from various data sources. Through the transportation pooled fund study TPF-5(242): Traffic and Data Preparation for AASHTO Pavement-ME Analysis and Design, a full-production software called PrepME with comprehensive database features was developed to assist state DOTs in data preparation and improve the management and workflow of the Pavement-ME design input data. Specifically, the PrepME is capable of pre-processing, importing, checking the quality of raw Weigh-In-Motion (WIM) traffic data, and generating three traffic input levels with in-built clustering analysis methods. This tool can be used not only by pavement design engineers to prepare input for the Pavement-ME, but also traffic data collection engineers to collect better traffic data and manage those data for other applications. The software has the following basic functions with more specific features requested by individual States.

- Imports an agency's PTR traffic data complying with FHWA Traffic Monitoring Guide (TMG) file formats, and stores the data in SQL server local database with exceptional computation efficiency.
- Conducts Travel Monitoring Analysis System (TMAS 2.0) data check during data import and generates TMAS check error log for each imported raw file.
- Performs automatic quality control checks by direction and lane for both classification and weight data based on the TMG recommendations.
- Provides user friendly interfaces to review monthly, weekly and daily traffic data, and investigate the PTR data that is incomplete or fails the automatic QC check through various manual, sampling, and analyzing operations.
- Generates three levels of traffic inputs: Level 1 site specific, Level 2 clustering average, Level 3 state average, LTPP TPF-5(004), and the Pavement-ME defaults.
- Offers clustering methods developed by North Carolina and Michigan DOTs, Kentucky Transportation Cabinet (KYTC), Truck Traffic Classification (TTC) method, simplified TTC approach, and flexible clustering for generating Level 2 loading spectra inputs for the Pavement-ME based on the availability of traffic data.
- Generates input files in the file formats that can be directly imported into the Pavement-ME software.

5.2 UPDATES IN PREPME

Several major functional improvements have been made in the updated PrepME software, including:

5.2.1 Traffic Data Import Module

- The updated PrepME has the capability to automatically check and determine the data format of WIM data, and import WIM data following both the 2001 and 2013 TMG formats into the PrepME SQL database.
- A new function has been developed to merge multiple classification (CLA) or Weight (WGT) files into a single file. Due to the characteristic of PrepME data flow, the speed of importing a single combined CLA or WGT file is much faster than that of multiple files separately. Users can find this new feature in the Tool menu.
- Besides the detailed TMAS check report developed in the past, a summary TMAS quick check report is also generated during data import process. The summary TMAS report could help state agencies diagnose the sensor issues.

5.2.2 Traffic Data Check Module

- New functions are added to display data for multiple user-selected months. This feature is helpful to investigate the traffic patterns for WIM stations on low volume roads.
- Several error prevention operations are added in the process of "Run Quality Control" in the Classification Data Check Module to prevent software crashes for some specific stations which have no data.
- A function that is able to cancel users' manual operation
- Two changes have been made for the "Monthly Sampling" operation to allow the data to be classified as "accepted" after a monthly sampling operation was performed.
- The team re-examined the data flow of the "Daily Sampling" operation. The updated PrepME software now only allows users to select complete weekly data to represent the traffic data for the month.

5.2.3 Traffic Data Output

- A function is developed to automatically compute several key traffic parameters for a selected PTR site, including AADTT, Trucks% in Designed Direction, Trucks% in Designed Lane. This function can compute AADTT in either both directions or one direction for Level 1 site-specific output. In addition, the updated PrepME can automatically determine design direction & design lane for such calculations.
- All traffic output files generated by PrepME are re-validated with Pavement ME Design, since the XML data format for Pavement ME Design has been changed.

In addition, several software bugs have been fixed including:

- Previously PrepME crashes when users try to enter the traffic output dialog if either CLA or WGT data are available. This bug has been fixed in the most recent software.
- Due to Google Map API changes, the previous version of PrepME software encounters a script error and crashes when the Google Map capability is called by the software. The software has been updated using the most recent Google Map API. In addition, if no GPS information is available for a specific PTR site, the Google Map

will mark this site in the middle of the Pacific Ocean. In the updated PrepME, if such information is missing, the location is pointed to the center of the state.

- After clicking the button "Show WIM Station" in STA Data Check Module, software will crash if there is no CLA and WGT data. New codes were added to (1) prevent software from crashing under this condition; (2) merge repeatable information in a STA file during the importing process;
- In the "View Output Data" in the Traffic Output Module, the logical order among the radio buttons is corrected.
- It is found that the output axle loading spectra in the previous version of the PrepME software were shifted by one load bin to the heavier side for all the four axle types. This bug has been fixed in the PrepME import module.

5.3 PREPME QC DATA CHECKS

The Traffic Data Check sub-menu is able to:

- Conduct QC check for weight data by direction and lane of traffic using data check algorithms defined in the TMG (Figure 5-1). Weight data check algorithms defined in the 2001 third edition of TMG are integrated in the PrepME software to evaluate weight data for class 9 vehicles. Specific weight bounds can be defined for the front axle and drive tandem axle weights of Class 9 trucks. In addition, the histogram plot of gross vehicle weights of Class 9 trucks should have two peaks, one representing unloaded Class 9 trucks between 28,000 and 36,000 lb (32,000 ± 4,000 lb), and the second peak representing loaded vehicle condition with a weigh between 72,000 and 80,000 lb (76,000 ± 4,000 lb).
- Provide interfaces for users to review monthly, weekly, and daily traffic data.
- Provide four sampling and repair options to analyze and utilize incomplete (that not have a minimum of 12-month data) or failed data (that cannot pass the automatic TMG data check algorithms), including Manual Operation (Accept and Reject), Replacement (Copy and Paste), and Sampling Operation (Daily Sampling and Monthly Sampling).
    - Manual Operation (Accept/Reject) allows users to review and double check the automated QC results.
    - Replacement (Copy and Paste) operation can be used to check the similarity of the data in adjacent months, opposite direction, or different lane, same month but different year, and then identify a suitable month which can be used as the “source month” to substitute the failed or missing month (the “target month”).
    - Daily Sampling operation can be used as a diagnostic tool to investigate the reason(s) for bad data that cannot pass automatic data check, and sample weekly data with good quality to represent this month. (Figure 5-2)
    - Monthly Sampling can be used to select twelve months of data with the highest data quality, either right after a WIM system calibration or any 12 months' data based on engineering judgment.

