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Development of Statewide WIM Data Quality Control and Axle Load Spectra and Traffic Volume Adjustment Factors for Oklahoma

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16. ABSTRACT

Oklahoma Department of Transportation (ODOT) operates weigh-in-motion (WIM) stations statewide and is actively adopting portable WIM programs. Recognizing that no comprehensive study has been conducted before to evaluate the quality of WIM data in Oklahoma, this collaborative project aims to develop quality control (QC) metrics and associated software interfaces for checking the quality of statewide WIM data, and to develop site-specific, region-specific, and statewide traffic inputs that are required for the Mechanistic-Empirical (ME) based pavement design in Oklahoma.

The project deliverables include (1) a user friendly WIM data software that offers efficient WIM data import capability, data quality review and control functions, data visualization and analysis, and three levels of traffic outputs to meet ME based pavement design needs; (2) a guideline on how often and under what circumstances a WIM station should be calibrated and the supporting software tool; (3) comprehensive database and software interface to incorporate results from completed materials studies by ODOT; (4) software training and technical support during the project period to meet ODOT's special needs in pavement design and analysis.

This project lasts for two years, while this report documents the results from Year 1.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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1. INTRODUCTION

1.1 Background

Traffic loads are one of the key data elements required for the design and analysis of pavement structures. Traditionally the mixed traffic stream was aggregated into equivalent single-axle loads (ESALs). The Mechanistic Empirical Pavement Design Guide (MEPDG), later named as DARWin-ME and Pavement ME Design, proposes a more rational approach to characterize traffic in terms of full axle-load spectrum. MEPDG, DARWin-ME, and Pavement ME Design are used in this report interchangeably. It provides users with the flexibility to input three levels of traffic inputs based on data availability and the importance of the project: Level 1 site specific with the highest quality, Level 2 regional specific with medium quality, and Level 3 state or national defaults with the lowest quality. To meet the traffic data requirements in DARWin-ME, automated traffic collection techniques are needed. However, automated traffic data often have errors, particularly for data collected from weigh-in-motion (WIM) sites. A national study concludes that only 15% to 25% of the WIM data collected are of "good" quality (Lu and Harvey, 2006). One of the primary causes is that many state agencies are lacking in staffing, resources, and relevant supporting software to examine the huge amount of raw WIM data for quality assurance (QA), while most WIM sensor vendors do not include details for quality control (QC) in reports. It is impractical to manually process the data files even with computer assistance, and this process needs to be automated with software for routine implementation.

In addition, with limited number of available WIM sites within a state highway agency, how to generate traffic inputs required in MEPDG for any design location remains a challenge. If no prior Level 1 traffic WIM data are available for a pavement design, utilizing Level 3 state-wide default traffic input parameters may lead to estimation of inconsistent pavement performance. Therefore, Level 2 regional traffic inputs should be developed and used for pavement design by combining existing site-specific data from WIM systems located on sites that exhibit similar traffic characteristics. How to qualify these similarities and develop loading groups (also called traffic clusters) are therefore critical for the successful implementation of Pavement ME Design at any design location.

Currently, Oklahoma Department of Transportation (ODOT) operates approximately 20 WIM stations statewide and is actively adopting portable WIM programs. It is vital to utilize the abundant WIM data sets and develop such traffic input parameters for ODOT to successfully implement the DARWin-ME. Recognizing that no comprehensive study has been conducted to evaluate the statewide WIM data quality, in this collaborative project we propose to develop WIM quality control metrics and associated software interfaces for checking the quality of Oklahoma WIM data and generating site-specific (Level 1), region-specific (Level 2), and statewide (Level 3) traffic inputs that are required for local calibration and implementation of the Pavement ME Design in Oklahoma.

In addition, ODOT has performed extensive material testing and characterization work during the past decade, much of which can be used to generate Level 1 and Level 2 material inputs for DARWin-ME. It is necessary to examine these data sets and evaluate their suitability for use in Pavement ME Design. The different types of materials shall include asphalt mixes, binders, aggregate base, stabilized subgrade, natural subgrade. Meanwhile, a software interface is needed to retrieve Level 1 and Level 2 material design values from the developed materials database for a specific design project.

1.2 Objectives

The objective of this research is to develop WIM QC metrics and associated software interfaces that ODOT can use to assess and improve WIM data quality, and generate site-specific (Level 1), region-specific (Level 2), and statewide average (Level 3) traffic inputs that are required for the Pavement ME Design in Oklahoma. This research will include the following tasks to achieve the objective: (1) perform a comprehensive review of current literature and methodologies on WIM data quality and use of WIM data for DARWin-ME; (2) identify and develop WIM data QC metrics and the relevant software for Oklahoma WIM data check and process; (3) conduct statewide WIM data check using developed software to evaluate the health of WIM sensors; (4) identify available material data in Oklahoma and develop software to generate Level 1 and Level 2 material inputs for DARWin-ME; (5) develop traffic clusters and loading groups and software interface to generate three levels of traffic inputs for Pavement ME Design at any design location in Oklahoma; and (6) provide training and technical support to meet ODOT' special needs in pavement design and analysis.

1.3 Report Outline

This final report has seven chapters which are organized as below.

Chapter 1 provides the background and the presents the objectives and tasks of this project.

In Chapter 2, summary of a comprehensive literature review is provided aiming to develop an in-depth understanding of traffic and materials input parameters and sensitivity analysis of MEPDG. In particular, materials and traffic data input requirements and existing research efforts, WIM systems data quality check methods, how WIM data are used to generate axle loading spectra and volume adjustment factors for MEPDG, and related sensitivity analyses are investigated.

Chapter 3 primarily focuses on the preparation of traffic data in Oklahoma for Pavement ME Design. The Prep-ME software and its capabilities for traffic are introduced, followed by how Prep-ME can be used to assist statewide traffic data check and the results of statewide traffic data check results.

Using multiple years of WIM and vehicle classification data from Oklahoma which passed the quality check, Chapter 4 illustrates how the three levels of traffic inputs are generated for Pavement ME Design: Level 1 site-specific data with the highest quality, Level 2 cluster data with medium quality, and Level 3 state or national defaults with the lowest quality. Cluster analysis is applied to develop homogeneous groups for each traffic input. Subsequently, decision tree model and multinomial regression model are developed for the selection of appropriate traffic clusters under given site design conditions. In addition, a case study is included to evaluate the variations of pavement performance at various levels of traffic inputs.

The Prep-ME software is customized for the traffic data generation at three levels for Pavement ME Design in Oklahoma. For Level 1 input, Prep-ME allows users to export site-specific traffic data “By Direction” or “By Station”. A new clustering method is proposed for Level 2 traffic input based on four clustering parameters: the rural or urban classification, function class of highway, average daily truck traffic volume (AADT) and ratio of single unit and multiple unit trucks (SU/MU). In addition, the Prep-ME software also includes the Truck Traffic Class (TTC) approach, simplified TTC approach, and the "Flexible Clustering" method which can be used for lower volume roads or design sites without relevant traffic data inputs based on engineering judgments. For level 3 output, three methods are provided in Prep-ME: State Average, LTPP-5(004) and Pavement ME defaults. The generated output files from Prep-ME, XML format for Pavement ME Design and text format for MEPDG, can be directly imported to the ME design software.

In Chapter 5, the traffic data from the Long Term Pavement Performance (LTPP) are extracted for the state Oklahoma and the traffic inputs for Pavement ME Design are summarized for Pavement ME Design.

In Chapter 6, the available material characterization data at ODOT are investigated and summarized. Subsequently, two new features are developed in the Prep-ME software to retrieve resilient modulus data of natural subgrade soils and dynamic modulus data of Oklahoma asphalt mixes for directly importing into Pavement ME Design.

Finally, the conclusions and findings from this study are presented in Chapter 7.

2. LITERATURE REVIEW

2.1 The Pavement ME Design Procedure

The Pavement ME Design approach consists of three major stages, as shown in Figure 1 (AASHTO, 2014). Stage 1 of this procedure is to develop input values and identify potential strategies or trial designs. Pavement materials inputs, traffic characterization data, and climatic data are developed and fed into the Pavement ME Design software. Stage 2 consists of the structural/performance analysis, in which the trial section is analysed incrementally over time using the pavement response and distress models, and the outputs of the analysis are accumulated damage amounts of distress and smoothness over time. A pavement structural design is therefore obtained through an iterative process in which predicted performance is compared against the design criteria until all are satisfied to the specified reliability level. Stage 3 of the process includes the evaluation of the structurally viable alternatives, such as life cycle cost analysis and constructability analysis.

The hierarchical approach is a unique feature in Pavement ME Design with regard to traffic, materials, and environmental inputs, which provides the designer with flexibility in obtaining design inputs based on the criticality of the project and available resources. Level 1 inputs, generally in terms of site-specific inputs, provide for the highest level of accuracy and would have the lowest level of uncertainty. Level 2 inputs provide an intermediate level of accuracy, typically would be user-selected either from an agency’s database, a limited testing program, or estimation through correlations. Level 3 inputs provide the lowest level of accuracy. National default values provided in the Pavement ME Design software are generally used as level 3 inputs.

2.2 Sensitivity Analysis

Pavement ME Design requires hundreds of inputs to model traffic, environmental, materials, and pavement performance to provide estimates of pavement distress over the design life. Many designers may lack specific knowledge of the data required. Sensitivity study is therefore beneficial to assess the relative sensitivity of an input to the model used in the Pavement ME Design so that designers can select appropriate inputs and focus on those inputs having the most significant effect on desired pavement performance. Many agencies or institutions have conducted sensitivity analysis research, such as Arkansas (Hall and Beam, 2005), Iowa (Coree et al, 2005), California (Kannekanti, 2006), Kentucky (Graves, 2006), New Jersey (Sauber, 2006), Texas (Freeman, 2006), and NCHRP 1-47 (Schwartz, 2011). The sensitivity analyses suggested that the most significant input parameters be determined or analyzed further at the state level for the implementation of the Pavement ME Design, including: (1) climate data; (2) traffic load spectra data; (3) HMA inputs such as dynamic modulus, indirect tensile strength and creep compliance; (4) PCC inputs such as coefficient of thermal expansion (CTE), modulus of rupture, compressive strength, and Poisson's ratio; (5) unbound material inputs in terms of resilient modulus.

2.3 Traffic Inputs in Pavement ME Deign

The equivalent single axle load (ESAL) approach used for traffic characterization in AASHTO 1993 version is no longer needed in the MEPDG (AASHTO, 1993). The MEPDG requires axle load spectra along with different types of distribution factors of various types of vehicles (AASHTO, 2014). Therefore, development of traffic input parameters is essential for successful implementation of MEPDG for design and analysis of new pavements and rehabilitation of existing pavements. The MEPDG uses a hierarchical approach (Level 1 through Level 3) for development of traffic input parameters. The Level 1 – Site Specific, Level 2 – State/Regional Specific and Level 3 – National/default, indicate a good, modest, and poor knowledge of past and future traffic characteristics, respectively. Dozens of research has been conducted in the past 10 years primarily focusing on three research areas: (1) Required traffic Inputs for MEPDG, (2) traffic input levels and cluster analysis, (3) WIM Data Quality and Data Check, (4) and (5) Existing Tools for WIM Data Analysis.

2.3.1 Required Traffic Data and Inputs

Ideally, site-specific traffic data regarding traffic count, time distribution, axle configuration, and axle load spectra should be collected for each design project. This will provide the most accurate traffic input for the MEPDG design. However, such an effort is impractical, and the data are rarely available, due to the associated cost. A more rational practice would be using site-specific traffic data for especially important roads and regional- or national-default values for less important roads. Table 2 presents the data required at different input levels for all required traffic inputs in the MEPDG.

Many researchers have reported that utilization of Level 3 (default) traffic input parameters may result in inconsistent and incorrect performance of a pavement design and analysis using the AASHTOWare-ME (Lu and Harvey 2006, Tran and Hall 2007a and 2007b, Swan et al. 2008, Elkins and Higgins 2008, Jiang et al. 2008, Buch et al. 2009, Li et al. 2009, Ishak et al. 2009 and 2010, Smith and Diefenderfer 2010, Haider et al. 2011, Romansochi et al. 2011, Stone et al. 2011, Selezneva et al. 2014). All of the aforementioned studies found significant differences between the default and site-specific values. Therefore, it was recommended that every state must develop Level 1 (site specific) and Level 2 (regional or cluster-based) traffic input parameters for successful implementation of AASHTOWare-ME.

Specifically, in order to generate Level 2 traffic inputs, many studies performed clustering analysis to identify typical axle load spectra for a region. Papagiannakis et al. (2006) applied hierarchical cluster analysis technique on LTPP WIM data to identify groups of sites with decreasing similarities based on either the vehicle percentage by class or the percentage of axles by load interval. Wang et al. (2007) conducted clustering analysis on the spatial and temporal variations of the load distributions from the LTPP traffic database. Wang et al. (2011) proceeded cluster analysis approach to identify loading patterns and estimation of full axle-load spectrum data using Arkansas WIM data. Sayyady et al. (2011) accomplished multidimensional clustering approach to generate regional average truck axle load distribution factors for North Carolina. Mai et al (2013) considered the effects of traffic inputs on pavement design thickness and applied correlation-based clustering to determine the number of clusters objectively. Abbas et al. (2014) performed clustering analysis on WIM stations across the state of

Ohio and evaluated site-specific, statewide average, cluster average, and MEPDG default axle load spectra traffic load effect on asphalt pavement design with the MEPDG. Li et al. (2015) employed the K-means cluster algorithm and developed simplified Truck Traffic Classification clusters for secondary road pavement design. In addition, several state specific clustering analysis methods were developed to incorporate their state specific traffic characteristics for the Mechanistic-Empirical pavement design (Jiang Y. et al. 2008, Buch et al 2009, Stone et al. 2011, and Wang et al. 2014).

2.3.2 Traffic Input Levels and Clustering Analysis

Ideally, Level 1 site-specific traffic data should be collected for each design project, which provides the most accurate traffic inputs for the Pavement ME Design. However, such an effort is impractical since the data are rarely available due to the associated cost. A more rational practice would be using site-specific traffic data for especially important roads and regional (Level 2) or state (Level 3) defaults for less important roads.

Many researchers have reported that utilization of Level 3 traffic input parameters may result in inconsistent and incorrect ME based pavement performance (Lu and Harvey 2006, Tran and Hall 2007a, 2007b, Swan et al. 2008, Elkins and Higgins 2008, Jiang et al. 2008, Buch et al. 2009, Smith et al. 2010, Ishak et al. 2010, Haider et al. 2011, Romansochi et al. 2011, Sayyady et al. 2011, and Selezneva et al. 2014). All the aforementioned studies found significant differences between the default and site-specific values, and recommended that state should develop Level 1 and/or Level 2 traffic inputs for the implementation of Pavement ME Design based on WIM systems located on sites that exhibit similar traffic characteristics based on clustering analysis.

Several states studied traffic data using rigorous cluster analysis to incorporate their state specific traffic characteristics for the Pavement ME Design (Prozzi and Hong 2005, Lu and Harvey 2006, Jiang Y. et al. 2008, Lu and Harvey 2009, Buch et al 2009, Ishak et al. 2010, Syyady et al. 2011, Haider et al. 2011, Darter et al. 2013, Tarefder 2013, Abbas et al. 2014a, 2014b, Wang et al. 2014). Various clustering methods have been used for this purpose, such as hierarchical technique (Papagiannakis et al., 2006, Wang et al., 2011, Li et al., 2016), multidimensional clustering approach (Sayyady et al., 2011), K-means algorithm (Li et al., 2015, Li et al., 2016), model-based (Li et al., 2016), and fuzzy c-means algorithms (Li et al., 2016). These research activities have simplified the understanding and applicability of traffic patterns and ultimately eased the preparation of the traffic load spectra inputs based on WIM data for the Pavement ME Design procedure.

2.3.3 WIM Data Quality and Data Check

ASTM E1318-09 (2009) defines weigh-in-motion (WIM) as "the process of estimating a moving vehicle's gross weight and the portion of that weight that is carried by each wheel, axle, or axle group, or combination thereof, by measurement and analysis of dynamic vehicle tire forces". It classifies WIM systems into four types based on their application and details their respective functional, performance, and user requirement.

There are a number of quality control (QC) procedures for WIM data check. LTPP (2013) provided mandatory, logic, range and verification QC checks on traffic data collected in the field prior to entry into the data base to guarantee data quality. LTPP (2001) developed traffic QC software to load, process, and produce reports for the LTPP program. FHWA (2013) and AASHTO (2009) guides are industry standards and emphasize the need for quality control measures in traffic monitoring programs. ASTM E2759-10 (2010) also disclosed how traffic data was managed from field data collection through evaluation, acceptance, summarization and reporting. There are also state and project specific traffic data QC requirements, e.g., QC procedures developed to apply to New Mexico and North Carolina WIM data (Brogan et al., 2011, Ramachandran et al, 2011 and Stone et al, 2011), validation and QC checks for type I WIM traffic data to insure reliable and representative load spectra for MEPDG (Quinley, 2010), QC program for INDOT to improve the accuracy of WIM data to identify overweight vehicles (Nichols et al, 2004), and QC with peak-range check, peak-shift check and correlation analysis to quantify the axle loading spectra comparison process of rational checks (Mai, 2013).

Both the FHWA Traffic Monitoring Guide (FHWA, 2001) and AASHTO Guidelines for Traffic Data Programs (AASHTO, 2009) emphasize the need for QC measures in traffic monitoring programs. As a result, a number of quality control (QC) procedures have been developed for WIM data check. ASTM E2759-10 (2010) disclosed how traffic data was managed from field data collection through evaluation, acceptance, summarization and reporting. The LTPP (2013) provided mandatory, logic, range and verification QC checks on traffic data collected in the field prior to entry into the database to guarantee data quality. Several states have developed specific traffic data QC requirements and procedures, such as Indiana (Nichols et al, 2004), California (Quinley, 2010), North Carolina (Sayyady et al., 2010, Ramachandran et al, 2011), and New Mexico (Brogan et al., 2011).

In particular, the traffic data check procedure included in the FHWA Traffic Monitoring Guide (TMG) (FHWA, 2001) has been widely adopted. For vehicle classification data, a four-step data check procedure is recommended: (1) to compare the manual classification counts with the hourly vehicle classification data; (2) to check the number of Class 1 (motorcycles); (3) to check the reported number of unclassified vehicles; (4) to compare the current truck percentages by class with the corresponding historical percentages. No significant changes in the vehicle mix should be anticipated. For weight data check, there are two basic steps to evaluate recorded vehicle weight data (FHWA, 2001). Firstly, to check the front axle and drive tandem axle weights of Class 9 trucks. The front axle weight should be between 8,000 and 12,000 lb (10,000 ± 2,000 lb). The drive tandems of a fully loaded Class 9 truck should be between 30,000 and 36,000 lb (33,000 ± 3,000 lb). Secondly, to check the gross vehicle weights of Class 9 trucks. The histogram plot should have two peaks. One represents unloaded Class 9 trucks and should be between 28,000 and 36,000 lb (32,000 ± 4,000 lb). The second peak represents the most common loaded vehicle condition with a weigh between 72,000 and 80,000 lb (76,000 ± 4,000 lb).

Other procedures, primarily based on the FHWA TMG procedure but customized to individual states, have been also proposed by various researchers. For example, Mai. (2013) developed a QC procedure including peak-range check, peak-shift check and correlation analysis to quantify the axle loading spectra comparison process of rational checks. A structured quality control check procedure was suggested by Tarefder et al. (2013) for New Mexico to eliminate erroneous data.