- Conduct QC check for classification data by direction and lane of traffic using data check algorithms defined in the TMG. The data check criteria includes the check of percentages of unclassified vehicles, class 1 vehicles, and the consistency check in the vehicle mix so that no significant changes are observed. The consistency check is executed by comparing the current truck percentages by class with the corresponding historical percentages. The PrepME software provides similar software interface (Figure 5-3), which is able to perform automatic data check, daily check, replacement, and sampling operations for classification data. Daily sampling function is illustrated in Figure 5-4.

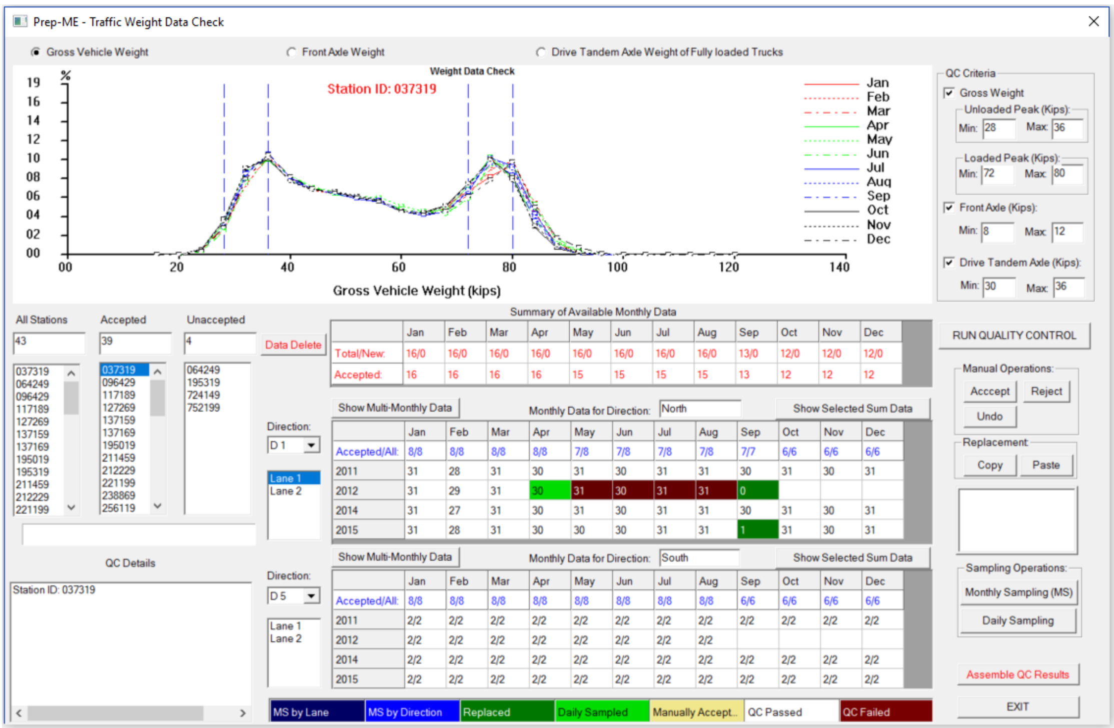


Figure 5-1 Weight data check by direction and by lane

Figure 5-2 Daily check and sampling

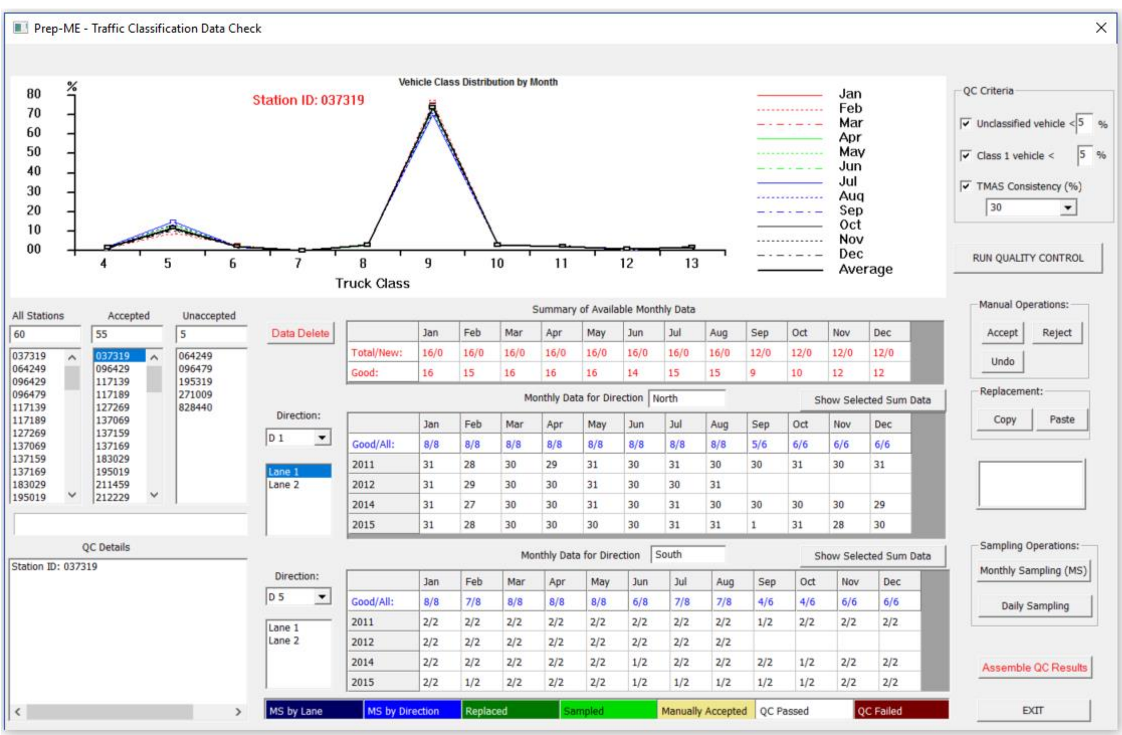


Figure 5-3 Classification data check by direction and by lane

Figure 5-4 Classification daily data check

5.4 NEW GROUPING DEVELOPMENT IN PREPME

The existing Level 2 traffic data output for Michigan Department of Transportation (MDOT) in the previous PrepME software is based on (1) sensitivity of the various traffic inputs to the predicted pavement performance, (2) cluster analyses to group sites with similar characteristics for critical traffic inputs, and (3) discriminant analysis to develop a set of linear regression equations to select the appropriate traffic input cluster group for at a particular pavement design site. The independent variables for the discriminant equations mostly rely on the truck freight data, which may not be always available for a route.

In the current project, a simplified approach (Level 2B) is developed based on a combination of attributes for grouping PTR locations for different traffic inputs:

- Functional classification (Freeway vs. Non-Freeway),
- Development type (Urban vs. Rural),
- AADTT levels (1 "<1000", 2 "1000-3000", 3 ">3000"),
- Corridors of highest significance (National, Regional and Statewide),
- Number of lanes (2, 3 and 4),
- Road type (divided, freeway etc.)
- Vehicle class 9 (VC 9) distribution levels (< 45, 45-70, >70)