2.3.4 Existing Tools for WIM Data Analysis

With the wide use of WIM data for various applications, several tools have been developed to aid WIM data process and analysis. The BullPiezo software could compute Seasonal Adjustment Factor (SAF), Annual Average Daily Traffic (AADT), and Monthly Average Daily Traffic (MADT) from WIM data based on TMG (Kwon, 2015). TrafLoad, final product of the NCHRP Project 1-39 project, is able to converted standard FHWA classification count and weight data files into vehicle classification, load spectra and traffic growth forecasts to the 2002 AASHTO pavement design software without QC procedures (NCHRP 1-39, 2004). Prep-ME is developed to pre-process, import, check the quality of raw WIM traffic data, and generate the required three levels of traffic inputs for DARWin-ME software (Wang et al. 2013, and Wang et al. 2014). Long-Term Pavement Performance Pavement Loading User Guide (LTPP PLUG) software helped users select site-specific or default axle loading conditions from its traffic loading library and produced axle load distribution input files for the MEPDG or DARWin-ME software (Selezneva and Hallenbeck, 2013).

With the increasing use of WIM data for various applications especially for the Pavement ME Design in recent years, several tools have been developed to aid WIM data processing and analysing. The BullPiezo developed a software to compute AADT, seasonal and monthly adjustment factor from WIM data (Kwon, 2015). TrafLoad, the final product of the NCHRP 1-39 Project (NCHRP 1-39, 2004), is able to process standard FHWA classification and weight data for MEPDG but without data QC procedures and several data requirements for MEPDG not met. Many state highway agencies have developed Excel® spreadsheet based tools to reduce raw vehicle classification and weight data, and to generate volume adjustment factors and axle load spectra for the Pavement ME Design (Tran et al 2007a 2007b, Tarefder et al. 2013, Hasan et al 2016). However, the quality control and updating procedure needs to be repeated manually when new traffic data are available. In particular, LTPP developed a spreadsheet based tool, named Pavement Loading User Guide (PLUG), to help users select site-specific or default axle loading conditions from its traffic loading library and produce axle load distribution input files (Selezneva and Hallenbeck, 2013).

The state pooled fund study TPF-5(242), *Traffic and Data Preparation for AASHTO MEPDG Analysis and Design*, has developed a full production software named Prep-ME to store and process climate, traffic, and materials data required for the Pavement ME Design Software. This software complies with FHWA TMG and Travel Monitoring Analysis System (TMAS) for quality control and quality check. State highway agencies' experience has been built into the QA/QC of traffic data collection. The software has the following key functions with more specific features requested by individual states (Wang et al. 2013, and Wang et al. 2014).

- Perform automatic quality control check by direction and by lane of a WIM station for both classification and weight data following the algorithms defined in TMG.
- Provide user friendly interfaces to review monthly, weekly and daily traffic data, and investigate the WIM data that is incomplete or fails the automatic QC check through various manual sampling and analysing operations.
- Generate three levels of traffic inputs that can be directly imported into the MEPDG and Pavement ME Design Software.: Level 1 site specific, Level 2 clustering average, Level 3 state average, and LTPP TPF-5(004) defaults. Clustering methods developed by North Carolina and Michigan DOTs, the Truck Traffic Classification (TTC) method, and the simplified TTC approach are fully implemented offering state agencies the flexibility of generating Level 2 loading spectra inputs based on the availability of traffic data.

2.4 Material Inputs in Pavement ME Deign

2.4.1 Asphalt Materials

Required asphalt binder properties include the complex shear modulus and associated phase angle (G^* and δ) at multiple temperatures at a frequency of 10 radians/sec (AASHTO T315) for Level 1 and 2 input, while the default A-VTS viscosity temperature susceptibility parameters based on Superpave Performance Grade (PG) for Level 3 input.

Dynamic modulus (|E*|) is the principal mechanical property input for hot mix asphalt (HMA) in the Pavement ME Design, which requires testing two or three replicate asphalt concrete specimens at five temperatures (14°F, 40°F, 70°F, 100°F, and 130°F) and six loading frequencies (25, 10, 5, 1, 0.5, and 0.1 Hz) (AASHTO TP62). Due to the substantial amount of time required, reducing the testing time for |E*| has been the focus of several studies (Dougan et al., 2003, Bonaquist and Christensen, 2005, Bonaquist, 2008). Recently, the Asphalt Mixture Performance Tester (AMPT), a servo-hydraulic Simple Performance Tester (SPT) device, was developed to test asphalt mixtures over a range of temperatures and frequencies in accordance with AASHTO TP 79.

Creep compliance and low temperature tensile strength are additional mechanical properties required in the Pavement ME Design for predicting thermal cracking distress. Creep compliance can be measured at three temperatures (-4°F, 14°F, and 32°F) and various loading times up to 1,000 sec while tensile strength at 14^0F in accordance with AASHTO T322 (AASHTO, 2008), both of which can be conducted on the same specimen. Default values can also be determined from empirical relations built into the Pavement ME Design based on functions of mix volumetric and binder viscosity properties.

General asphalt mixture properties include asphalt binder content, in-place air voids (%), aggregate gradation, and volumetric properties. Other parameters, such as thermal properties, Poisson's ratio, and total unit weight, are also required inputs in the Pavement ME Design, while default Level 3 values are recommended due to either the lack of certified testing protocols or the insignificant effects to performance.

Lastly, the primary difference between characterizing new and existing HMA layers is that the dynamic modulus for existing HMA layer must be adjusted for the damage caused to the pavement by traffic loads and environmental effects (NCHRP 1-37a, 2004).

Several state DOTs including Arizona, Colorado, Florida, Idaho, Kansas, Minnesota, Missouri, North Carolina, Ohio, Oklahoma, Virginia, and Wisconsin have completed a significant portion of the implementation effort for asphalt materials through research contracts or in-house studies, with the following objectives (Von Quintus et al.

2015):

- Evaluating the sensitivity of inputs at different hierarchy to the field performance.
- Developing site-specific material inputs for the Pavement ME Design.
- Including specialty mixtures, such as stone-matrix asphalt (SMA), cold-recycled and mixes with high reclaimed or recycled asphalt pavement (RAP) material, which were not included in the original material database used in developing Level 3 models and defaults.
- Developing an input data library for typical materials used for new and reconstruction and rehabilitation designs.

In particular, the characterization of asphalt materials is specifically focused on the dynamic modulus. The general approach employed by the highway agencies is to develop a dynamic modulus database and to assess the accuracy of the Witczak and Hirsch predictions against the measured results for both typical and specialty asphalt mixtures.

2.4.2 PCC Materials

The key PCC stiffness and strength properties are the elastic modulus (Ec) and the modulus of rupture (MOR) (Level 1), compressive strength (fc′) (Level 2) at various ages, or the 28-day fc′ (Level 3). Additional PCC properties required at all input levels include mix properties, thermal properties, and shrinkage properties. The strong influence of the coefficient of thermal expansion (CTE) on pavement performance has been demonstrated in several prior studies (Tanesi et al., 2007; Buch et al., 2008; Kampmann, 2008; Oh and Fernando, 2008; Haider et al., 2008, 2009; Velasquez et al., 2009). CTE can be measured using AASHTO TP60 (Level 1), approximated using mixture theory (Level 2), or estimated from historical values (Level 3), while little guidance nor acceptable practical test protocols on measurement of shrinkage properties and shortwave absorptivity for PCC mixes.

The primary difference between characterizing new concrete layers and existing layers is that the *Ec* and *MOR* values for existing PCC slabs need to be adjusted for the damage by traffic loads and environmental effects using recommended empirical factors at various pavement conditions (NCHRP 1-37a, 2004).

Implementation activities pertinent to the characterization of PCC materials have been primarily focused on the following (Von Quintus et al. 2015):

- Determining thermal properties of PCC with a special emphasis on measuring the CTE of typical PCC mixes with local aggregates and understanding the significance of CTE on performance predictions.
- Building a data library of material properties that include both strength and fresh concrete properties.

2.4.3 Unbound Materials

The principal mechanical property for unbound materials is the resilient modulus (M_R) at the optimum moisture and in-place density (NCHRP 1-37a, 2004). For Level 1 input, the regression coefficients k_1, k_2, and k_3 for the stress-dependent resilient modulus relationship are required. For Level 2, M_R can be determined from correlations with California Bearing Ratio, R-value, structural layer coefficient a_i, or plasticity index and gradation. For Level 3, default M_R are provided as a function of AASHTO soil type.

In addition to stiffness, hydraulic properties for the partially saturated unbound materials are required as inputs for the EICM model, including the saturated hydraulic conductivity (permeability) and the soil water characteristic curve (SWCC). Alternatively, default values can be determined as a function of gradation and plasticity index.

The implementation activities pertinent to the characterization of unbound materials have been primarily focused on the following (Von Quintus, et al. 2015):

- Developing a resilient modulus data library for typical granular aggregate base materials and subgrade soils.
- Developing a resilient modulus prediction model based on soil parameters.
- Utilizing FWD and other non-destructive tests to determine the resilient modulus.

It should be noted that the Level 3 resilient modulus values presented in the Pavement ME Design represent optimum moisture condition and maximum dry density typically anticipated in the field at the time of construction. An increase in compaction moisture content could significantly adversely affected the resilient modulus value primarily depending on the percent of material passing the No. 200 sieve and the plasticity of the fines. Engineering judgment should be applied to account for moisture sensitivity when these values are input (Von Quintus, et al. 2015).

2.4.4 Software Tools

Various tools and database for materials have been developed at both national and state level. ElHussein et al (2006) developed an Access® based material database that houses mechanistic properties for commonly used pavement materials to be used as input to run the M-E models, consisting of four components namely, the material database file, data access, database utility and a user interface. Zapata (2010) created a national database of pedologic soil families with soil properties for subgrade materials. The database focuses upon the SWCC parameters (Level 1), but also includes measured soil index. Schwartz and Li (2011) developed an Access® data management system named MatProp, which incorporated data entry, editing, and storing functionality for the material property inputs required by the Pavement ME Design for flexible, rigid, and unbound granular base and subgrade materials. Kutay and Jamrah (2013) conducted an extensive laboratory testing program to characterize asphalt mixtures commonly used in Michigan for |E*|, G* of binders and Indirect Tension Strength (IDT) at low temperatures. A standalone software, called DYNAMOD, was developed to serve as the database engine to allow engineers to easily reach the material testing data and generate input files that can be directly imported into Pavement ME Design.

3. TRAFFIC DATA CHECK AND PREPERATION

3.1 Relevant Prep-ME Capabilities

Through the transportation pooled fund study TPF-5(242), the Prep-ME software has been developed and enhanced based on extensive comments and feedback from participating states. The Pre-ME software is a full production software program to store and process climate, traffic, and materials data required for the AASHTO Pavement ME Design. This software complies with FHWA Traffic Monitoring Guide (TMG) and TMAS for quality assurance and quality control (QA/QC). State highway agencies' experience has been built into the QA/QC of traffic data collection. The software has the following basic functions with more specific features requested by individual states (Wang et al. 2013, and Wang et al. 2014). The software has been customized for Oklahoma Weigh-In-Motion (WIM) and Automated Vehicle Classifier (AVC) data and is used in this study.

(1) Imports an agency's WIM traffic data complying with FHWA Traffic Monitoring Guide (TMG) file formats, and store the data in SQL server Local database with exceptional computation efficiency.

(2) Conduct TMAS 2.0 data check and generate TMAS check error log for each imported raw file.

(3) Perform automatic quality control checks by direction and lane of a WIM station for both weight (Fig. 3.1) and classification (Fig. 3.2) data following algorithms defined in TMG.

(4) Provide user friendly interfaces to review monthly, weekly and daily traffic data, and investigate the WIM data that is incomplete or fails the automatic QC check through various manual, sampling, and analyzing operations (Fig. 3.1).

(5) Generate three levels of traffic inputs: Level 1 site specific, Level 2 clustering average, Level 3 state average, and LTPP TPF-5(004) defaults (Fig. 3.3).

(6) Provides several clustering methods, offering state agencies with the flexibility of generating Level 2 loading spectra inputs for Pavement ME Design based on the availability of traffic data.

(7) Generate input files in the file formats that can be directly imported into MEPDG and Pavement ME Design software.

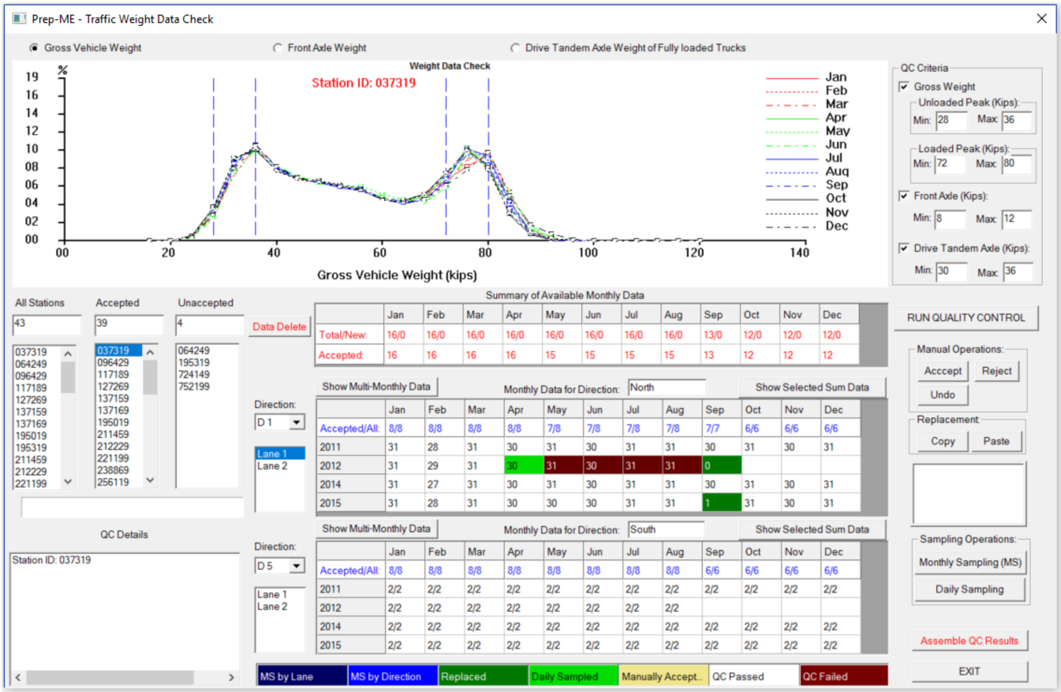


Fig. 3.1 Weight Data Check by Direction and by Lane

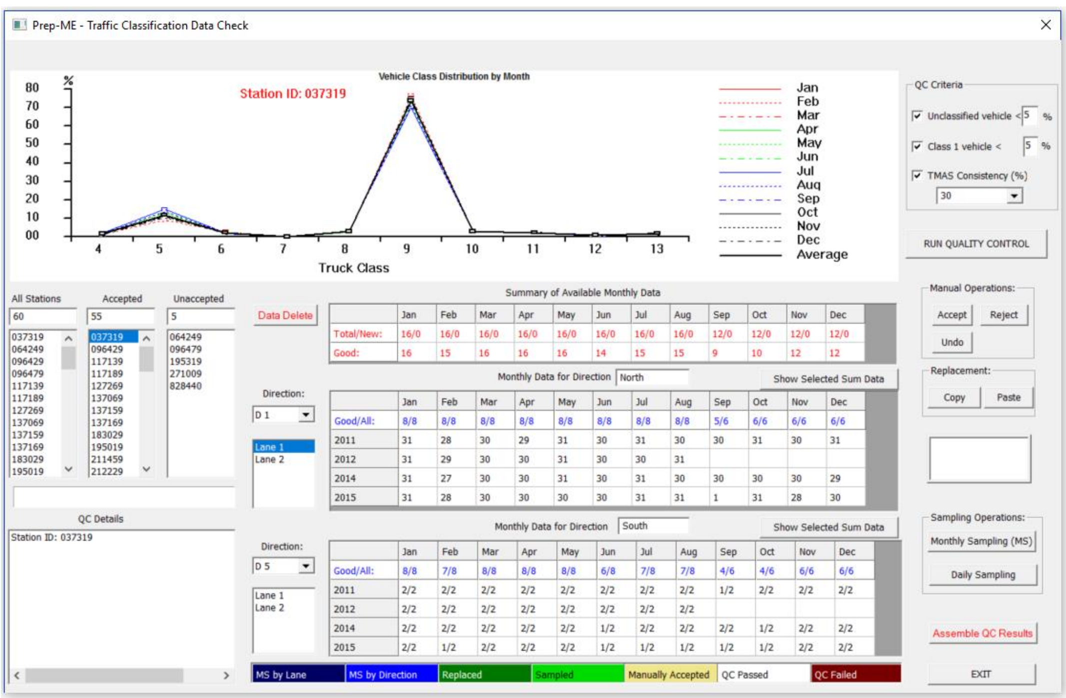


Fig. 3.2 Classification Data Check by Direction and by Lane

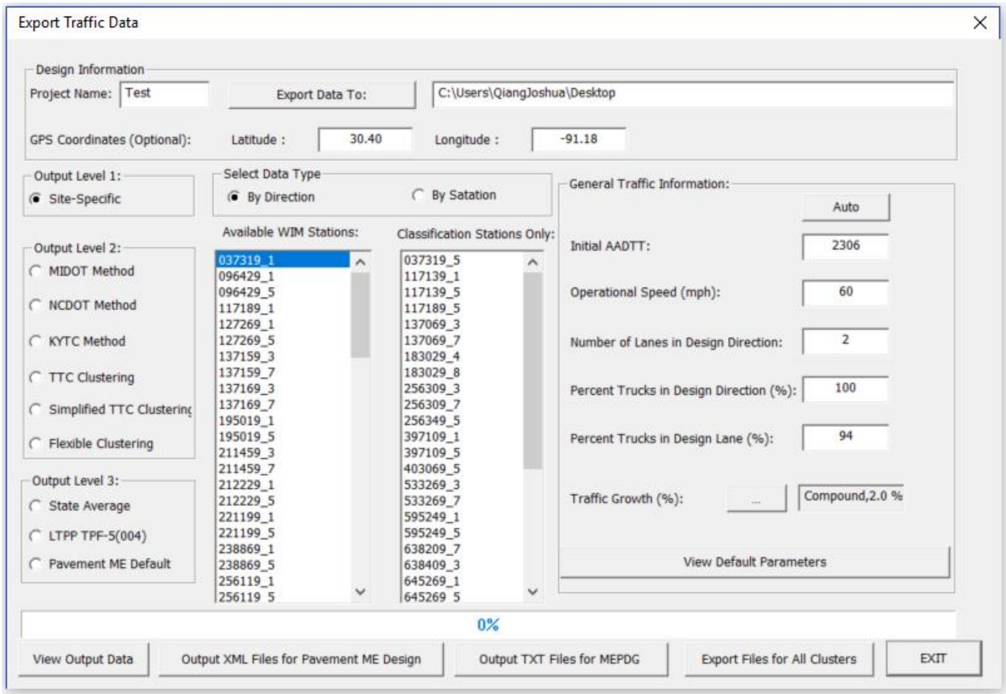


Fig. 3.3 Three-Level Traffic Outputs for Pavement ME Design

3.2 Traffic Data Source

Currently, Oklahoma Department of Transportation (ODOT) operates approximately 90 Automatic vehicle classification stations, out of which 21 are also WIM stations (Oklahoma traffic characteristics report, 2009). Five years (2008-2012) of continues WIM data and vehicle classification data is provided by ODOT from the 21 WIM stations. Also, approximately four years (2013-2016) of additional AVC data is available for the analysis. All the 90 stations are located on one of the interstate highway, US highway or state highway spread throughout the state. Table3.1 describes the location of each WIM and AVC station along with the route and county details. Figure 3.4 is the map with AVC and WIM stations.

Table 3.1 Description of AVC and WIM station locations

Station ID	County	Route	Location
AVC001	Cleveland	SH-37	On SH-37, 1.70 miles W of I-35, in Moore
AVC002	Cleveland	US-77	On US-77, 1.10 miles S of SH-9, in Norman
AVC003	Cleveland	SH-9	On SH-9, 2.10 miles E of I-35, in Norman
AVC004	Canadian	SH-152	On SH-152, 0.55 miles W of SH-4, in Mustang
AVC005	Oklahoma	US-62	On US-62, 9.75 miles E of I-35, in Choctaw

Station ID	County	Route	Location
AVC006	Oklahoma	SH-66	On 39th St (SH-66), 1.00 miles W of I-44, in Oklahoma City
AVC007	Oklahoma	I-40	On I-40, 2.00 miles W of I-44, in Oklahoma City
AVC008	Oklahoma	I-40	On I-40, 3.80 miles E of I-35, in Midwest City
AVC009	Creek	SH-66	On SH-66, 1.40 miles E of 81st St, in Sapulpa
AVC010	Tulsa	US-169	On US-169, 2.10 miles N of I-244, in Tulsa
AVC011	Tulsa	US-75	On US-75, 0.80 miles N of SH-117, in Jenks
AVC012	Tulsa	SH-266	On US-266, 0.40 miles E of US-169, in Tulsa
AVC013	Tulsa	SH-97	On SH-97, 3.00 miles S of US-412, in Sand Springs
AVC014	Tulsa	US-64	On US-64 (Memorial Rd), 1.10 miles S of the Creek Tpk
AVC015	Comanche	I-44	On I-44, 0.50 miles N of SH-7 (Lee Blvd), in Lawton
AVC016	Kay	US-60	On US-60, 0.60 miles W of I-35
AVC017	Jackson	US-62	On US-62, 3.50 miles W of US-283, in Altus
AVC018	Tulsa	US-64	On US-64, 0.38 miles W of 49th W Ave, E of Sand Springs
AVC019	Tulsa	I-44	On I-44, 200 ft W of Exit 236 (129th E. Ave)
AVC020	Oklahoma	I-35	On I-35, 500 ft S of the Grand Ave (SE 36th St) Bridge
AVC021	Muskogee	US-64	On US-64 , 2.39 miles N of SH-2, N of Warner
AVC022	Garvin	US-77	On US-77, 1.74 miles S of SH-19, in Pauls Valley
AVC023	Oklahoma	I-44	On I-44, 0.5 miles N of SW 29th St , in Oklahoma City
AVC024	Oklahoma	US-77	On US-77, 0.1 miles S of Britton Rd
AVC025	Tulsa	SH-51	On SH-51, 0.50 miles W of 145th Ave
AVC026	Oklahoma	I-44	On I-44, 0.40 miles E of Kelly Ave, in Oklahoma City
AVC027	Woodward	US-270	On US-270, 3.80 miles E of SH-34. SE of Woodward
AVC028	Love	I-35	On I-35, 0.10 miles N of the Red River Bridge at TX
AVC029	Bryan	US-69	On US-69, 5.30. miles S of SH-22, NE of Durant
AVC030	Muskogee	US-69	On US-69, 11.30 miles N of US-266, S of Muskogee
AVC031	Kay	I-35	On I-35, 0.10 miles S of the Kansas/Oklahoma SL
AVC032	Payne	SH-51	On SH-51, 3.50 miles E of SH-51C, W of Stillwater
AVC033	Grady	US-81	On US-81, 2.10 miles S of SH-37, S of Minco
AVC034	Garfield	US-60	On US-60 , 5.00 miles E of SH-45, N of Enid
AVC035	Okmulgee	US-75	On US-75, 3.80 miles N of US-62, in Okmulgee
AVC036	Cotton	I-44	On I-44, 0.20 miles N of the Red River Bridge at the TX
AVC037	Washita	SH-152	On SH-152, 1.50 miles W of US-183, W of Cordell
AVC038	Woods	US-64	On US-64, 4.30 miles E of SH-144, W of Alva
AVC039	Kingfisher	SH-51	On SH-51, 2.60 miles E of US-81, E of Hennessey
AVC040	Payne	SH-33	On SH-33, 0.50 miles E of SH-18, W of Cushing
AVC041	Osage	US-60	On US-60, 4.90 miles E of US-177, E of Ponca City
AVC042	Craig	US-60	On US-60, 0.10 miles NW of SH-66, W of Vinita

Station ID	County	Route	Location
AVC043	Craig	SH-66	On SH-66, 3.00 miles SW of US-60, W of Vinita
AVC044	Adair	US-59	On US-59, 2.50 miles S of SH-100, S of Stillwell
AVC045	Latimer	SH-2	On SH-2, 7.70 miles S of SH-31, N of Wilburton
AVC046	Murray	US-77	On US-77. 2.00 miles N of SH-7, N of Davis
AVC047	Lincoln	SH-66	On SH-66, 2.40 miles E of SH-18N, E of Chandler
AVC048	Jefferson	US-81	On US-81, 2.00 miles N of US-70, N of Waurika
AVC049	Jefferson	US-70	On US-70, 3.20 miles E of US-81, E of Waurika
AVC050	Hughes	SH-9	On SH-9, 6.00 miles E of US-75, E of Wetumka
AVC051	Pittsburg	US-270	On US-270, 8.00 miles W of US-69, NW of McAlester
AVC052	Coal	US-75	On US-75, 3.00 miles SE of SH-3, NW of Coalgate
AVC053	Seminole	SH-99	On SH-99, 2.10 miles S of US-270, S of Seminole
AVC054	Beckham	I-40	On I-40, 400 ft E of the Texas SL
AVC055	Grady	US-81	On US-81, 2.50 miles N of US-62, N of Chickasha
AVC056	Oklahoma	I-35	On I-35, 0.40 miles S of NE 10th St
AVC057	Major	US-60	On US-60, 3.50 miles N of SH-8, N of Fairview
AVC058	Texas	US-54	On US-54, 8.60 miles NE of US-64, NE of Guymon
AVC059	Texas	SH-3	On SH-3, 1.30 miles SE of SH-94, W of Hardesty
AVC060	Caddo	SH-9	On SH-9, 1.50 miles W of.SH-146, W of Ft Cobb
AVC061	Oklahoma	I-240	On I-240, 2.00 miles E of I-44, in Oklahoma City
AVC062	Choctaw	US-70	On US-70, 4.40 miles E of US-70B E of Hugo, vicinity Sawyer
AVC063	Tulsa	I-244	On I-244, 0.30 miles N of 23rd St OP
AVC064	Tulsa	I-244	On I-244, 0.40 miles E of Harvard Ave
AVC065	Oklahoma	SH-74	On Hefner Pkwy, 0.70 miles N of 63rd St Bridge, OKC
AVC067	Oklahoma	I-40	On I-40, 0.80 miles E of I-240
AVC068	Tulsa	US-169	On US-169, 0.35 miles S of 31st St
AVC069	Cleveland	I-35	On I-35, at S end of SE 89th Street Bridge
AVC070	Pottawatomie	SH-18	On SH-18, 1.62 miles N of I-40
AVC071	Oklahoma	SH-74	On SH-74, 0.32 miles S of Waterloo Rd
AVC072	Oklahoma	I-40	On I-40 Crosstown, EB 265 ft W of Shields Blvd OP
WIM001	Washington	US-75	On US-75, 6.30 miles S of US-60, S of Bartlesville
WIM002	Murray	I-35	On I-35, 3.60 miles S of SH-7, S of Davis
WIM003	Oklahoma	I-240	On I-240, 2.57 miles E of I-35, in Oklahoma City
WIM005	Wagoner	US-69	On US-69, 6.50 miles S of US-412, S of Chouteau
WIM006	Okfuskee	I-40	On I-40, 1.00 miles W of US-75 South, E of Okemah
WIM007	Blaine	US-270	On US-270, 2.70 miles W of SH-8, W of Watonga
WIM009	Pontotoc	SH-3	On SH-3, 1.10 miles E of SH-1, in Ada
WIM010	Pittsburg	US-69	On US-69, 5.40 miles N of SH-113 S, N of McAlester
WIM011	Grady	US-81	On US-81, 2.46 miles S of US-81B S, S of Rush Springs

Station ID	County	Route	Location
WIM016	Mayes	US-412	On US-412, 2.60 miles W of US-69, W of Chouteau
WIM021	Bryan	US-69	On US-69, 1.10 miles N of the Red River Bridge
WIM022	LeFlore	SH-112	On SH-112, 1.20 miles E of US-59, E of Poteau
WIM023	Major	US-412	On US-412, 2.10 miles W of SH-58, W of Ringwood
WIM025	Cimarron	US-287	On US-287, 5.60 miles N of SH-325
WIM027	Kay	I035	On I-35, 3.50 miles N of US-60, S of Blackwell
WIM028	Canadian	I-40	On I-40, 300 ft W of Gregory Road
WIM029	Sequoyah	I-40	On I-40, 0.96 miles E of US-64
WIM030	McClain	I-35	On I-35, 0.47 miles W of SH-74
WIM032	McCurtain	US-70	On US-70, 4.50 miles W of US-259
WIM104	Logan	I-35	On I-35, 0.50 miles N of Waterloo Rd
WIM114	Washita	I-40	On I-40, 1.46 miles E of SH-34
WIM118	Comanche	US-62	On US-62, 1.30 miles W of SH-115

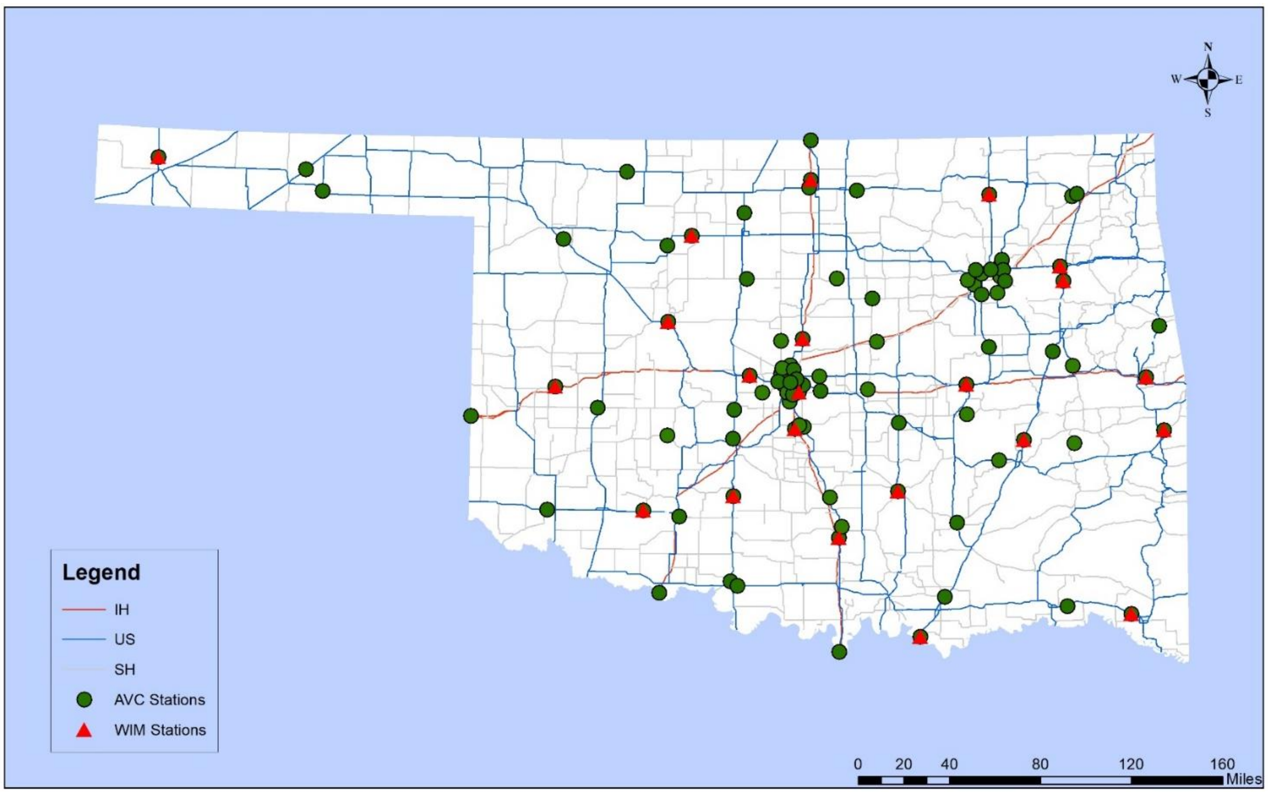


Fig. 3.4 AVC and WIM Stations in Oklahoma

3.3 Statewide Traffic Data Check Using Prep-ME

The Prep-ME software is used to read the data WIM from the SQL database and used as an efficient tool to perform statewide traffic data check. The quality check for the available data is performed in the following stages:

- Importing WIM and AVC data into the Prep-ME software.
- Performing automatic Quality check.
- Investigating the data QC results.
- Enhancing the Quality of data with assisted data repair and sampling based on engineering judgements.

3.3.1 Importing Traffic Data

The AVC and WIM data are imported into the Prep-ME database by specifying the State name. The Travel Monitoring Analysis System (TMAS 2.0) data checks are implemented for each line of raw data, and the errors are summarized into an error log file for each imported file. Duplicate data and data with fatal and critical TMAS errors are not imported into the Prep-ME database. The software interface reports the number of rows of data importation, number of records failed the TMAS check, the failure rate in percentage, and number of duplicated rows. The error logs could assist traffic engineers in identifying WIM sensor issues. The data, which have passed the TMAS data, check and save them in the Prep-ME database tables.

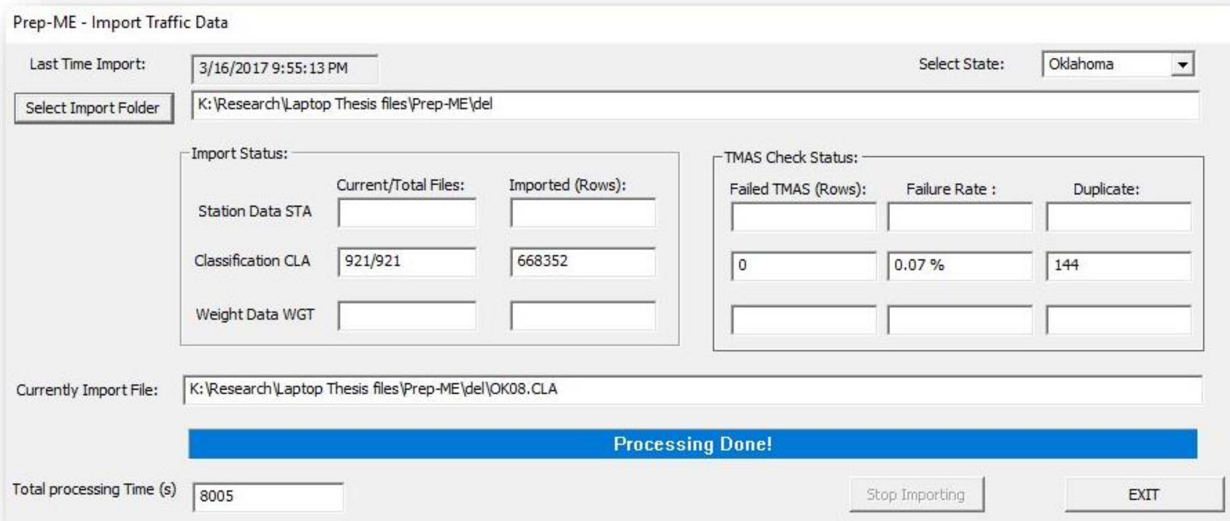


Fig. 3.5 Importing ODOT WIM Data into Prep-ME

3.3.2 Performing Automatic Quality Check

In this process, three QC parameters define the evaluation of recorded vehicle weight data. All the weight data check processes are based on vehicle class 9 because they account for the majority of the truck traffic stream.

- Gross weight distribution for unloaded and fully loaded trucks,
- Ranges of front axle load, and drive tandem axle weight for fully loaded trucks.

Gross Weight Histogram Check: The first step is to check the gross vehicle weights of Class 9 trucks. This step requires a histogram plot of the gross vehicle weights of Class 9 trucks, which should have two peaks for most sites. Although the height of these peaks may be seasonally changed, the location of the two peaks is fairly constant over time. One represents unloaded Class 9 trucks and should be between 28,000 and 36,000 lb (32,000 ± 4,000 lb). The second peak represents the most common loaded vehicle condition, whose weigh should be between 72,000 and 80,000 lb (76,000 ± 4,000 lb). If the WIM scale was not properly calibrated, the histograms may vary from station to station, but four general cases are observed (FHWA, 2001):

- **Fluctuated Data**: if the weight data collected from the station were fluctuated, the WIM scale was classified as failed, and the calibration should be checked immediately.
- **Two Peaks Shifted**: If a plot shows both peaks shifted from their expected location in the same direction, the scale is most likely out of calibration. The participating agency should then recalibrate that scale at that site and collect a new sample of data.
- **One Peak Shifted**: If a plot shows one peak correctly located but another peak shifted from its expected location, the site should be reviewed for other potential scale problems. Additional information on that site may also need to be obtained to determine whether the scale is operating correctly.
- **Overweight Trucks**: If the percentage of overweight vehicles (particularly vehicles over 100,000 lb.) for vehicle class 9 is high, the scale calibration is questionable.

In the process of quality check using Prep-ME, the ranges of two peaks in the gross weight histogram is automatically verified, as shown in Fig. 3.6.

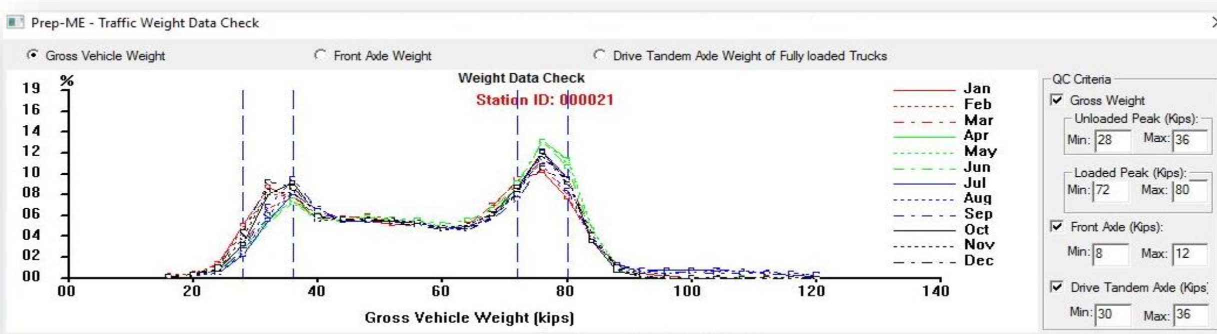


Fig. 3.6 Gross Weight Distribution

Axle Weight Check: In this step, the front axle and drive tandem axle weights of Class 9 trucks are checked. Although the front axle is heavier when a truck is loaded, the front axle weight should be between 8,000 and 12,000 lb (10,000 ± 2,000 lb). The drive tandems of a fully loaded Class 9 truck (generally more than 72,000lb.) should be between 30,000 and 36,000 lb (33,000 ± 3,000 lb). These limits are based on the extensive analyses of vehicle weight data at a national scale (FHWA, 2001).