The possible 2-, 3-, and 4-way combinations of the attributes are investigated in the project. Pairwise Euclidean distances between each sublevel combinations are calculated to identify the combination of the attributes that show different traffic patterns. Due to the extensive computing complexity required in the process, the optimal combination of the attributes has not been fully integrated in the software programming. Instead, only 2-way combination results are implemented in the updated PrepME software. Note that the traffic loading spectra output data are averaged based on the selected WIM sites. In addition, the attributes used in the site selection process are hardcoded in the software. The users cannot implement addition of new sites and attribute modifications in the software currently.

Figure 5-5 shows the new software interface. Users should select any two attributes (out of the seven) to generate output averages for various traffic parameters. The steps to export desired traffic inputs for the Pavement-ME design are as follows:

1. *Traffic data preparation*: Follow the Prep-ME User's Guide to import traffic data and perform necessary quality checks.
2. *Export traffic data setup*: Provide the "Project Name" and the directory for data output using the "Export Data To…" button. The GPS coordinates are optional, which are only used for the Google Map utility. Subsequently, the "MIDOT Method 2" should be selected to use the simplified Level 2B approach. In the popped-up attribute selection window, users can select two of the attributes for their design. If a different combination is desired, the "Reset Selection" button can clear the previous selection of attributes so that new combinations can be selected.
3. *Export traffic data for Pavement ME Design*: Click the "OK" button after the attribute combination is set and the traffic data is ready for review and export.

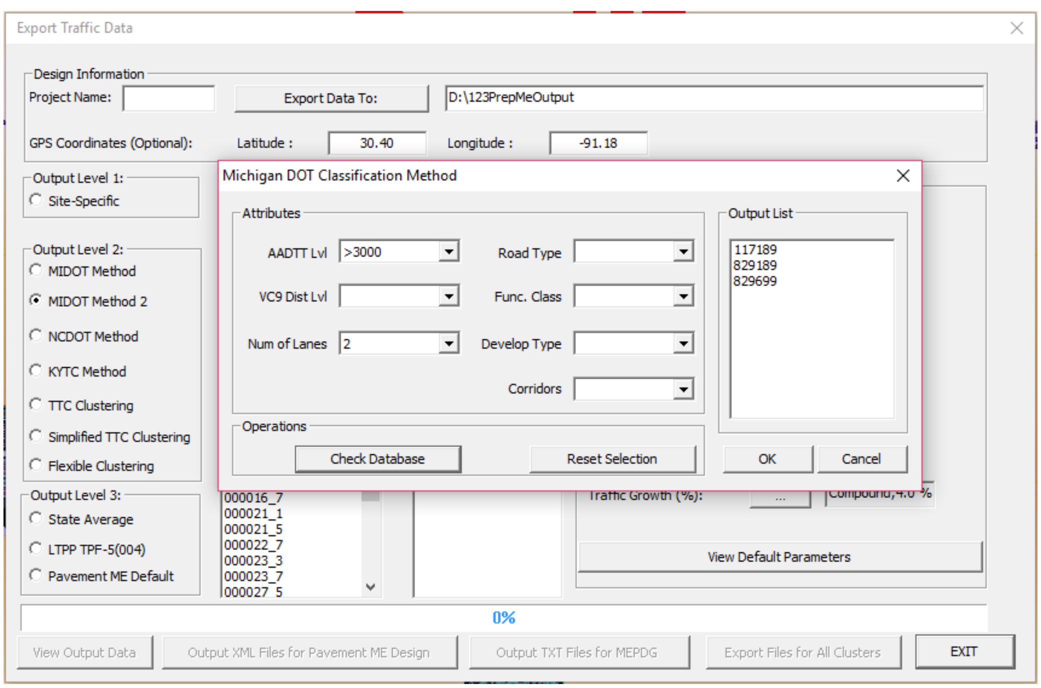


Figure 5-5 New developed Level 2B two-way combination grouping approach

CHAPTER 6 - CONCLUSIONS & RECOMMENDATIONS

Based on the analyses of traffic data collected during the years 2011 to 2015, the following conclusions and recommendations are drawn for traffic inputs for the Pavement-ME analysis and design in the State of Michigan.