The quality check criteria in Prep-ME is that the axle weight should be distributed among the provided specific limits, as shown in Fig. 3.7 and Fig. 3.8.

Fig. 3.7 Front axle load distribution

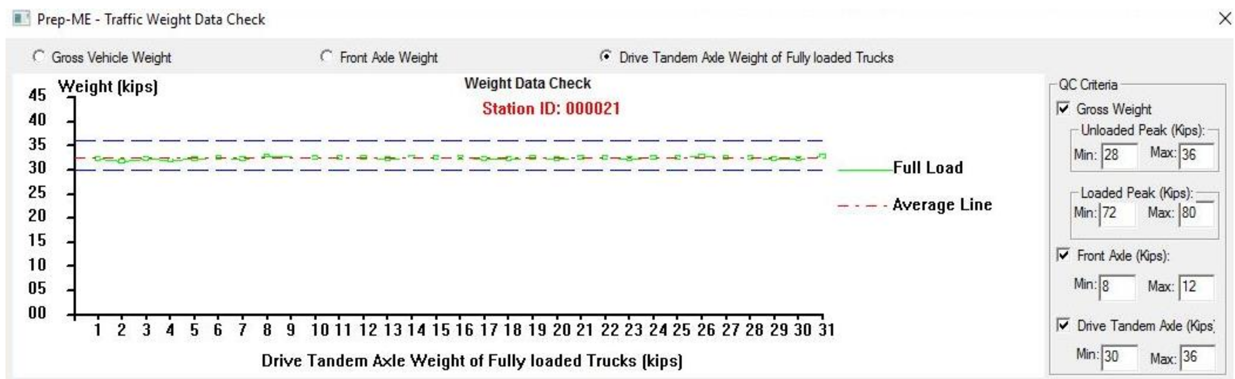


Fig. 3.8 Tandem Axle Load Distribution for Fully Loaded Truck Traffic

3.3.3 Investigating the Data QC Results

If the three parameters (peaks of the gross weight histograms, ranges of front axle and drive tandem axle weight for fully loaded trucks) are not within the specified limits, the data set of the corresponding year, month and lane will be rejected automatically by the Prep-ME software. If all the four lanes of a particular moth are rejected, the month is rejected as a whole. If any month in a year got rejected by QC, the corresponding year data will be considered as failed or rejected by QC.

After the automated quality check by the Prep-ME software, daily data for each individual month which are rejected by the software via the automatic QC are verified based on the following three major parameters:

- Daily class 9 truck counts (Fig. 3.9).
- Percent of front axle within TMG tolerance (Fig. 3.10).
- Percent of tandem axle within TMG tolerance for fully loaded trucks (Fig. 3.11).

Any one of them might be a reason for the rejection of data during the quality check process. This process can help users to understand potential data problems or traffic patterns within that particular month that cannot pass the automated QC. The investigation will be further used in the following step for assisted data repair and sampling.

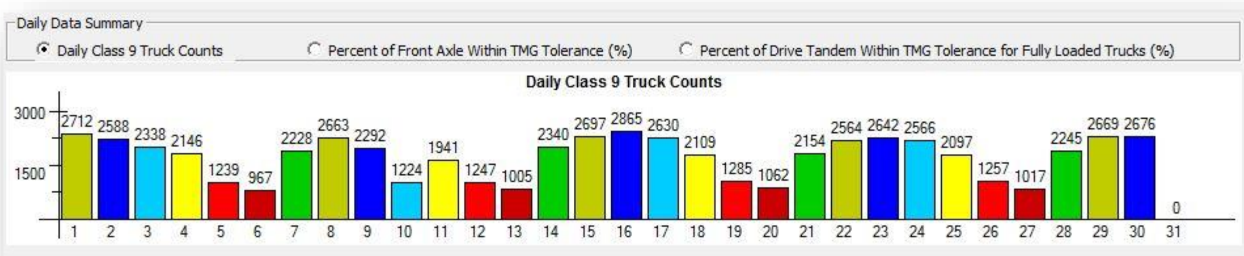


Fig. 3.9 Daily Class 9 Truck Counts

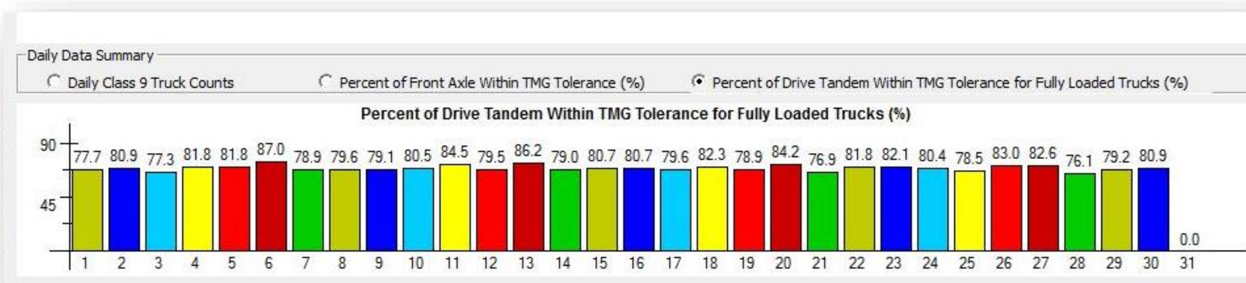


Fig. 3.10 Percent of Front Axle within TMG Tolerance

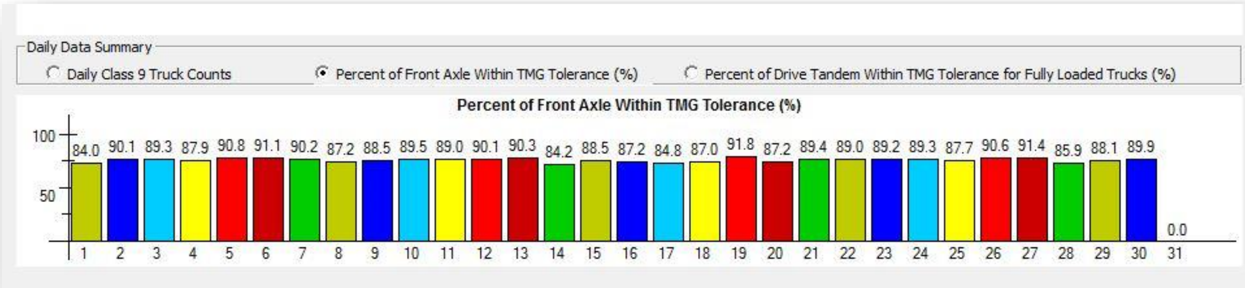


Fig. 3.11 Percent of Tandem Axle within TMG Tolerance for Fully Loaded Trucks

3.3.4 Enhancing Data Quality with Assisted Data Repair and Sampling

After the review process in the previous step, the Prep-ME software provides several tools that can perform specific data repair and sampling on the existing data sets based on engineering judgments. The Prep-ME software provides interfaces for users to review monthly, weekly and daily traffic data. Four sampling and repairing operations are designed 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 Replacement (Copy and Paste), Sampling Operation (Daily Sampling and Monthly Sampling), and Manual Operation (Accept and Reject).

- **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 for a particular month. If the data is good for a specific period of a month and the data set is rejected as a whole for that month during the automated QC process, the data at the specific period verified to have good quality are sampled and represented for the particular month.
- **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. This process can be used when many years of data that have passed the automated QC are available.

- **Manual (Accept/Reject)** Operation allows users to review and change the automated QC results. If the site maintains a good condition with and the data sets are considered to be good based on engineering judgement, the data set can be manually accepted.

If none of the cases apply, the data are unmodified and they are marked as unaccepted. The data sets are manually checked using Prep-ME by month by direction and by lane for each station, and the comprehensive quality check process and results of 2008 as the example are summarized in Table 3.2. The legends and color coding of the data check are shown in Fig. 3.12.

a	Gross Weight Peak 1 Shifted
b	Gross Weight Peak 2 Shifted
c	Front Axle Criteria Out of Range
d	Drive Axle Criteria Out of Range
e	No sufficient Fully Loaded Trucks
f	No Data

	Daily Sampled
	Replaced with Adjacent Month
	Unaccepted and Unmodified
	Low Volume & Unmodified
	QC Failed
	Manually Accepted

Fig. 3.12 Legends for Statewide Traffic Data Check

Table 3.2 Statewide WIM Data Check in 2008

WIMID	Dir.	Lane#	Lane	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	N	3	P												
1	N	4	D												
1	S	1	D					d							
1	S	2	P	a,b,d											
2	N	3	P												
2	N	4	D					b							
2	S	1	D			b						e	e	e	
2	S	2	P												
3	E	3	P		a,b		a,b,d	a,b		b,d		b,d	b,d	b,d	b,d
3	E	4	D												
3	W	1	D	a,b	a,b	a,b	a,b	a,b							
3	W	2	P						b,e	b		b,e	b,e		b,e
5	N	3	P												
5	N	4	D				a,b	a,b	a,b	a,b	a,b				
5	S	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
5	S	2	P		a,b	a,b	a,b	a,b			a,b				
6	E	3	P												
6	E	4	D						a,b	a,b					
6	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b		a,b	a,b
6	W	2	P		a,b,d	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
7	E	3	P												
7	E	4	D												
7	W	1	D												
7	W	2	P												
9	E	3	P												
9	E	4	D	d			a,d	d	d	a,b,d	a,b,d	b,d	a,b,d	b,d	b,d
9	W	1	D												
9	W	2	P	b,d	b,d	b,d	b,d						d	d	b,d
10	N	3	P	a,b	a,b	a,b									a,b
10	N	4	D				a,b	a,b	a,b						
10	S	1	D				a,b	a,b	a,b	a,b	a,b	a,b			
10	S	2	P	a,b	a,b	a,b	a,b	a,b							
11	N	3	P												
11	N	4	D												
11	S	1	D							a,b					
11	S	2	P	a,b,d	a,d	b,d	b,d	a,d							
16	E	3	P	b,d	a,b,d										

WIMID	Dir.	Lane#	Lane	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
16	E	4	D												
16	W	1	D												
16	W	2	P												
21	N	2	D												
21	S	1	D												
22	E	2	D												
22	W	1	D												
23	E	2	D												
23	W	1	D												
27	N	3	P							a,b					
27	N	4	D	a,b,d	a,b,d	a,b,d		a,b							
27	S	1	D												
27	S	2	P	a,b,d	a,b,d										
28	E	3	P	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d
28	E	4	D	a,b,d	a,b,d	a,b,d	a,b,d	a,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,d	a,d
28	W	1	D			a,b	a,b			a,b	a,b	a,b	a,b	a,b	a,b
28	W	2	P												
29	E	3	P												
29	E	4	D												
29	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
29	W	2	P		a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	
30	N	3	P												
30	N	4	D												
30	S	1	D							a,b	a,b,d	a,b,d	a,b	a,b,d	a,b
30	S	2	P						b.d	b.d	b.d	b.d	b.d	b.d	b.d
104	N	3	P	b.d	d	b.d								d	b,d
104	N	4	D						a,b						
104	S	1	D											a,b	
104	S	2	P	b.d	b.d									d	b.d
114	E	3	P												
114	E	4	D												
114	W	1	D												
114	W	2	P												
118	E	3	P	b.d	b.d	b.d									
118	E	4	D	b.d	b.d	d									
118	W	1	D												
118	W	2	P	b.d											

4. TRAFFIC CHARACTERIZATION AND INPUTS FOR PAVEMENT ME DESIGN

4.1 Required Traffic Inputs

Traffic is one of the most important inputs in pavement design. Instead of using Equivalent Single Axle Load (ESAL) in the 1993 AASHTO Design Guide to characterize traffic throughout the pavement design life, the Mechanistic Empirical Pavement Design Guide (MEPDG), subsequently named as Pavement ME Design, requires the full axle-load spectrum traffic inputs for estimating the magnitude, configuration and frequency of the loads to accurately determine the axle loads that will be applied on the pavement in each time increment of the damage accumulation process (NCHRP 1-37A, 2004). This axle load spectra approach is widely viewed as a quantum leap forward in pavement design technology, and requires four basic categories of traffic inputs for the structural pavement design as follows (NCHRP 1-37A, 2004):

(1) The base year traffic volume. One important input in this category is annual average daily truck traffic (AADTT) of Vehicle Classes 4 through 13. This information can be derived from WIM, AVC, or vehicle count data and is available within a state highway agency.

(2) The base year AADTT must be adjusted by using traffic volume adjustment factors, including monthly distribution, hourly distribution, class distribution, and traffic growth factors. These factors can be determined on the basis of classification counts obtained from WIM, AVC, or vehicle count data.

(3) axle load distribution factors (axle load spectra). The axle load distribution factors represent the percentage of the total axle applications within each load interval for a specific axle type (single, tandem, tridem, and quad) and truck class (class 4 to class 13). The axle load distributions or spectra can be determined only from WIM data.

(4) general traffic inputs, such as number of axles per truck, axle configuration, and wheel base. These data are used in the calculation of traffic loading for determining pavement responses. The default values provided for the general traffic inputs are recommended if more accurate data are not available.

Traffic data collection in accordance with the FHWA's Traffic Monitoring Guide (TMG) would meet the traffic characterization requirements for MEPDG. However, due to unlimited resources, to is impractical to obtain site-specific traffic data for any pavement design. Therefore, the Pavement ME Design defines a three-level hierarchical traffic input system, in regard to the accuracy of axle load spectra data, which allows users to have the flexibility of preparing traffic inputs based on the availability of data sets and the importance of the design project. The traffic design inputs at Level 1 are the most accurate inputs generated from project or segment-specific weigh-in-motion (WIM) and automatic vehicle classification (AVC) data; the traffic design inputs at Level 2 use regional WIM and AVC data and provide intermediate accuracy which are generally based on clustering analysis; traffic design inputs at Level 3 use regional or statewide default values and provide poor accuracy

4.1.1 Monthly Adjustment Factors

Based on the traffic counts by class obtained from WIM data, the monthly adjustment factors can be calculated:

(1) Determine the total number of trucks (in a given class) for each 24-hour period.

(2) Determine the Average Monthly Daily Truck Traffic for each month (AMDTT) in the year.

(3) Sum up the average daily truck traffic for each month for the entire year.

(4) Calculate the monthly adjustment factors by dividing the average daily truck traffic for each month by summing the average daily truck traffic for each month for the entire year and multiplying it by 12 as given below:

$$MAF_i = 12 \times \frac{AMDTT_i}{\sum_{i=1}^{12} AMDTT_i} \qquad (4.1)$$

Where MAF_i = Monthly Adjustment Factor for month i; $AMDTT_i$ = Average Monthly Daily Truck Traffic for month i.

4.1.2 Vehicle Class Distribution

The vehicle class distribution factors can be determined as follows. The sum of Class Distribution Factors (CDF) for all classes should equal 100%.

$$CDF_j = \frac{AADTT_j}{AADTT} \quad (4.2)$$

Where: CDF_j = Class Distribution Factor for vehicle class j; $AADTT_j$ = Annual Average Daily Truck Traffic for class j; $AADTT$ = Annual Average Daily Truck Traffic for all classes. Analysis performed at one of the WIM station is shown in Fig. 4.1 for vehicle class distribution. Class 5 trucks and Class 9 Trucks contributes the majority of the truck traffic. Similar kind of results are observed at other WIM stations, while the magnitude of the two peaks vary among stations.

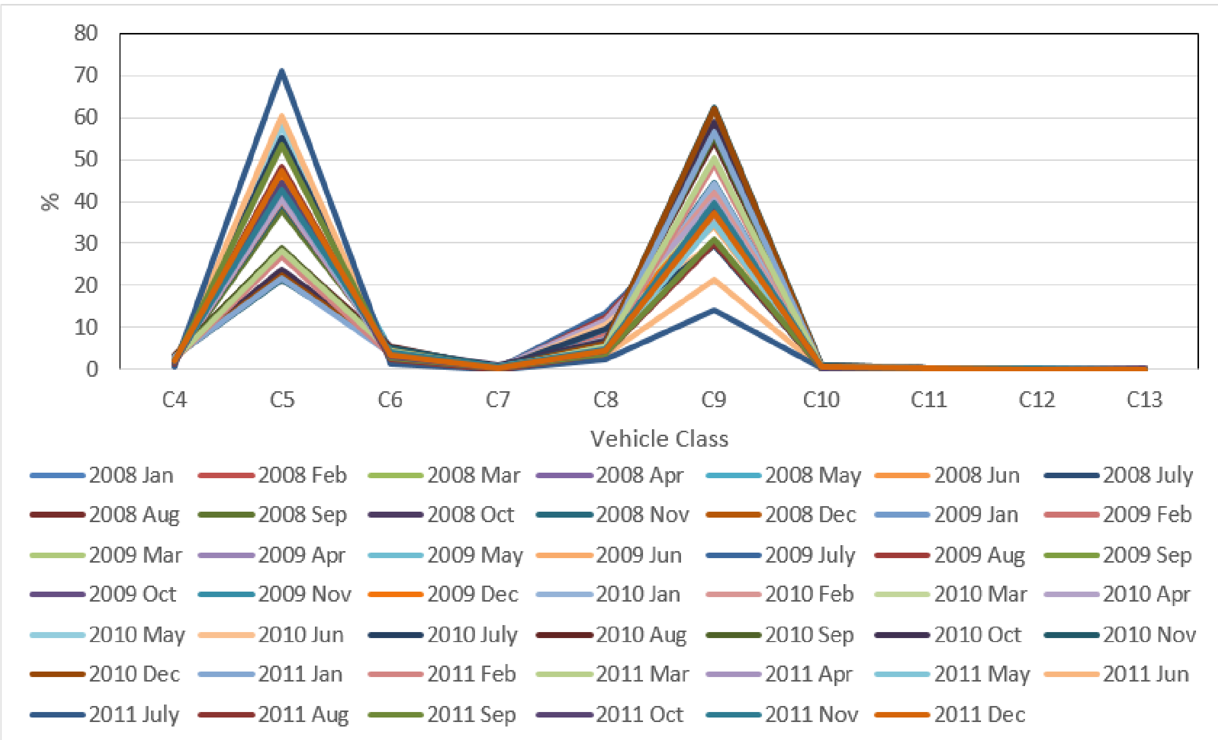


Fig. 4.1 Vehicle Class Distribution

4.1.3 Hourly Truck Distribution

The hourly data are used to determine the percentage of total trucks within each hour as follows:

(1) Determine the total number of trucks counted within each hour of traffic data in the sample.

(2) Average the number of trucks for each of the 24 hours of the day in the sample.

(3) Total the 24 hourly averages from step 3.

(4) Divide each of the 24 hourly averages from step 2 by the total from step 3 and multiply by 100 and get the Hourly Distribution Factors (HDF), which is shown in Equation 4 (*2*). The sum of the percent of daily truck traffic per time increment must add up to 100%.

$$HDF_i = \frac{HATT_i}{\sum_{j=1}^{24} HATT_j} \qquad (4.3)$$

Where: HDF_i = Hourly Distribution Factor for ith one-hour time period; $HATT_i$ = Hourly Average Truck Traffic for ith one-hour time period.

4.1.4 Axle Load Distribution Factors

Axle load distribution factors can be calculated using WIM data to average the daily number of axles measured within each load interval of an axle type for a truck class divided by the total number of axles for all load intervals (2):

(1) Find the range containing all weight data from a specific WIM station.

(2) Count the number of axles in each weight bin for different vehicle classes using the following load intervals:

- Single axles – 3,000 lb to 40,000 lb at 1,000-lb intervals;
- Tandem axles – 6,000 lb to 80,000 lb at 2,000-lb intervals;
- Tridem and quad axles – 12,000 lb to 102,000 lb at 3000-lb intervals.

(3) Summarize the monthly axle load distribution in the previous step and determine the axle load spectra for the site.

The tandem axle distributions of one of the WIM station at both directions are shown in Fig. 4.2. Two peaks are observed, one representing empty and the other fully loaded tandem axles.

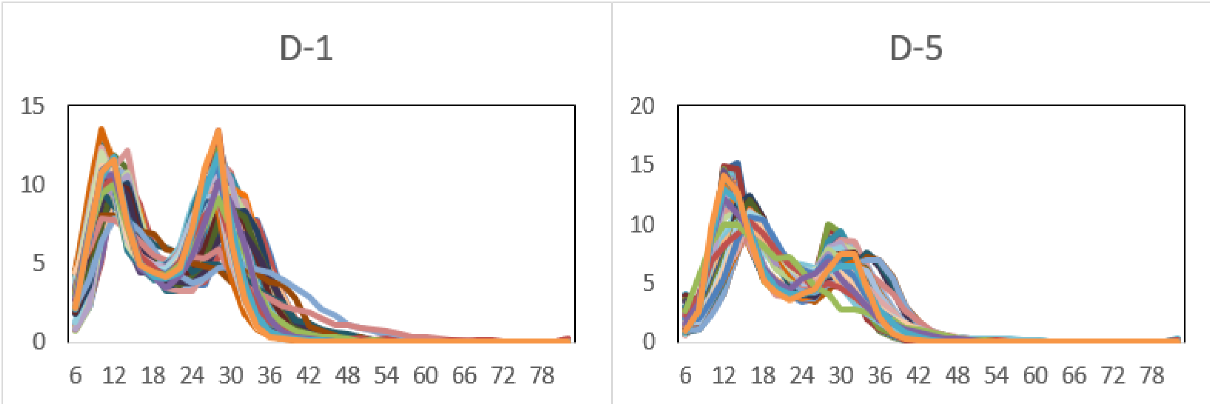


Fig. 4.2 Tandem axle distribution spectrum

4.2 Traffic Data Clustering Analysis

4.2.1 Clustering Procedure

The purpose of generating Level 2 traffic clustering inputs is to identify the similarities in the time-series traffic patterns and classify them into groups. The process of developing clusters involves three major steps: firstly, construct a distance matrix for each traffic input parameter; secondly, determine the optimum number of cluster for that particular parameter; finally, select an algorithm to define clusters (Wang et al., 2011). In this study, the distance matrix is constructed for each matrix VCD, ALS, and MDF using Euclid distance technique. Considering data matrix X(nxm) with n measurements and m variables, the distance matrix D(nxn) is defined as shown in Equation 1 (Li et al. 2015). The distance values are calculated to measure the dissimilarity among vectors: the higher the value, the less the similarity among those vectors (Li et al. 2015).

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ \vdots & d_{22} & & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nn} \end{bmatrix} \qquad d_{ij} = \left\| x_i - x_j \right\|_r = \left\{ \sum_{k=1}^{p} \left| x_{ik} - x_{jk} \right|^r \right\}^{1/r} \tag{4.4}$$

The number of clusters should be neither too high (fails the purpose of clustering) nor too low (loses the significant variations or patterns). Therefore, the optimum number of clusters at which adding another cluster does not explain significant variation is to be determined. Elbow method (Hardle and Simar 2003) is used to determine the optimal number of clusters or K-value, in which the total sum of squares within a cluster is plotted against the number of clusters. The change in slope is observed, and significant change (flattens) is considered as optimum K-value.

Subsequently, K-means clustering technique is performed to identify the clusters among datasets. This process starts with K-random vectors that act as centroids, around which clustering of each vector to the nearest one is observed, and then the mean of each cluster is considered as the new centroid. This process continues till the mean becomes the centroid of the cluster. This sequence of procedure to obtain clusters is called Lloyd's algorithm (Hardle and Simar 2003).

4.2.2 Clustering Results

After removing the QC outliers, missing data is identified and separated. Only data that passed the QC is considered for further analysis. The three major datasets are generated according to the requirement of traffic input for Pavement ME Design software:

- Vehicle Class distribution dataset (VCD): a two-dimensional vector with the percent of truck traffic (VC4 - VC13) for each month of five years at every station.
- Monthly distribution factor (MDF): multiple two-dimensional vectors with percentage of truck traffic per month in a year and similar vectors for each year at every station.
- Axle loading spectrum (ALS): multiple two-dimensional matrices of axle load distribution for single, tandem, tridem, and quad axle types.

Considering monthly data for cluster analysis can account the seasonal variation of truck traffic also the truck-loading patterns. Twelve months of five-year data from all stations are used for clustering analysis. Cluster results of VCD, MDF, and ALS are summarized as following using the optimal number of clusters determined above. For ALS, datasets are analyzed separately as two-dimensional matrices for single, tandem, tridem, and quad axle loading spectrum. Single axles correspond to 3 kips to 40 kips at 1-kip interval; tandem axles are 6 kips to 80 kips at 2 kips interval; tridem and quad axles indicate 12 kips to 102 kips at 3 kips interval.

- Vehicle Class Distribution: as shown in Fig. 4.3, datasets having a higher proportion of class 9 trucks are grouped as Cluster 1; higher fraction of class 5 trucks is observed in Cluster 2; approximately similar percent of class 5 and class 9 trucks are clustered as Cluster 3.

- Monthly Distribution Factor (as shown in Fig. 4.4): Cluster 1 consists of datasets having pretty consistent truck traffic throughout the year; datasets having a higher proportion of truck traffic in March through June are grouped as Cluster 2; the Cluster 3 explains the datasets have higher truck traffic in the months June through September.
- Single Axle (Fig. 4.5): Cluster 1 consists high proportion of light axles (unloaded trucks) while Cluster 2 contains much higher portion of heavy single axles.
- Tandem Axles (Fig. 4.6): Cluster 3 has dominant very light axles; Cluster 2 consists of two axle peaks with empty and full loading; Cluster 1 has slightly heavier axles as compared to Cluster 2.
- Tridem Axles (Fig. 4.7): Cluster 1 has dominant very light axles; Cluster 2 indicates the presence of both very light but distinctive axle peak with partial loading axles; in Cluster 3, significant portion of heavy axles with full loading are observed.
- Quad Axles (Fig. 4.8): Cluster 1 has significant proportion of partially loaded heavy Quad axles; Cluster 2 is grouped with dominant light axles; while Cluster 3 has both significant amount of both light and fully loaded heavy axles.