6.1 CONCLUSIONS

The following hierarchical traffic inputs can be used in the Pavement-ME:

- Level 1 – Convert WIM and classification site-specific data to the Pavement-ME format using PrepME.
- Level 2 – Utilize groups based on the road attributes with similar traffic characteristics. The group traffic characteristics were averaged to create Level 2 traffic inputs.
- Level 3 – Average traffic characteristics from all PTR sites were used to generate for freeway and non-freeway Level 3 data.

6.1.1 Findings based on the Cluster Analysis and Traditional Approaches

The development of Level 2A inputs established the following findings:

- Vehicle class distribution (VCD) clustering identified five specific traffic patterns each distinguished by the proportions of VC5 and VC9. Sites in cluster 1 have percentage VC9 trucks in the ranges of 45 to 70 while the VC5 truck percentage was in the range of 15 to 25. Cluster 2 contained a majority of sites with percentage VC9 trucks less 45 while the VC5 truck percentage was in the range of 20 to 30. Cluster 3 has sites that have slightly higher percentage of VC5 trucks than VC9 trucks. Sites in cluster 4 have the highest percentage of VC9 trucks (above 75) with very low percentage of VC5 trucks (below 10). Sites in cluster 5 have percentage of VC9 trucks between 55 and 70 with percentage of VC5 trucks between 10 and 20.
- Monthly adjustment factors (MAF) clustering resulted in four clusters based on VC5. Cluster 1 exhibits reasonable seasonal variability, having MAF close to 1.4 during summer months with lower values in winter. Cluster 2 depicts very little seasonal variability with MAF close to 1. Cluster 3 displays higher MAF in summer and fall, with much lower MAF in winter and spring. Sites in cluster 4 also have higher MAF in summer and fall and are mostly located on north-south routes such as I-75 and US-127. Cluster analysis based on VC9 resulted in five clusters. Almost all the sites in all the clusters have no seasonal variability between months. Since, VC9 trucks are used for long haul throughout the year, a uniform presence of such trucks is expected on all the sites.
- Hourly distribution factors (HDF) were grouped into five clusters. Cluster 1 contains heavier evening proportions of trucks. Cluster 2 has similar percentage of trucks as sites in cluster 1, but on average, shifts left by an hour (earlier). Cluster 3 average has

roughly a 1-2% lower truck percentage between the hours of 7:00 am and 4:00 pm than either clusters 1 or 2. Sites in cluster 4 have the highest HDF during 8 am to 12 noon of all clusters. Sites in cluster 5 have the flattest curve among all the clusters suggesting minimum hourly variations for long-haul trucks.

- Single axle load spectra (SALS) were grouped into four clusters based on VC5 trucks. For all the sites in the clusters the first peak occurs at approximately 4 to 6 kips while the second peak occurs at 8 to 10 kips. Cluster 1 has almost equal proportion of axles in the 4-6 kip range and the 8-10 kip range. Cluster 2 has higher proportion of 4-6 kip axles than 8-10 kip axles. Cluster 3 has only one site (US-2) in the Upper Peninsula and the pattern is unique to that site. Cluster 4 has sites with higher proportion of axles in the 8-10 kip range than the 4-6 kip range.
- Tandem axle load spectra (TALS) based on VC9 resulted in five clusters. The two peaks in the clusters correspond to unloaded (9-14 kips) and loaded (30-33 kips) trucks. Clusters 1, 3 and 4 have more light axles than heavy, whereas Clusters 2 and Cluster 5 have heavier tandem axles.
- Tridem axle load spectra (TRALS) based on VC13 formed six clusters. The general trend of the tridem axle clusters show a large proportion of light axles around 12 kips followed by a peak value around 40-45 kips.
- Quad axle load spectra (QALS) based on VC13 resulted in 3 clusters. Peak values for the quad axle load spectra occur at the 18-24 kips, 45-60 kip ranges.

The development of Level 2B inputs established the following findings:

- It was anticipated that the MDOT will know the AADTT at a site (i.e., from historical traffic data or short-term counts). Therefore, AADTT was grouped into low, medium, and high traffic volume. Low was under 1000 AADTT, medium was from 1000 to 3000 AADTT, and high was greater than 3000 AADTT for the design lane in one direction. Fourteen sites had low AADTT, eighteen sites had medium AADTT, and the remaining nine had high AADTT. Note that the AADTT brackets were determined based on the distribution of the latest AADTT levels from the 41 PTR sites.
- For VCD, the attributes of VCD level and development type (urban vs. rural) resulted in six groups. Three distinct patterns with varying levels of VC9 irrespective of the development type were observed. All the sites in high VC9 groups are located on the interstates while most of the sites in low VC9 groups are located on state routes. Sites in the medium VC9 groups have a mix of both intestates and state routes in rural and urban areas.
- For MAF, the attributes of commercial AADT and development type resulted in six groups. Almost all the groups have similar MAF patterns for VC5 except for sites with low AADTT in the rural areas suggesting seasonal traffic patterns. No differences in MAF for VC9 trucks were found between the groups and are always close to 1.
- For HDF, the attributes of VCD level and development type resulted in six groups. The sites having low VC9 levels in the urban areas have the highest peak among all other groups between 8:00 am and 4:00 pm suggesting local traffic patterns. Sites having high VC9 levels have the flattest peaks in both urban and rural areas

suggesting long haul traffic patterns. All the sites in high VC9 groups are on interstate routes.

- For SALS, the attributes of COHS and development type resulted in six groups. For all the sites in different groups, the first peak occurs at approximately 4-6 kips while the second peak occurs at 8-10 kips. Road groups in the urban areas have almost equal proportion of axles in the 4-6 kip range and the 8-10 kip range while the sites in the rural areas have higher proportion of 4-6 kip axles than 8-10 kip axles. The road group of regional corridor in the urban area has only one site on US-2 with a unique loading pattern.
- For TALS, the attributes of number of lanes and development type resulted in five groups. The two peaks seem to correspond to unloaded (9-14 kips) and loaded (30-33 kips) tandem axles. Other characteristics could not be established for the groups as they have varying functional classifications and AADTT levels and also due to the fact that some groups only have one site.
- For TRALS, the attributes of COHS and development type resulted in six groups. The general trend of the tridem axle groups appears to be a large proportion of light axles around 12 kips followed by a peak value around 40-45 kips. All the sites in the national corridors are located on interstates while the sites on regional and statewide corridors are on state routes with varying AADTT levels irrespective of the development type.
- For QALS, the attributes of COHS and development type resulted in six groups. Again, all the sites in national corridors are on the interstates while the sites on regional and statewide corridors are on state routes with varying AADTT levels irrespective of the development type.

6.1.2 Significant Traffic Input Levels

For pavement design, it is recommended that site specific data (Level 1) be used if available. For sites with no site-specific data, it is necessary to know whether Level 2 or Level 3 data are acceptable for design purposes. To investigate the impact of traffic input levels on predicted pavement performance for flexible and rigid pavements, the Pavement-ME was used. The results of the sensitivity analyses were used to establish the appropriate traffic input levels. Such analyses were performed on the absolute life differences ($|\text{Life}_{\text{Level 1}} - \text{Life}_{\text{Level X}}|$) to detect the differences between the clusters or groups for each traffic input.

The sensitivity of inputs at Levels 2 and 3 was determined using statistical and practical significance criteria. The next step was to identify if there are any differences between predicted lives for Levels 2A and 2B. If there are no differences between the Levels 2A and 2B, then Level 2B can be used since it will simplify the input selection process. Also, the number of under- and over-designed WIM sites due to the use Levels 2A and 2B inputs were determined. A pavement at a location will be over-designed when the difference in design lives ($\text{Life}_{\text{Level 1}}$ - $\text{Life}_{\text{Level x}}$) is positive and under-designed when the difference ($\text{Life}_{\text{Level 1}}$ - $\text{Life}_{\text{Level x}}$) is negative. While a positive life difference would suggest increasing the thicknesses making the project over-designed, a negative life difference will require to reduce the thicknesses making the project under-designed relative to Level 1. If there were statistically significant differences, either Level 2A or 2B was selected for that traffic input after careful evaluation of the average design life differences. If there were no differences between Levels 2A and 2B, comparisons were made between Levels 2A and 3A or 2B and 3A to see if Level 3A would suffice for pavement designs. Again, if there are no differences between Levels 2 and 3A, comparisons were made between Levels 3A and 3B to see if Level 3B would suffice for pavement designs. Levels 2A, 2B, 3A and 3B traffic inputs can be found in Appendix E. The following is the summary of findings:

- VCD significantly impacts predicted rigid and flexible pavement performance. In addition there is a statistical difference between Levels 2A and 2B for rutting only in flexible pavements. The number of under designed sites are higher for Level 2A compared to Level 2B. Thus, VCD groups (Level 2B) are suggested for use in flexible and rigid pavement design.
- MAF have negligible impact on predicted rigid and flexible pavement performance. No statistical differences in design lives between Level 2A clusters or 2B road groups were observed. Also, there are no statistically significant differences between Levels 2B and 3A. Since there are statistically significant differences between Levels 3A and 3B, Level 3A inputs are recommended for MAF for both flexible and rigid pavements
- HDF significantly impacts rigid pavement performance. Level 2A is slightly better with the number of undersigned sites for transverse cracking than Level 2B. However, due to relatively high misclassification rates of the classification models, practically insignificant difference between Levels 2A and 2B, and ease of use, group average (Level 2B) HDFs should be utilized for rigid pavement design.
- AGPV had a negligible impact on predicted rigid and flexible pavement performance. Therefore, it is suggested that statewide averages (Level 3B) be used for this traffic input.
- Single axle load spectra have a significant effect on predicted flexible pavement performance. Cluster (2A) and group (2B) averages produced comparable results. Also no significant difference was detected between Levels 2B and 3A. Therefore, it is recommended that statewide averages (Level 3A) be used for this traffic input.
- Tandem axle load significantly impacted rigid and flexible pavement performance. Therefore, group averages (Level 2B) are suggested for both rigid and flexible pavement designs.
- Tridem and quad axle load spectra do not have a significant impact on rigid and flexible pavement performance. Consequently, statewide average tridem and quad axle load spectra (Level 3A) can be used for this traffic input.
- The Pavement-ME defaults traffic inputs don’t accurately reflect the local traffic conditions in the state of Michigan. In general, statewide or cluster averages produced performance lives that were closer to the site-specific values than the Pavement-ME defaults. Consequently, the Pavement-ME defaults are not recommended for use in the state of Michigan.