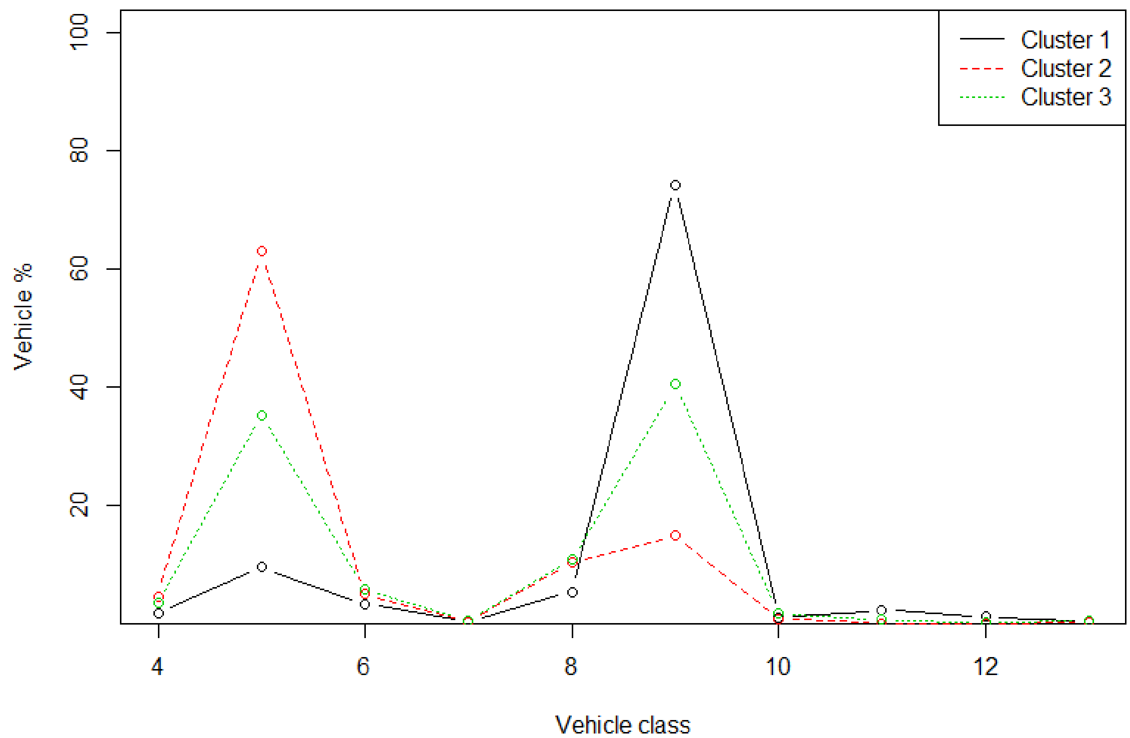


Fig. 4.3 Clusters for Monthly VCD Data

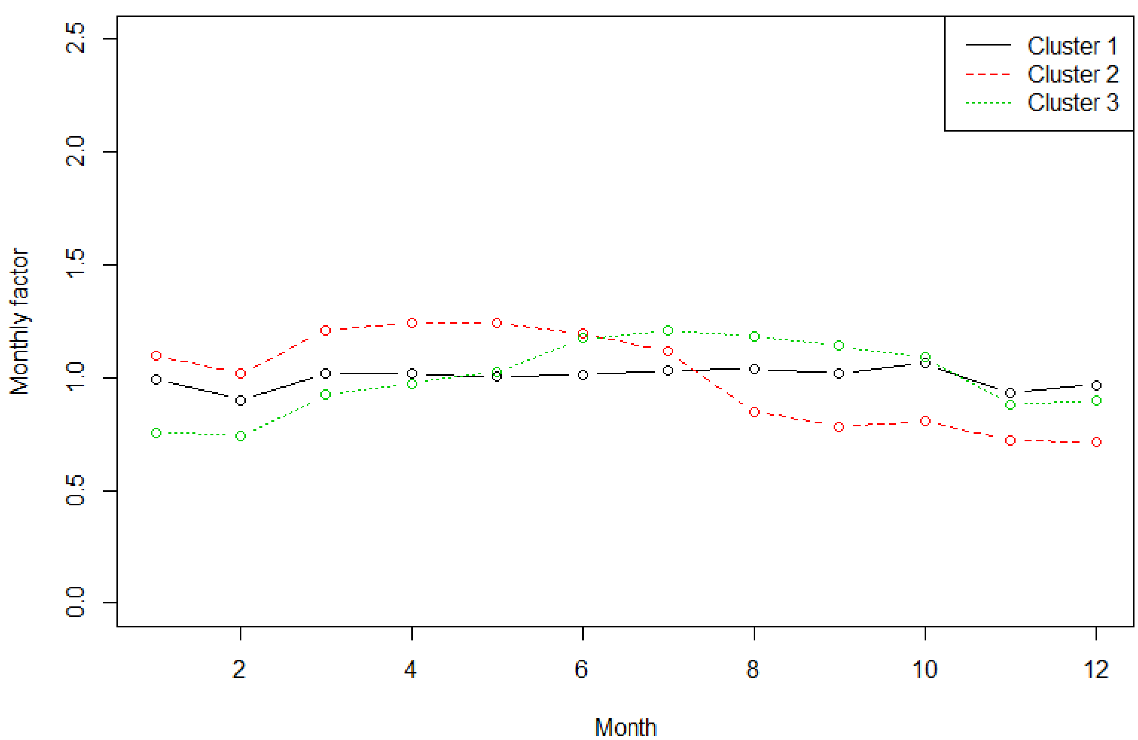


Fig. 4.4 Clusters for Monthly Distribution Factor

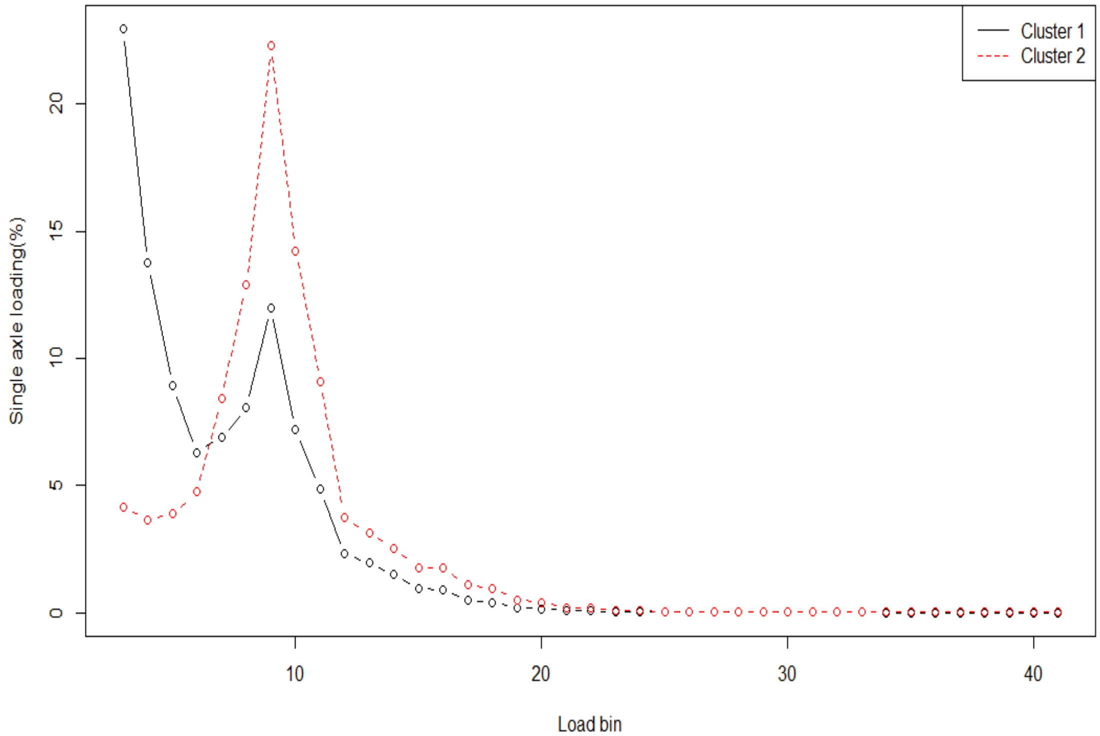


Fig. 4.5 Clusters for Single Axle Loading

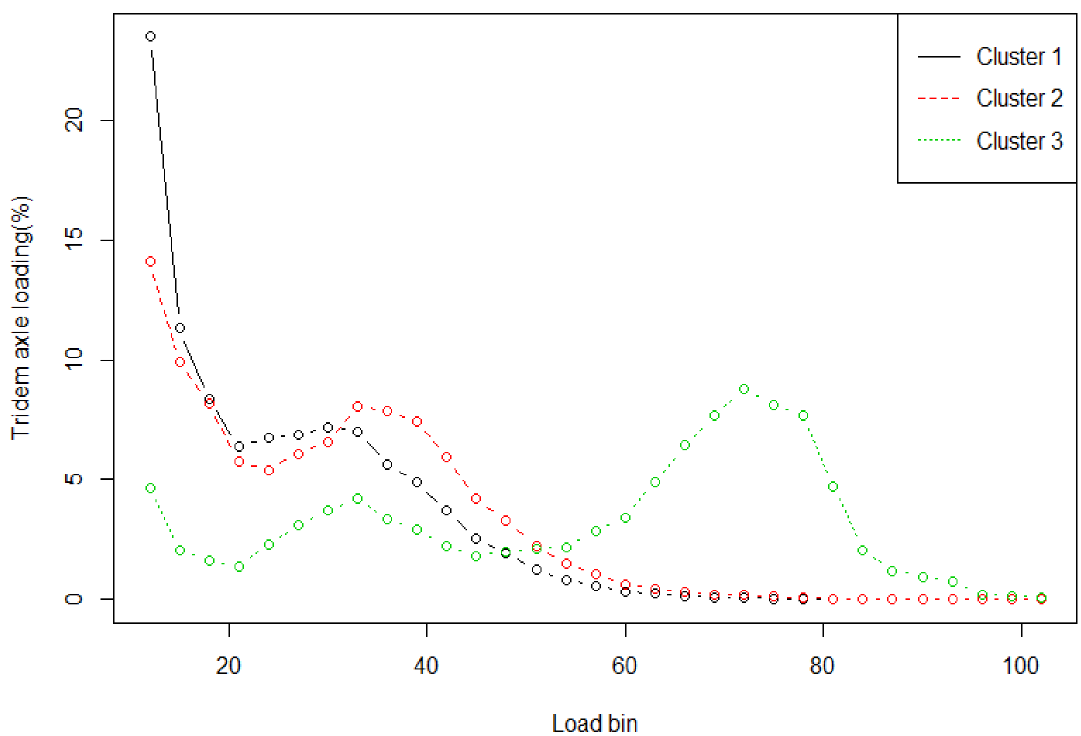


Fig. 4.6 Clusters for Tandem Axle Loading

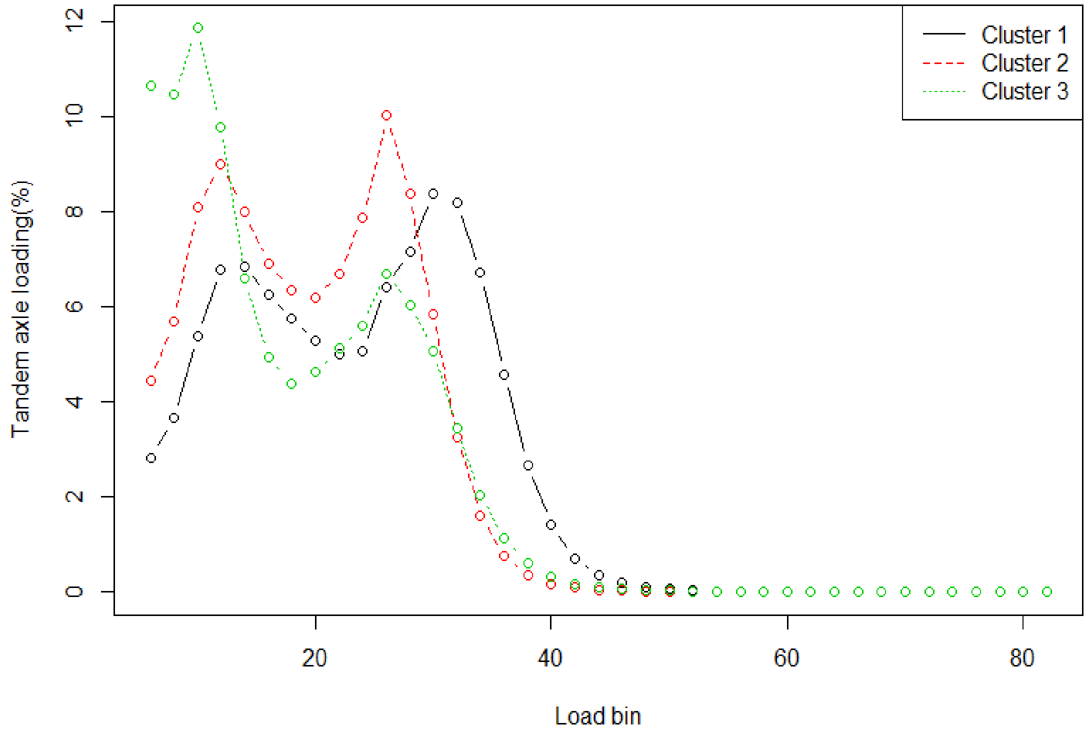


Fig. 4.7 Clusters for Tridem Axle Loading

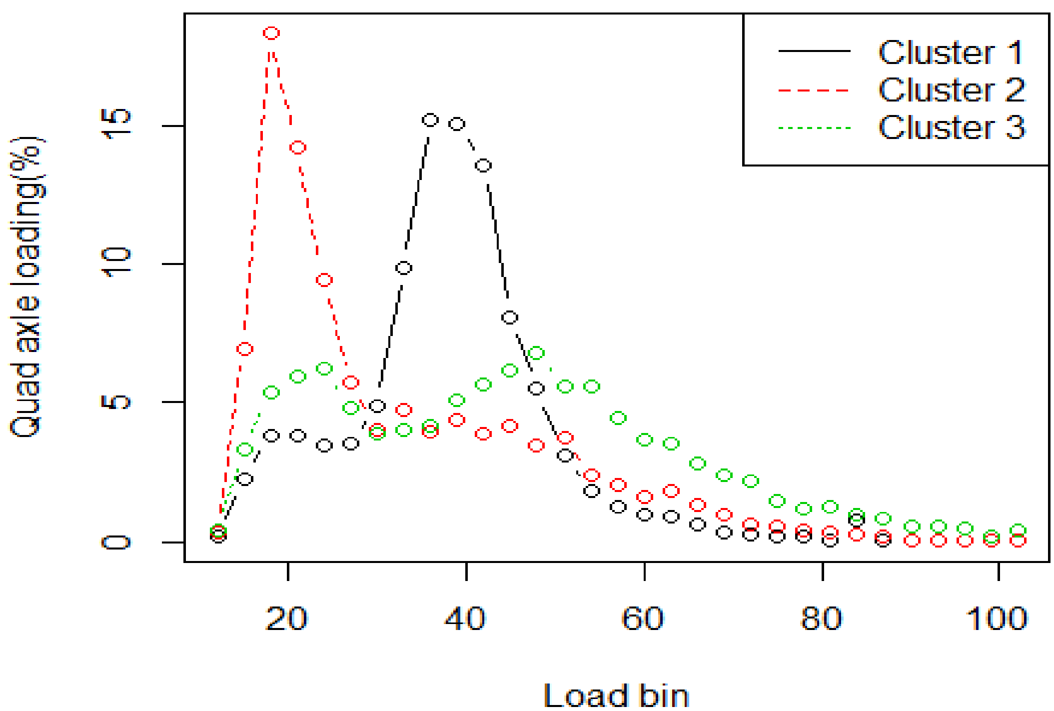


Fig. 4.8 Clusters for Quad Axle Loading

4.3 Estimating Level 2 Traffic Inputs

After identifying and defining the clusters of traffic data, it is necessary to select suitable traffic input cluster at a given site for MEPDG design. Thus far, several methodologies, including decision tree models, support vector machine models, adaptive neuro fuzzy inference system, regression models etc., have been implemented to train models by the existing site-specific traffic input clusters and corresponding independent variables (Pradhan et al. 2009, Stone et al. 2011, and Wang et al. 2013). In this study, decision tree and multinomial logit regression model are particularly investigated. Decision tree model can explain and visualize the cluster determination based on each independent variable, while the multinomial logit regression model can perform regression analysis by considering both discrete, continuous data and provide the relative probability of determining one cluster over other.

4.3.1 Selection of Independent Variables

Based on the literature review (Haider et al. 2011), annual average daily truck traffic (AADTT), Truck traffic percentage (% TT), ratio of class 5 trucks to class 9 trucks (VC5/VC9), ratio of single unit trucks (class 5 through class 8) to multiple unit trucks (class 9 through class 13) (SU/MU), rural/urban and functional classification are considered as independent variables that may influence the clustering of both VCD and MDF. In addition to the variables mentioned above, upon investigating the pattern of ALS clusters, significant relation is observed with a fraction of single axles to the tandem axles.

Correlation analysis is performed for these potential variables to quantify the association between two variables. The absolute value of correlation coefficient larger than 0.5 indicates highly correlation between two variables which should not be considered together in a single model. The interpretation of the correlation matrix as shown in Table 4.1 is described below for each variable.

- The rural or urban classification, function class of highway, average truck traffic volume and truck traffic percentage does not have highly correlation with any other variable, which can be consider as independent variables.
- Percentage class 5 trucks are highly correlated with percentage class 9, the

ratio of class5 to class 9, and ratio of single unit trucks to multiple unit trucks. In other words, no two of them should come together as independent variables. In this study, ratio of single unit trucks to multiple unit trucks is considered as the fifth independent variable.

Table 4.1 Correlation Matrix for Independent Variables

Variable	Rural.Ur	FC	VC5%	VC9%	VC5.VC9	SU.MU	MADTT	TT
Rural.Ur	1.00							
FC	0.28	1.00						
VC5%	-0.19	0.44	1.00					
VC9%	0.20	-0.47	-0.95	1.00				
VC5.VC9	-0.23	0.38	0.71	-0.65	1.00			
SU.MU	-0.23	0.42	0.83	-0.78	0.91	1.00		
MADTT	-0.48	-0.46	-0.23	0.24	-0.21	-0.21	1.00	
TT	0.45	-0.21	-0.42	0.45	-0.35	-0.41	0.05	1.00

4.3.2 Decision Tree Analysis

Decision tree is a hierarchical model developed with set of procedure that splits dependent variables into homogeneous groups. Wide ranges of tools are available to perform recursive partitioning, such as classification and regression tree (CART), chi-square automatic interaction detector decision tree (CHAID), ID3 classification algorithm and C4.5 (Biswajeeth et al. 2013). Classification tree based models are efficient for categorical data, which is used to build the decision trees in this analysis.

In the process of building a decision tree, the complexity parameter (cp) is used to control the size of the decision tree and to select the optimal tree size. Complexity ranges from 0 to 0.5, smaller value of complexity represents the higher number of splits and accuracy. The complexity table for VCD as the example, as shown in Table 4.2, lists their complexity parameter, the number of splits (n-split), the resubstitution error rate (rel-error), the cross-validated error rate (x-error), and the associated standard error (x-std). In addition, this algorithm can also rank each independent variable with the percent of its influence on the determining cluster (Maechler et al., 2009), as shown in Table 4.3.

Table 4.2 Complexity Table for VCD Data

CP	n-split	rel-error	x-error	x-std
0.497	0	1.000	1.000	0.012
0.401	1	0.503	0.504	0.012
0.004	2	0.102	0.108	0.006
0.002	5	0.092	0.102	0.006
0.002	11	0.076	0.092	0.006
0.002	13	0.072	0.088	0.006
0.002	16	0.065	0.087	0.006
0.001	19	0.060	0.083	0.005
0.001	24	0.055	0.080	0.005
0.001	29	0.051	0.081	0.005
0.000	33	0.048	0.079	0.005
0.000	34	0.048	0.079	0.005

Table 4.3 Ranking of Independent Variables for VCD Data (%)

SU.MU	TT	AADTT	FC	Rural.Ur
65	17	9	8	1

Selecting the number of splits is on a trial and error basis to ensure that the decision tree includes a maximum number of influencing variables. The secondary criterion is to investigate the complexity parameter and the corresponding error terms. It is inefficient to include more number of splits for a small decrease in error. For VCD as the example, the decision tree developed to choose VCD cluster is demonstrated in Fig. 4.9. Each internal node represents an independent variable listed in Table 4.1. SU.MU represents the ratio of single unit trucks to multiple unit trucks, TT represents the percent of truck traffic, AADTT is the average annual truck traffic, FC is function class of the highway if it is interstate, US highway or state highway, and Rural.Ur represents the rural or urban classification. Each leaf node represents a class label of the VCD cluster: “a” is the Cluster 1 group, “b” represents the Cluster 2 and “c” is Cluster 3. For instance, if the design location has the SU.MU ration as 1.3 and having AADTT as 300 can probably have the vehicle class distribution similar to Cluster 2.

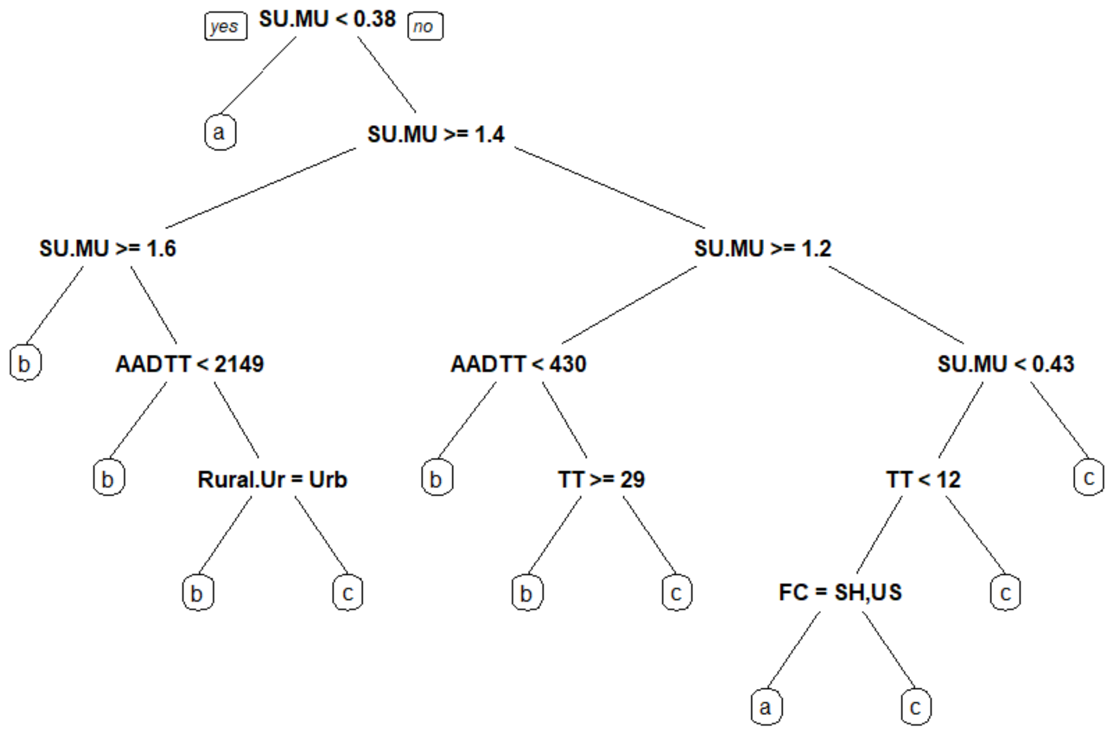


Fig. 4.9 Decision Tree to Choose VCD Cluster

4.3.3 Multinomial Logit Regression Model

Since one of the selected independent variables and the dependent variable are categorical, multinomial logit regression model should be developed. The output of the model has a summary block with coefficients and standard errors for each independent variable at each corresponding dependent variable category. A one-unit change in a variable may affect the probability of dependent variable to the corresponding fraction of the coefficient. This regression model can determine the ratio of the probability of selecting one cluster over the other for the five independent variables. For instance, monthly vehicle class distribution data has three clusters. Cluster-1 has taken base criteria and ran the multinomial logit regression model for the independent variables SU.MU, TT, MADTT (continues data) and FC (categorical variable). Results as shown in Table 4.4 from the coefficient block can be interpreted as the equation given below. The low standard errors for the coefficients indicate their sufficiency of the variables used in the model.

$$Ln\left(\frac{P(Cluster\ \mathrm{i})}{P(Cluster\ 1)}\right) = c_i + c_{\frac{SU}{MU}}\left(\frac{SU}{MU}\right) + c_{SH}(SH) + c_{US}(US) + c_{\%TT}(\%\,TT) + c_{MADTT}(MADTT)$$

For instance, assuming a site with 9 times higher amount of single unit trucks than multiple unit trucks and classified as state highway with 10 percent truck traffic, 1900 monthly average truck traffic, probability of cluster 2 over cluster 1 is higher than probability of cluster 3 over 1. This particular location can be classified as Cluster-2.

Table 4.4 Coefficients Block for VCD data

Variable	C2 vs. C1: Coefficient	C2 vs. C1: Standard error	C3 vs. C1: Coefficient	C3 vs. C1: Standard error
(Intercept)	-19.635	0.021	-14.108	0.026
SU.MU	34.572	0.041	30.279	0.043
FC_SH	1.066	0.037	0.459	0.041
FC_US	1.280	0.041	1.053	0.048
TT	-0.006	0.011	0.056	0.008
MADTT	0.000	0.000	0.000	0.000

4.4 Pavement ME Design Case Study

To demonstrate the implementation of proposed decision tree model and multinomial logit regression model for traffic data cluster selection, a case study of Pavement ME Design is performed considering different levels of traffic inputs. The layer structure of the case study flexible pavement is shown in Fig.4.10. The initial two-way AADTT of this site is 6483. Two Oklahoma Department of Transportation (ODOT) mix types: S3 and S4 (ODOT, 2009), are used in the surface and binder layers. In order to evaluate the variation of pavement performance predicted by MEPDG software, the following four different traffic inputs scenarios are considered:

- Scenario-1: Level 1 Site specific traffic inputs derived from WIM 021. Significant proportion of heavier truck traffic is observed on US-69 within Muskogee County, corresponding site-specific data can be obtained for the WIM station 021.

- Scenario-2: Level 2 cluster specific traffic inputs based on decision tree model.
- Scenario-3: Level 2 cluster group traffic inputs based on Multinomial logit regression model.
- Scenario-4: Level 3 statewide average traffic inputs. Irrespective of location or traffic patterns or independent variables, average of traffic data form every station within Oklahoma is considered as input.

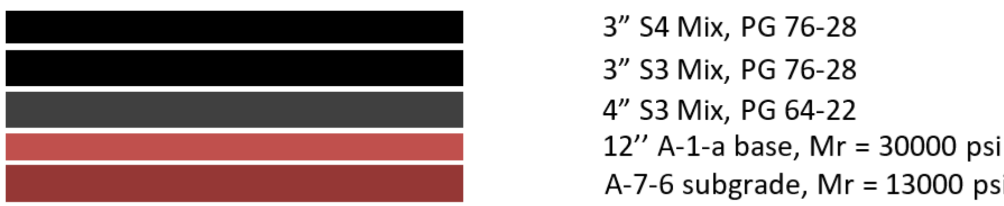


Fig. 4.10 Case Study Flexible Pavement Structure

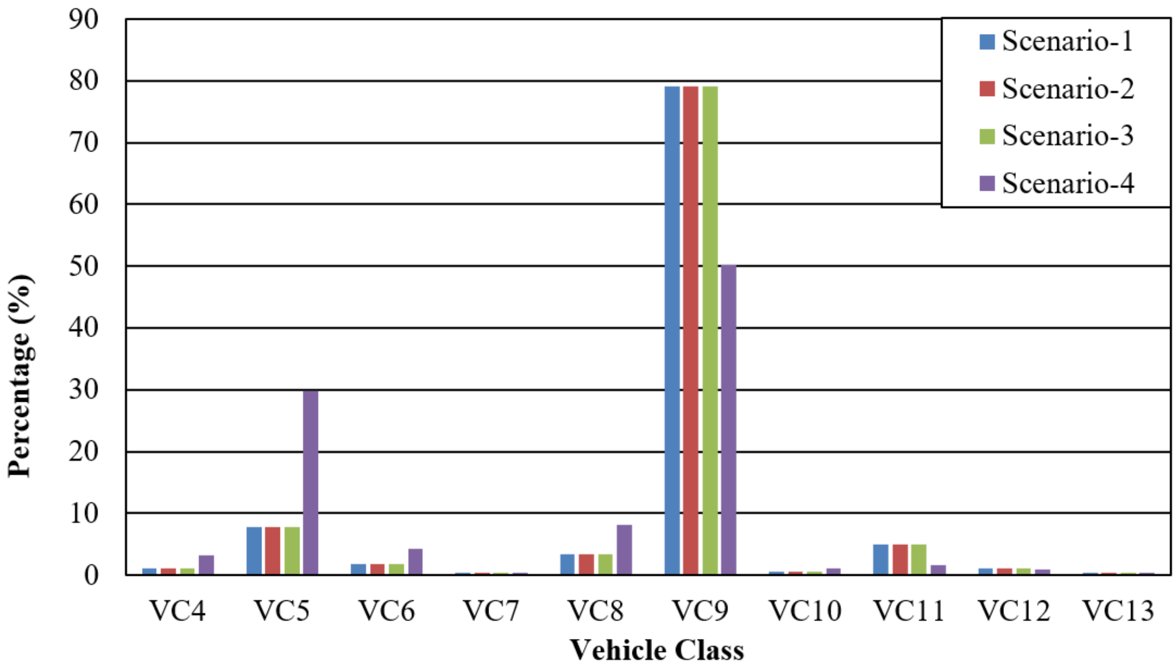


Fig. 4.11 Comparisons of VCD under Four Scenarios

As shown in Fig. 4.11, Level 2 vehicle class distribution is similar to the site specific Level 1 traffic inputs, while statewide Level 3 traffic inputs is significant different from site-specific traffic data sets. The performance of flexible pavement for 20-year design life includes international roughness index (IRI), pavement total rutting, fatigue cracking, which are obtained from the Pavement ME Design software (Version 2.3) (shown in Fig. 4.12, Fig. 4.13, Fig. 4.14). If using pavement performance derived from Level 1 site-specific traffic inputs as the benchmark, Level 2 scenarios generates more accurate predictions than those from Level 3 statewide average inputs. In addition, it is observed that the equivalent single axle loading (ESALs) during the design life for the four scenarios vary significantly, especially if Level 3 inputs are used (Fig. 4.15).