The summary of the above findings is presented below:

Traffic Characteristic	Impact on Pavement Performance		Suggested Input Levels (when Level I is unavailable)	
	Rigid Pavement	Flexible Pavement	Rigid Pavement	Flexible Pavement
VCD	Moderate	Moderate	Level 2B	
HDF	Moderate	-	Level 2B	-
MAF	Negligible		Level 3A	
AGPV	Negligible		Level 3B	
Single ALS	Negligible	Moderate	Level 3A	
Tandem ALS	Moderate	Moderate	Level 2B	
Tridem ALS	Negligible	Negligible	Level 3A	
Quad ALS	Negligible	Negligible	Level 3A	

Note: All traffic inputs are delivered as a separate excel file. MDOT can choose the recommended inputs from the excel file.

6.1.3 Assigning a Site to a Cluster or a Group

The above table presents the summary of suggested traffic levels for each traffic input. For the traffic inputs where site-specific (Level 1) data or only statewide values (Levels 3A or 3B) need to be used, selection of the appropriate traffic input is obvious. For traffic inputs where Level 2B are suggested, the following road attributes can be used to obtain the inputs:

- Vehicle class distribution (VCD) — VC9 distribution (< 45%, 45 – 70%, >70%) and development type (Urban vs. Rural)
- Hourly distribution factor (HDF) — VC9 distribution (< 45%, 45 – 70%, >70%) and development type (Urban vs. Rural)
- Tandem Axle Load Spectra (TALS) — Number of lanes (2, 3 and 4) and development type (Urban vs. Rural)

6.1.4 General Findings

Additionally, the following observations were made based on the analyses of the traffic inputs:

- In general, insignificant seasonal (month to month) variations existed in axle load spectra for the most vehicle classes except the vehicle classes (VC4, VC7, VC8, VC11, and VC12) that constitute a very low percentage of the traffic volume and are on roads with low AADTT.
- The impact of directional difference in axle load spectra for most vehicle classes is negligible. Only VC10 and VC13 exhibited directional difference. This is most likely local nature of these specific VC trips (for e.g., traveling to and from a logging site or gravel pit). This is an important observation as it substantiates the need to analyze only a single direction in the cases where VC10 and VC13 are predominant. This

difference should be observed for each PTR location where directional difference for VC13 is more than 5%.

- The single axle load distribution depends on the percentages of VC5 and VC9 in the traffic stream. The sites with higher proportions of VC5 peak at 4-8 kips while sites with higher proportions VC9 peak at 8-10 kips.
- The tandem axle load distributions are mostly dependent on the axle load spectra of VC9.
- The tridem and quad axle load spectra are a function of VC7, VC10 and VC13.

6.2 RECOMMENDATIONS

It is recommended, wherever possible, to expand the geographic coverage of traffic data in Michigan. When a new PTR site needs to be installed, it should be located in areas where limited traffic data are available. Short duration and continuous counts should be shared between agencies to ensure wider and recurrent data collection coverage. Effective communication between traffic data collection personnel and pavement design engineers is recommended for addressing the traffic input requirement for the Pavement-ME. Additionally, the following specific traffic data collection efforts should be considered as recommended by the Traffic Monitoring Guide (TMG):

- The short duration volume coverage count program should provide comprehensive coverage across the roadway infrastructure on a cycle of 6 years. Short duration classification counts should account for at least 25-30% of all volume counts being conducted (i.e., at all PTR locations) wherever possible. In addition, at least one vehicle classification count should be made on each route annually.
- At least six continuous vehicle classification PTR be established for each road group. Continuous counts should be placed on different functional classes and different geographic regions within the state. Emphasis should be placed on roads that are primarily local or long hauls. When new sites are added, the data should be placed into the appropriate existing road groups.
- A minimum of six WIM should be monitored within a group, with at least one of the WIM sites operating continuously and recording two or more lanes of traffic. The amount of permanent WIM stations and discontinuous portable systems is a function of the number of groups, the accuracy at which the measured weights are taken, and the budget of the State agency.

With proper coverage of existing groups and a gradual expansion into unmonitored areas within the State through installation of permanent devices, the data collection program could be more robust. In addition to above mentioned general suggestions, based on the results of this study following are the specific recommendations to improve traffic data collection to facilitate the use of the Pavement-ME design process in the State of Michigan:

1. The attributes selected for the road group development for different traffic inputs were determined based on the traffic data collected at 41 WIM sites distributed across the State. In addition, most of the traffic data were collected between years 2011 to

2015. However, there will be a need to revise these groups for Level 2B traffic inputs if the following updates or changes are anticipated:

   a. Addition of new classification and WIM sites at different geographical locations or change in the status of existing site (e.g., down- or up-grading from WIM to classification or vice versa).
   b. Significant change in the land use (for e.g., industrial development or commercial zoning) in the vicinity of the existing WIM locations.
   c. Change in the WIM technology for a number of locations. For example if less accurate piezo sensors are replaced with more accurate quartz or bending plate sensors. The accuracy and bias in WIM sensor will affect the axle load spectra which might influence the selection of attributes for Level 2B inputs.

   If MDOT anticipates the above-mentioned updates or changes in the near future (e.g., 5 or 10 years), then there will be a need to re-evaluate the attributes or the group averages for all traffic inputs.