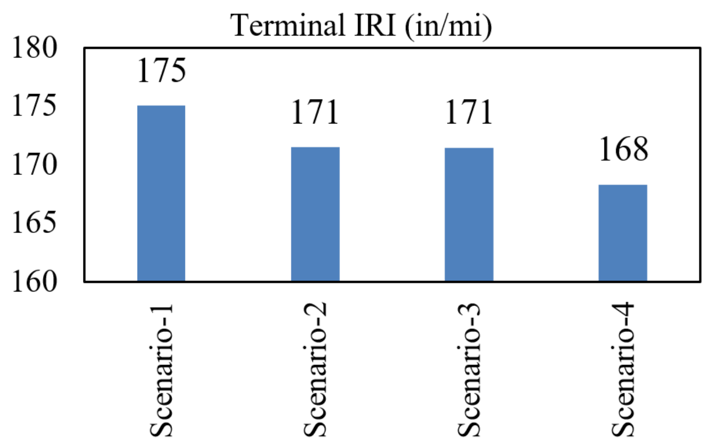


Fig. 4.12 Comparisons of Predicted IRI

Fig. 4.13 Comparisons of Predicted Rutting

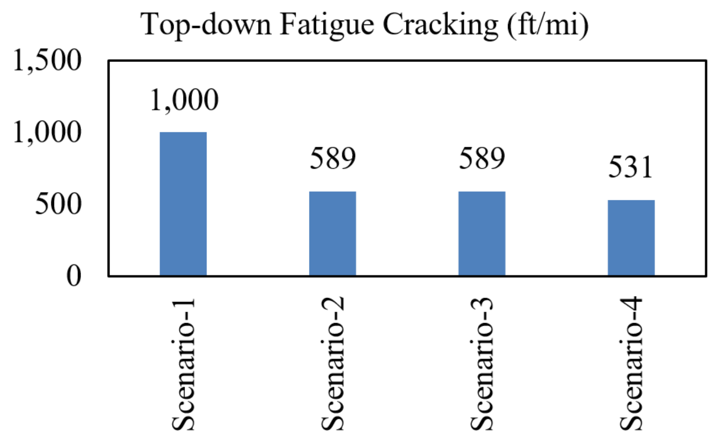


Fig. 4.14 Comparisons of Predicted Fatigue Cracking

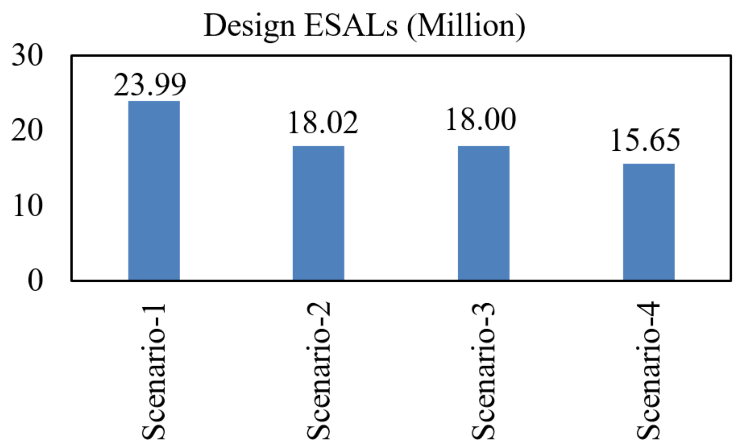


Fig. 4.15 Comparisons of Design ESALs

4.5 Prep-ME Software Implementation

Pavement ME Design provides users with the flexibility of preparing three levels of traffic inputs based on the availability of traffic data sets and the importance of the design project. Ideally, Level 1 traffic inputs for Pavement ME Design can be obtained from a WIM system operating continuously at the design site over extended periods of time. In practice, however, in most cases when new pavements are designed, no prior Level 1 traffic WIM data are available. In such case, Levels 2 traffic inputs are considered for design by combining existing site-specific data from WIM systems located on sites that exhibit similar traffic characteristics. Level 3 inputs provide the lowest level of accuracy, and typically average values for the region. Prep-ME can generate all the three traffic level of data for Pavement ME Design, as shown in Fig. 4.16.

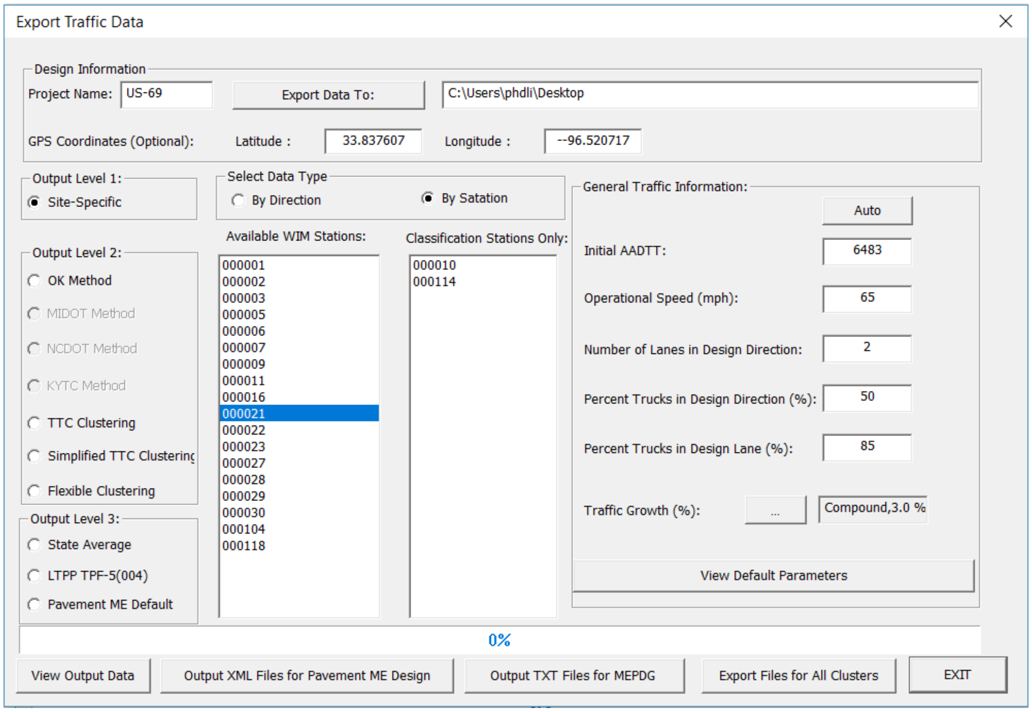


Fig. 4.16 Three-Level traffic outputs for Pavement ME Design

For Level 1 input, Prep-ME allows users to export site-specific traffic data “By Direction” or “By Station”. The data shown by station contains the average data for both directions whereas the data shown by direction is only for the specified direction.

Based on the analysis results presented in Section 4.4.1, a new clustering method is proposed for Level 2 traffic input in Oklahoma, and implemented in Prep-ME. The rural or urban classification, function class of highway, average daily truck traffic volume (AADT) and ratio of single unit and multiple unit trucks (SU/MU) are adopted as the clustering parameters for generating Pavement ME Design traffic inputs (Fig. 4.17). Three levels, low, medium, and high, are defined for the “SU/MU” and ADTT parameters. The traffic stations that meet the criteria of the four retrieving parameters will be used to generate Level 2 traffic inputs for Pavement ME Design.

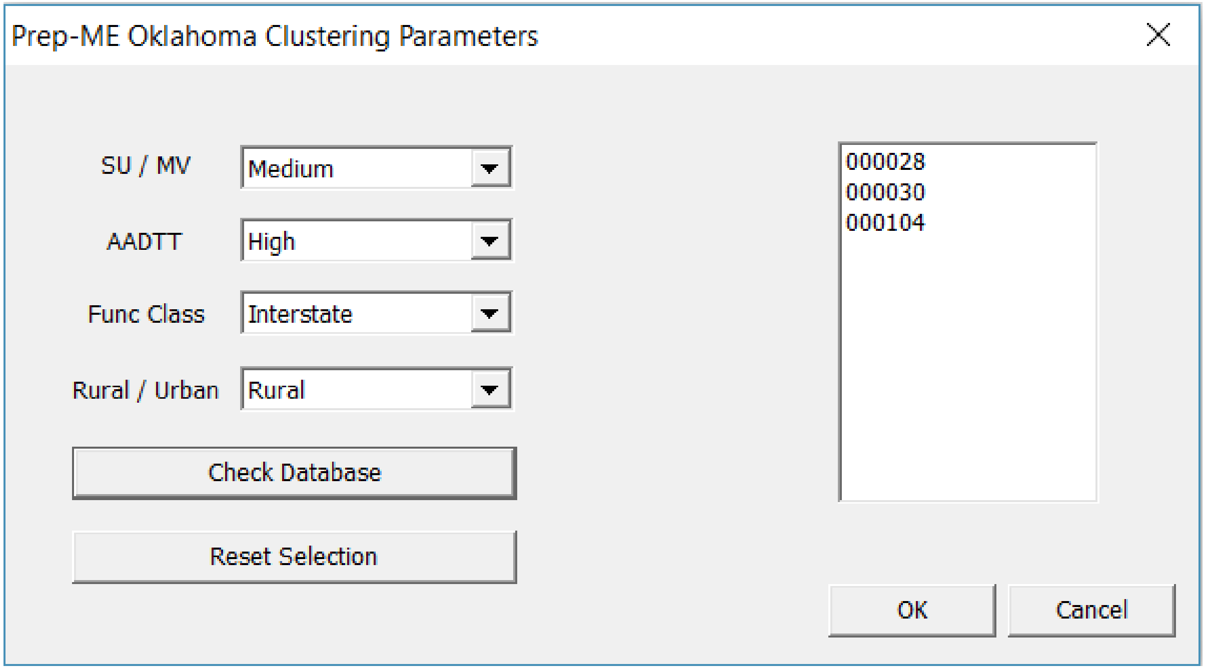


Fig. 4.17 Proposed ODOT Level 2 Method

In addition, the Prep-ME software includes the TTC approach and simplified TTC approach are shown in Fig. 4.18 and Fig. 4.19, which have much simpler user interfaces and less data requirements. The TTC approach requires manual traffic counts for vehicle classes 4, 5, 9, and 13 to determine the cluster of a pavement under design; while the simplified TTC approach only need engineers' judgment on the majority classes of trucks on a roadway. The two methods can be used for lower volume roads or design sites without relevant traffic data inputs.

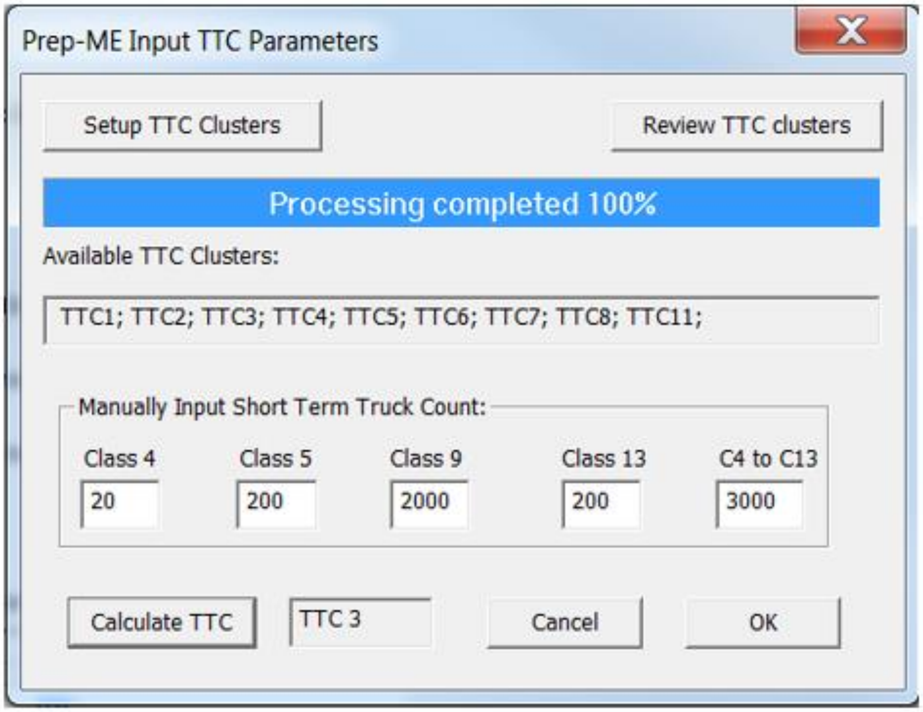


Fig. 4.18 TTC Approach

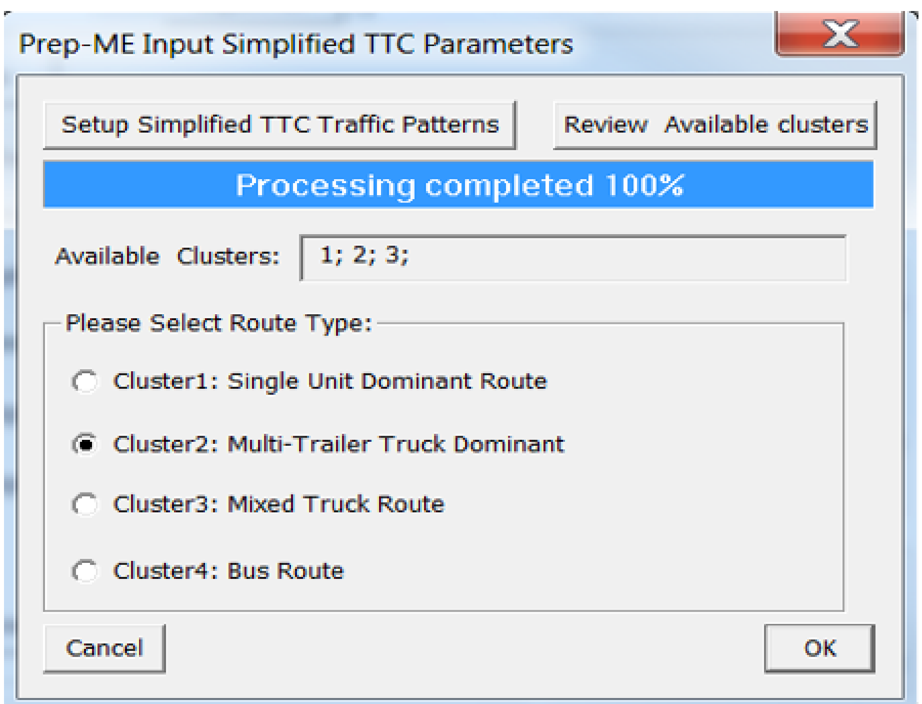


Fig. 4.19 Simplified TTC Approach

In many cases, traffic engineers are familiar with the traffic patterns on the highway segments where WIM stations are located. Based on local engineering judgment, traffic engineer may decide to use the data from the WIM stations on US-69 in Oklahoma, for example, for a major arterial pavement design in the same area. The "Flexible Clustering" method is available in the Prep-ME software that allows user to apply local engineering judgment and select WIM sites with similar traffic patterns for the traffic data preparation for Pavement ME Design, as shown in Fig. 4.20. Since "Flexible Clustering" doesn't use any statistical methodology, the desired number of clusters for each parameter is one. Users only need to manually select relevant WIM stations for traffic data export for the traffic parameters. The example in Fig. 4.20 uses all the WIM stations on US-69 to generate Single Axle Load Distribution factors.

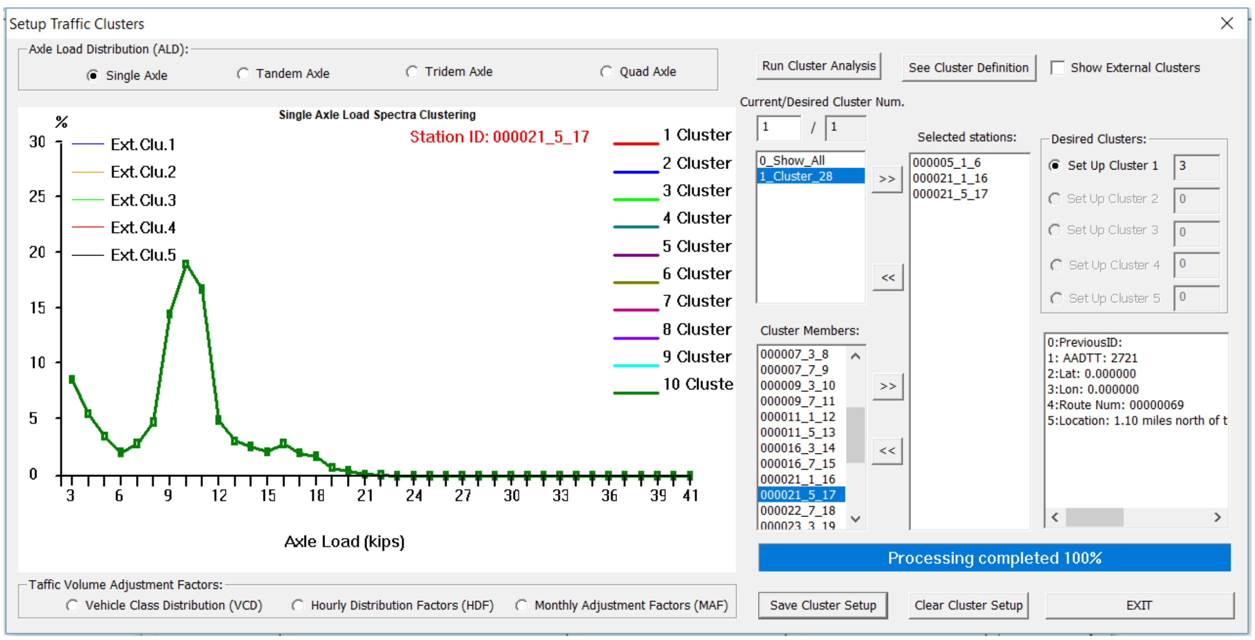


Fig. 4.20 Flexible Clustering Method

For level 3 output, three methods are provided in Prep-ME: State Average, LTPP-5(004) and Pavement ME Default.

For each output level, Prep-ME can automatically process Pavement ME Design required traffic data. By clicking "View Output Data" button in Fig. 4.21, users can view four types of traffic data: Vehicle Class Distribution (VCD), Hourly Distribution Factors (HDF), Monthly Adjustment Factors (MAF), Axle Load Distribution Factors (ALDF) including those for single, tandem, tridem, and quad axles, as shown in Figure 4.1. Prep-

ME also allows users to generate mixed levels of traffic inputs. The traffic files can be output in XML format for Pavement ME Design and text format for the MEPDG software. The generated output files can be directly imported to the ME design software, and greatly reduced pavement engineers' work load preparing traffic loading spectra data.

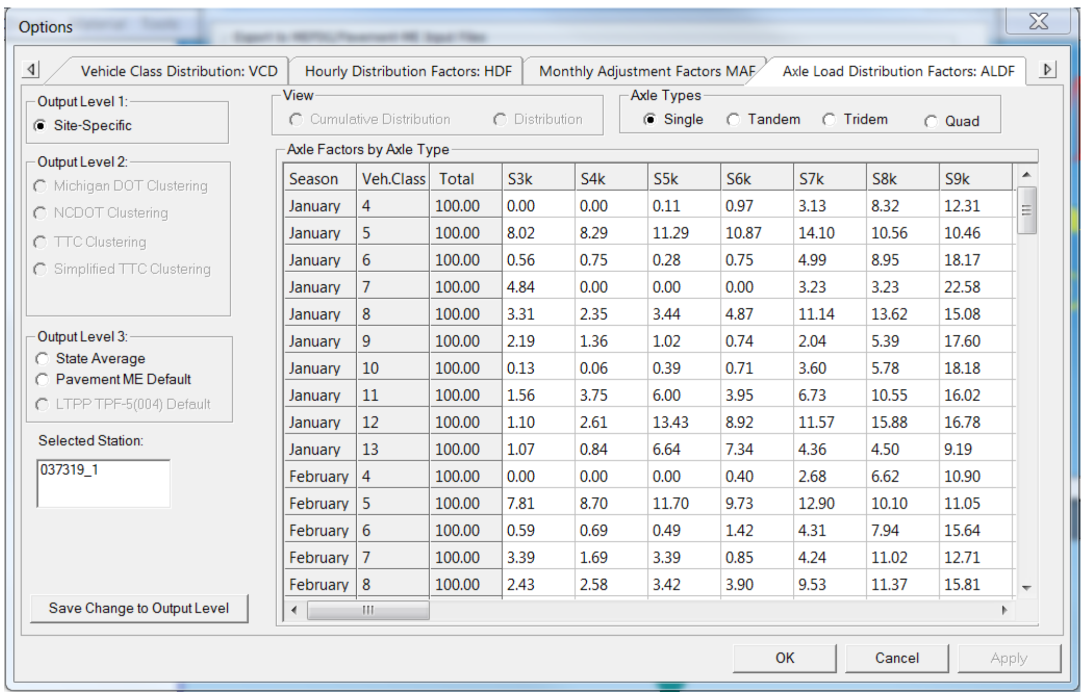


Fig. 4.21 Viewing Cluster Traffic Results

5. LTPP TRAFFIC INPUT DATA IN OKLAHOMA

5.1 LTPP Data Sources

The Long Term Pavement Performance (LTPP) issues Standard Data Release (SDR) each year. The SDR-27 (January, 2013) was used to develop the traffic input parameters for this study. In LTPP, each state is assigned a state code; Oklahoma's state code in LTPP is "40". According to the data supplied by ODOT, LTPP uses a total of 15 Weigh-in-Motion (WIM) stations from Oklahoma to collect the traffic data. Table 5.1 presents the locations of those WIM stations along with their Strategic Highway Research Program (SHRP) identity.