2. For a few sites, the traffic patterns over time were compared. Some changes in truck traffic distribution were observed for PTR locations with one-way AADTT < 1000. However, for sites having one-way AADTT > 1000, the truck traffic and tandem axle distributions did not vary substantially for the last 5 years (2011 to 2015). If changes are observed in traffic patterns (classifications and loadings) at a PTR location for at least 3 years, then the new 3 years traffic data should be used to update the traffic inputs. Otherwise, the new data should be combined with the available traffic database. These changes in traffic patterns include any of the following at a PTR location:

   a. A 10% change in VC9 and VC10,
   b. An 8% change in VC11, and
   c. A 5% change in VC13

3. The existing PTR locations were reviewed and the following specific WIM additions are recommended for the various regions in the State:

   a. Superior Region:
      - Because of the presence of heavy to very heavy axle loads, an additional WIM site along M28 between Ewen and Kenton.
      - To capture interstate truck traffic (between Michigan and Wisconsin), an addition WIM site should be considered on US2 west of Watersmeet.
   b. North Region:
      - The current WIM site distribution seems adequate with the addition of WIM site 3069 to cover the west side of the region.
      - An additional WIM sites should be considered on the eastern side along M-32 if land use demands change in future.
   c. Grand Region:

- The axle loading analysis revealed light to medium axle loadings in this region. Therefore, the current WIM site distribution seems adequate at this time.

d. Bay Region:
   - This region also contains light to medium axle loadings. The current WIM site distribution seems adequate at this time.

e. Metro Region:
   - Additional WIM can be considered on I-75 between Flint and Auburn Hills. No PTR is located on this part of I-75 with anticipated commercial truck traffic.

f. University Region:
   - Based on the new axle loading data, the current WIM site distribution seems adequate at this time.

g. Southwest Region:
   - Additional WIM site is recommended in future on US31 near Sodus Township. This location will capture traffic coming north from I-90.

4. It is strongly recommended to continue collecting short-term (48 hours) counts to obtain VCD data, especially for locations on interstate highways with higher frequency of VC13. The VCD obtained using short-term count can be directly used in the Pavement-ME as Level 1 input instead of Level 2B VCD input.

REFERENCES

Chapter 1

1. Zhang, Z., J. Leidy, I. Kawa, and W. Hudson, "Impact of changing traffic characteristics and environmental conditions on flexible pavements," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 125-131, 2000.
2. Carvalho, R. and C. Schwartz, "Comparisons of flexible pavement designs: AASHTO empirical versus NCHRP Project 1-37A mechanistic-empirical," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 167-174, 2006.
3. NCHRP, "Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures.," Washington D.C NCHRP Project 1-37A, 2004.
4. Buch, N., S. W. Haider, J. Brown, and K. Chatti, "Characterization of Truck Traffic in Michigan for the New Mechanistic-Empirical Pavement Design Guide " Michigan Department of Transportation, Lansing, MI Report # RC-1537, 2009.
5. NCHRP Project 1-37A, "Appendix AA: Traffic Loading," ARA, inc., ERES division, 505 West University Avenue, Champaign, Illinois 61820, 2004 Final Report: Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, 2004.
6. Haider, S. W., N. Buch, K. Chatti, and J. Brown, "Development of Traffic Inputs for Mechanistic-Empirical Pavement Design Guide in Michigan," *Transportation Research Record*, vol. 2256, pp. 179-190, 2011.
7. FHWA, "Traffic Monitoring Guide," Washington, DC 2016.
8. Selezneva, O., M. Ayres, M. Hallenbeck, A. Ramachandran, H. Shirazi, and H. Von Quintus, "MEPDG Traffic Loading Defaults Derived from LTPP Traffic Pooled Fund Study," Federal Highway Administration, Final Report, FHWA, In the publication, 2016.
9. Selezneva, O. I., and M. Hallenbeck, "Long-Term Pavement Performance Pavement Loading User Guide (LTPP PLUG)," Federal Highway Administration, FHWA-HRT-13-089, 2013.

Chapter 2

1. NCHRP, "Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures.," Washington D.C NCHRP Project 1-37A, 2004.
2. Olga, S. and V. Q. Harold, "Traffic Load Spectra for Implementing and Using the Mechanistic-Empirical Pavement Design Guide in Georgia," FHWA-GA-14-1009, 2014.
3. Tran, N. and K. Hall, "Development and significance of statewide volume adjustment factors in mechanistic-empirical pavement design guide," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 97-105, 2007.
4. Lu, Q., Y. Zhang, and J. Harvey, "Estimation of truck traffic inputs for mechanistic-empirical pavement design in California," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 62-72, 2009.
5. FHWA, "Traffic Monitoring Guide," Washington, DC 2016.

6. Lu, Q. and J. Harvey, "Characterization of truck traffic in California for mechanistic-empirical design," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 61-72, 2006.
7. On Tam, W. and H. Von Quintus, "Use of long-term pavement performance data to develop traffic defaults in support of mechanistic-empirical pavement design procedures," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 176-182, 2003.
8. NCHRP Project 1-37A, "Appendix AA: Traffic Loading," ARA, inc., ERES division, 505 West University Avenue, Champaign, Illinois 61820, 2004 Final Report: Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, 2004.
9. NCHRP, "NCHRP Report 538 : Traffic Data Collection, Analysis, and Forecasting for Mechanistic Pavement Design," Transportation Research Board, Washington, D.C. 2005.
10. Selezneva, O., M. Ayres, M. Hallenbeck, A. Ramachandran, H. Shirazi, and H. Von Quintus, "MEPDG Traffic Loading Defaults Derived from LTPP Traffic Pooled Fund Study," Federal Highway Administration, Final Report, FHWA, In publication, 2016.
11. Darter, M., L. Titus-Glover, and D. Wolf, "Development of a Traffic Data Input System in Arizona for the MEPDG," Arizona Department of Transportation, Phoenix, AZ FHWA-AZ-13-672, 2013.
12. Turochy, R. E., D. H. Timm, and D. Mai, "Development of Alabama Traffic Factors for use in Mechanistic-Empirical Pavement Design," FHWA/ALDOT 930-793, 2015.
13. Buch, N., S. W. Haider, J. Brown, and K. Chatti, "Characterization of Truck Traffic in Michigan for the New Mechanistic Empirical Pavement Design Guide " Michigan Department of Transportation, Lansing, MI Report # RC-1537, 2009.
14. Wang, K. C., Q. Li, K. D. Hall, V. Nguyen, and D. X. Xiao, "Development of truck loading groups for the mechanistic-empirical pavement design guide," *Journal of Transportation Engineering*, vol. 137, pp. 855-862, 2011.
15. Agresti, A. and M. Kateri, *Categorical data analysis*: Springer, 2011.
16. Mallela, J., L. Titus-Glover, S. Sadasivam, B. Bhattacharya, M. Darter, and H. Von Quintus, "Implementation of the AASHTO Mechanistic-empirical Pavement Design Guide for Colorado," CDOT-2013-4, 2013.
17. Stone, J. R., Y. R. Kim, G. F. List, W. Rasdorf, F. Sayyady, F. Jadoun, and A. N. Ramachandran, "Development of Traffic Data Input Resources for the Mechanistic Empirical Pavement Design Process," FHWA/NC/2008-11, 2011.
18. Sayyady, F., J. Stone, G. List, F. Jadoun, Y. Kim, and S. Sajjadi, "Axle load distribution for mechanistic-empirical pavement design in north carolina: Multidimensional clustering approach and decision tree development," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 159-168, 2011.
19. El-Badawy, S. M., F. M. Bayomy, and S. W. Fugit, "Traffic characteristics and their impact on pavement performance for the implementation of the mechanistic-empirical pavement design guide in Idaho," *International Journal of Pavement Research and Technology*, vol. 5, pp. 386-394, 2012.

Chapter 3

1. Wang, K. C., Q. J. Li, V. Nguyen, M. Moravec, and D. Zhang, "Prep-ME: A multi-agency effort to prepare data for DARWin-ME," in *Airfield and Highway Pavement 2013: Sustainable and Efficient Pavements*, 2013, pp. 516-527.
2. Turochy, R. E., D. H. Timm, and D. Mai, "Development of Alabama Traffic Factors for use in Mechanistic-Empirical Pavement Design," FHWA/ALDOT 930-793, 2015.
3. FHWA, "Traffic Monitoring Guide," Washington, DC 2016.
4. Milligan, G. W., "Clustering Validation: Results and Implications for Applied Analyses," in *Clustering and Classification*: World Scientific, 1996, pp. 341-375.
5. Tan, P. N., M. Steinbach, and V. Kumar, *Introduction to Data Mining*: Pearson, 2013.
6. Mooi, E. and M. Sarstedt, "Cluster analysis," in *A Concise Guide to Market Research*: Springer, 2010, pp. 237-284.
7. Everitt, B. S., S. Landau, M. Leese, and D. Stahl, "Cluster analysis: Wiley series in probability and statistics," Chichester: Wiley, 2011.
8. Baulieu, F., "A classification of presence/absence based dissimilarity coefficients," *Journal of Classification*, vol. 6, pp. 233-246, 1989.
9. Cheetham, A. H. and J. E. Hazel, "Binary (presence-absence) similarity coefficients," *Journal of Paleontology*, pp. 1130-1136, 1969.
10. Gower, J. C. and P. Legendre, "Metric and Euclidean properties of dissimilarity coefficients," *Journal of classification*, vol. 3, pp. 5-48, 1986.
11. Hubalek, Z., "Coefficients of association and similarity, based on binary (presence-absence) data: an evaluation," *Biological Reviews*, vol. 57, pp. 669-689, 1982.
12. Yim, O. and K. T. Ramdeen, "Hierarchical cluster analysis: comparison of three linkage measures and application to psychological data," *Quant. Methods. Psychol*, vol. 11, pp. 8-21, 2015.
13. Steinbach, M., L. Ertöz, and V. Kumar, "The Challenges of Clustering High Dimensional Data," in *New directions in Statistical Physics*: Springer, 2004, pp. 273-309.
14. Ferreira, L. and D. B. Hitchcock, "A comparison of hierarchical methods for clustering functional data," *Communications in Statistics-Simulation and Computation*, vol. 38, pp. 1925-1949, 2009.
15. Milligan, G. W. and M. C. Cooper, "An examination of procedures for determining the number of clusters in a data set," *Psychometrika*, vol. 50, pp. 159-179, 1985.
16. Caliński, T. and J. Harabasz, "A dendrite method for cluster analysis," *Communications in Statistics-theory and Methods*, vol. 3, pp. 1-27, 1974.
17. Matlab, 2016.
18. Tibshirani, R., G. Walther, and T. Hastie, "Estimating the number of clusters in a data set via the gap statistic," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, vol. 63, pp. 411-423, 2001.
19. Hallenbeck, M., M. Rice, B. Smith, C. Cornell-Martinez, and J. Wilkinson, "Vehicle volume distributions by classification," 1997.
20. Schneider, W. H. and I. Tsapakis, "Review of Traffic Monitoring Factor Groupings and the Determination of Seasonal Adjustment Factors for Cars and Trucks," University of Akron, Department of Civil Engineering 2009.

Chapter 4

1. Haider, S. W., G. Musunuru, M. E. Kutay, M. A. Lanotte, and N. Buch, "Recalibration of Mechanistic-Empirical Rigid Pavement Performance Models and Evaluation of Flexible Pavement Thermal Cracking Model," Report Number: SPR-1668, 2017.
2. Haider, S. W., N. Buch, W. Brink, K. Chatti, and G. Baladi, "Preparation for Implementation of the Mechanistic-Empirical Pavement Design Guide in Michigan Part 3: Local Calibration and Validation of the Pavement-ME Performance Models," *Rep. No. RC-1595, Michigan State Univ., East Lansing, MI*, 2014.
3. Freund, R. J., W. J. Wilson, and D. L. Mohr, *Statistical Methods*, 3rd ed. London, UK: Academic Press, An Imprint of Elsevier, 2010.
4. Tan, P. N., M. Steinbach, and V. Kumar, *Introduction to Data Mining*: Pearson, 2013.