Table 5.1 WIM Sites with SHRP ID for Oklahoma

Site	Highway	Lane of study	Latitude	Longitude	* SHRP ID.
WIM001	US-75 / Bartlesville	North Bound	36.636900	-95.935092	4155
WIM001	US-75 / Bartlesville	South Bound	36.636900	-95.935092	4158
WIM003	I-240 / OKC	West Bound	35.391594	-97.449061	3018
WIM005	US-59 / Mazie	North Bound	36.074053	-95.364325	4157
WIM007	US-270 / Watonga	West Bound	35.841792	-98.468253	4163
WIM009	SH-3 / Ada	West Bound	34.755883	-96.687108	4160
WIM010	US-69 / McAlester	North Bound	35.068658	-95.704933	4166
WIM011	US-81 / Rush Springs	South Bound	34.730339	-97.958519	4154
WIM016	US-412 / Chouteau	West Bound	36.170183	-95.387408	5021
WIM022	SH-112 / Poteau	unknown	35.105667	-94.615008	6010
WIM023	US-412 / Ringwood	West Bound	36.391300	-98.285628	4165
WIM027	I-35 / Blackwell	South Bound	36.746233	-97.345475	0600
WIM104	I-35 / Edmond	North Bound	35.733764	-97.416647	7024
WIM118	US-62 / Cache	West Bound	34.638367	-98.655322	0500
WIM118	US-62 / Cache	East Bound	34.638367	-98.655322	0100

* SHRP ID are only the last four digits.

To check the quality of the LTPP traffic data and to compare this database with the developed traffic input parameters from the ODOT WIM sites using Prep-ME software, it was decided to develop traffic input parameters from the selected eight LTPP stations for different years. In general, three years of data from each of these eight LTPP stations were used for this purpose (e.g, 2007, 2009 and 2011). Fig. 5.1 presents these selected eight LTPP stations.

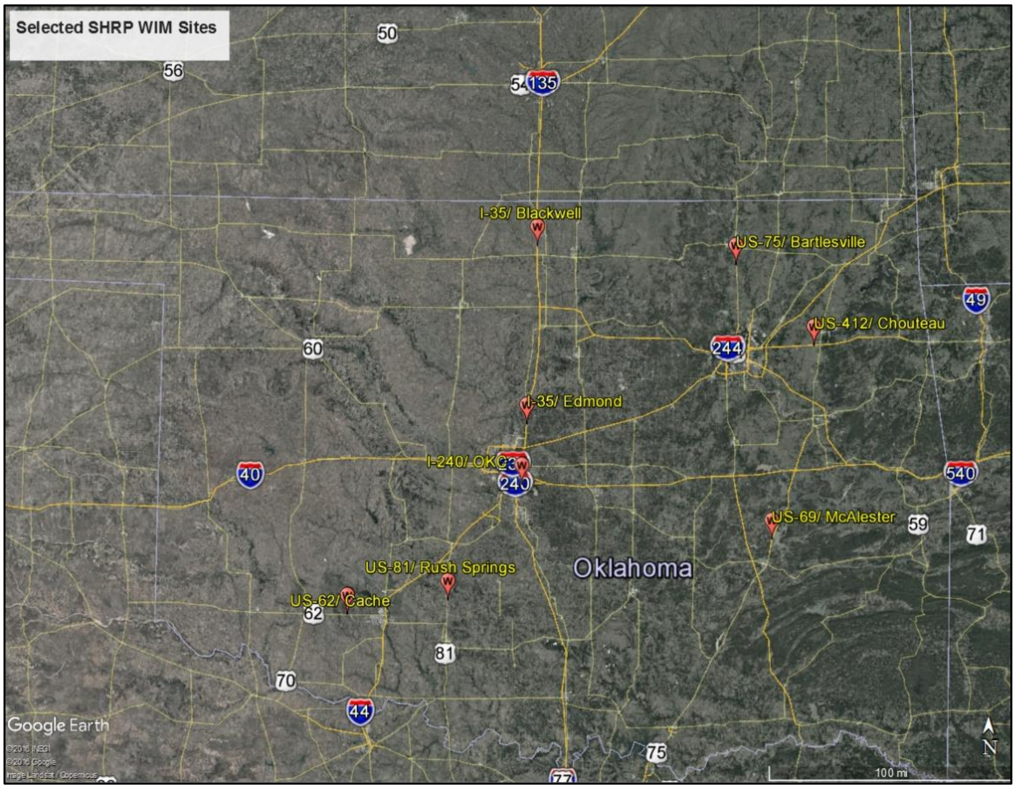


Fig. 5.1 Selected SHRP WIM Sites in Oklahoma

For the first year of the project, it was decided to develop and analyze the traffic input parameters from four stations located geographically approximately at four corners of the state. Those four stations are shown in Table 5.2:

Table 5.2 Data Analyses Performed for the LTPP WIM Sites

Site	Highway	Lane of study	Latitude	Longitude	* SHRP ID.
WIM010	US-69 / McAlester	North Bound	35.068658	-95.704933	4166
WIM016	US-412 / Chouteau	West Bound	36.170183	-95.387408	5021
WIM027	I-35 / Blackwell	South Bound	36.746233	-97.345475	0600
WIM118	US-62 / Cache	East Bound	34.638367	-98.655322	0100

In this study, three major types of traffic inputs were developed for the AASHTOWare software: a) Vehicle Class Distribution Factors, b) Monthly Adjustment

Factors, and c) Axle Load Spectra. These data were obtained from the LTPP database and then were analyzed and formatted in the AASTOWare software readable format. This database will be supplied to ODOT electronically so that the ODOT pavement engineer can call the data from the database easily using the AASTOWare software. Data from different stations and high level comparison between different stations are briefly described in the following paragraphs:

5.2 Vehicle Class Distribution

Vehicle Class Distribution Factors were developed using the vehicle classification guideline of the FHWA. FHWA divides all the vehicles traveling in the US highway in a total of 13 classes. It should be note that the developed VCD in this study from the LTPP sections are for truck traffic only (FHWA vehicle Class 4 through 13). Fig. 5.2 and Fig. 5.3 show the vehicle class distribution factors from three years of data for the SHRP stations 0100 (US 62/ Cache) and 5021 (US-412/ Chouteau), respectively. This can be observed from these figures that Class 9 vehicles had the highest percentage (approximately 40 to 60%) among all the trucks, followed by Class 5 vehicles (approximately 20 to 40%). However, the SHRP 5021 location has more Class 9 vehicles (percentage wise) than SHRP 0100 location. In addition, from the vehicle count data it was found that the SHRP 5021 location had approximately 0.4 million trucks compared to approximately 0.15 million trucks in the SHRP 0100 location.

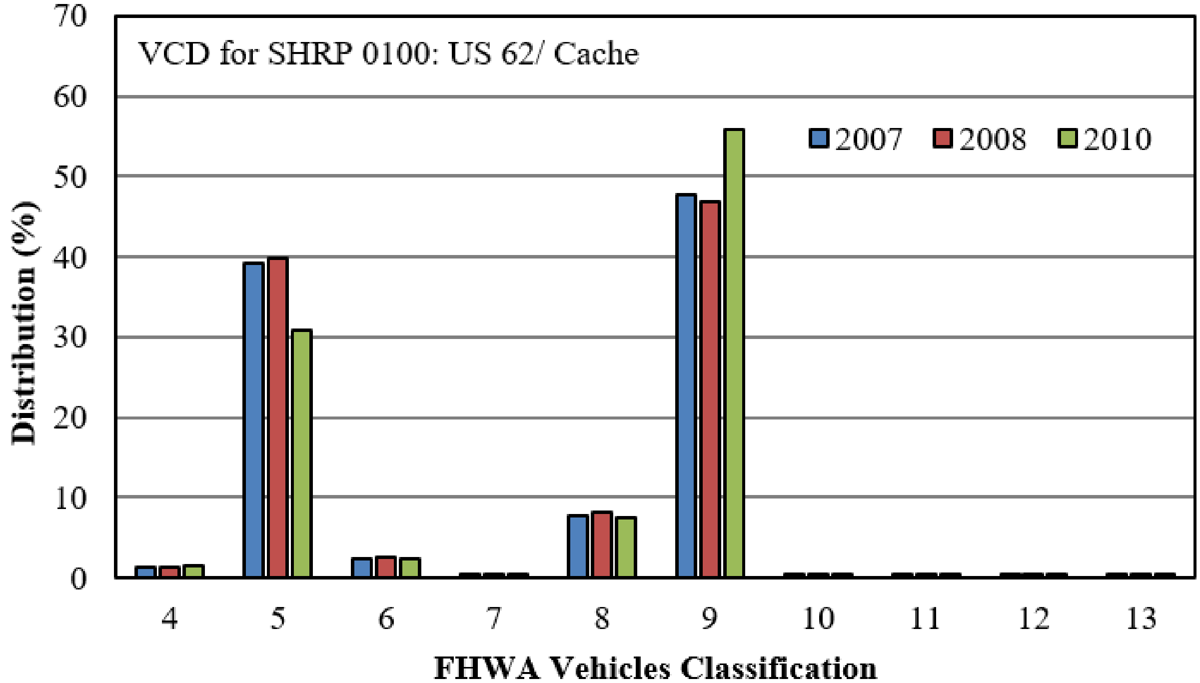


Fig. 5.2 VCD for SHRP 0100

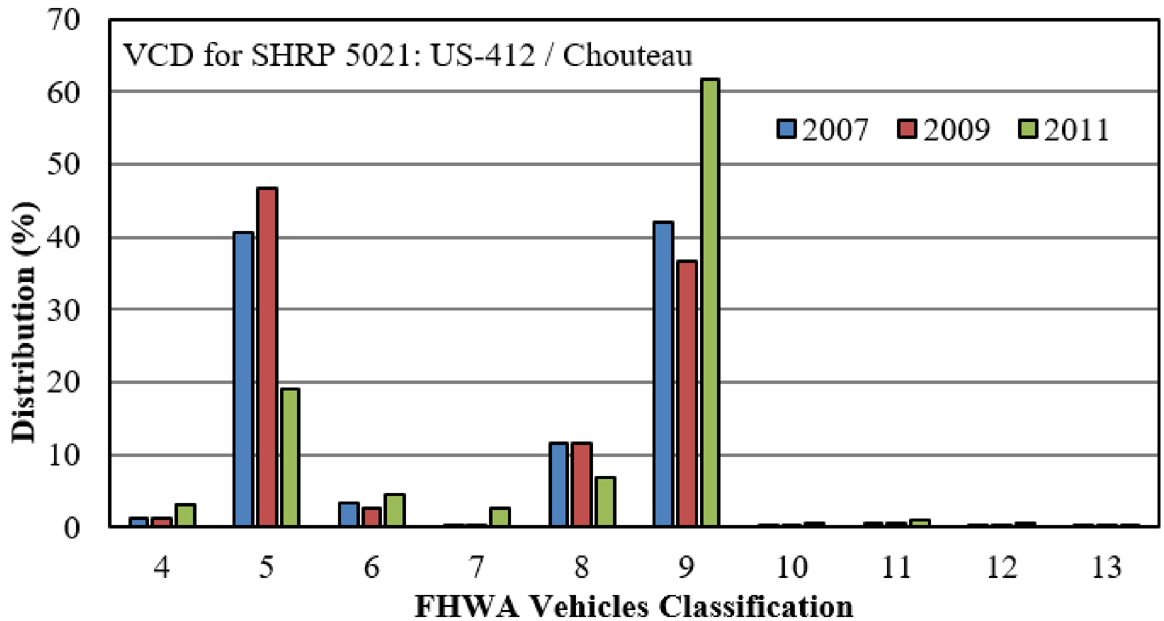


Fig. 5.3 VCD for SHRP 5021

Tables 5.3 and 5.4 also show the percentage of each vehicle class in the respective years, along with the minimum, maximum and standard deviation for the respective vehicle classes during these years for SHRP location 0100 and 5021, respectively. It was also observed from Tables 3.3 and 3.4 that Class 9 and Class 5 vehicles had the highest standard deviation on these two sites.

Table 5.3 VCD for SHRP site 0100

Year	VC4	VC5	VC6	VC7	VC8	VC9	VC10	VC11	VC12	VC13
2007	1.41	39.09	2.34	0.30	7.83	47.73	0.49	0.44	0.03	0.33
2008	1.25	39.74	2.61	0.25	8.08	46.95	0.51	0.32	0.03	0.27
2010	1.63	30.75	2.51	0.43	7.50	55.86	0.52	0.40	0.07	0.33
Min	1.25	30.75	2.34	0.25	7.50	46.95	0.49	0.32	0.03	0.27
Max	1.63	39.74	2.61	0.43	8.08	55.86	0.52	0.44	0.07	0.33
Standard Deviation (%)	0.15	4.09	0.11	0.08	0.24	4.03	0.01	0.05	0.02	0.03

Table 5.4 VCD for SHRP site 5021

Year	VC4	VC5	VC6	VC7	VC8	VC9	VC10	VC11	VC12	VC13
2007	1.23	40.61	3.25	0.09	11.49	42.03	0.36	0.54	0.25	0.14
2009	1.23	46.79	2.63	0.08	11.66	36.58	0.32	0.51	0.11	0.09
2011	3.06	19.07	4.44	2.77	6.94	61.60	0.50	0.94	0.59	0.11
Min	1.23	19.07	2.63	0.08	6.94	36.58	0.32	0.51	0.11	0.09
Max	3.06	46.79	4.44	2.77	11.66	61.60	0.50	0.94	0.59	0.14
Standard Deviation (%)	0.86	11.89	0.75	1.27	2.19	10.74	0.07	0.20	0.20	0.02

5.3 Monthly Adjustment Factors

The monthly adjustment factor (MAF) represents the proportion of annual truck traffic for a given class of a vehicle that occurs in a specific month. In other words, the monthly adjustment factors for a specific month is equal to the monthly truck traffic for a given class for the month divided by the total truck traffic for that truck class for the entire year. Tables 5.5 and 5.6 present the MAFs for 2007 from the SHRP sites 0100 and 5021, respectively. It can be observed from the tables that the MAFs varied from 0.15 to 3.15. Based on the standard deviation values reported in the tables, this can be observed that Class 7 vehicles had the maximum variation in MAF values in these two locations.

Table 5.5 MAF for SHRP site 0100 in 2007

Month	VC4	VC5	VC6	VC7	VC8	VC9	VC10	VC11	VC12	VC13
January	0.86	0.91	1.12	0.23	0.69	0.9	0.64	0.7	0.29	1.06
February	0.84	0.85	0.72	0.18	0.75	0.87	0.88	0.6	0.86	0.74
March	1.11	1.04	0.88	0.15	0.96	1	1.2	0.84	0.29	0.9
April	1.22	0.95	0.83	0.61	0.95	0.93	1.02	1.06	1.43	1.06
May	1.04	1.05	1.21	0.93	1.08	1.03	0.95	1.95	1.71	1.4
June	0.94	1	1.15	0.38	1.17	0.99	0.88	0.92	1.71	1.14
July	0.89	1.03	1.04	0.93	1.22	1.03	1	1.26	1.14	1.09
August	0.94	1.09	1.15	1.87	1.29	1.07	1.05	1.04	0.57	1.14
September	1.16	1.02	0.87	0.41	1.05	0.89	1.02	0.74	0.29	0.85
October	1.28	1.04	1.13	3.15	1.14	1.25	1.05	1.1	0.86	0.69
November	1.04	1.03	1.03	2.48	0.98	1.09	1.38	0.72	1.14	0.9
December	0.69	0.99	0.87	0.67	0.72	0.96	0.95	1.04	1.71	1.03
Min	0.69	0.85	0.72	0.15	0.69	0.87	0.64	0.60	0.29	0.69
Max	1.28	1.09	1.21	3.15	1.29	1.25	1.38	1.95	1.71	1.40
Mean	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Standard Deviation	0.17	0.06	0.15	0.94	0.19	0.10	0.17	0.34	0.54	0.19

Table 5.6 MAF for SHRP site 5021 in 2007

Month	VC4	VC5	VC6	VC7	VC8	VC9	VC10	VC11	VC12	VC13
January	0.61	0.83	0.72	1.2	0.57	0.77	0.72	0.68	0.47	0.65
February	0.84	1.06	0.87	1.73	0.74	0.98	0.77	0.9	0.96	1.01
March	1.19	1.3	1.1	1.23	1.06	1.18	1.17	1.01	0.87	1.47
April	1.04	1.2	1.04	1.17	0.96	1.02	1.19	0.97	0.76	1.11
May	1.16	1.49	1.07	1.03	1.13	1.06	1.13	1.11	0.74	0.92
June	0.99	0.83	0.93	0.8	1.02	0.86	0.69	0.97	0.94	0.8
July	0.98	1.12	1.18	0.97	1.31	1	1	1.17	1.15	1.21
August	1.13	1.15	1.2	1.33	1.24	1.05	1.39	1.25	1.37	1.21
September	1.02	0.83	0.9	0.63	1.2	0.98	1.11	1.03	1.22	1.07
October	1.21	0.82	1.04	0.67	1.2	1.11	1.09	1.08	1.29	0.86
November	0.99	0.71	1.04	0.7	0.89	1.08	0.91	1	1.34	0.86
December	0.84	0.66	0.92	0.53	0.68	0.93	0.83	0.83	0.9	0.84
Min	0.61	0.66	0.72	0.53	0.57	0.77	0.69	0.68	0.47	0.65
Max	1.21	1.49	1.20	1.73	1.31	1.18	1.39	1.25	1.37	1.47
Mean	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Standard Deviation	0.17	0.25	0.13	0.34	0.23	0.11	0.21	0.15	0.27	0.22

5.4 Axle Load Distribution

The axle load distribution factors represent the percentage of total axle applications within each load interval for a specific axle type and vehicle class (classes 4 to 13). Definition of load intervals for different axle types is provided below:

- Single Axles: 3 kips to 40 kips, at 1-kip interval.
- Tandem Axles: 6 kips to 80 kips, at 2 kips interval.
- Tridem and Quadrem Axles: 12 kips to 102 kips at 3 kips interval.

Axle load spectra for four axle types (single, tandem, tridem and quad) for all vehicles were developed using the LTPP WIM data for approximately three years for each stations. The axle load spectra were developed in the AASHTOWare readable format and will be supplied to ODOT. For reporting purposes, Tables 5.7 and 5.8 represent the single and tandem axle load spectra developed only for the year of 2007 for SHRP site 5021. This can be observed from the tables that all the vehicle classes have single axles. Class 5 did not have tandem axles, so axle load spectra for these vehicle classes were unavailable and therefore was shown as 0.00 in the Table 5.8.

Since, it was observed that Class 9 vehicles are predominant (approximately 40 to 60%), among all vehicle classes, axle load distribution for Class 9 was further analyzed. Fig. 5.4 and Fig. 5.5 show the axle load spectra for the year 2007 of SHRP sites 0100 and 5021 for the single and tandem axles of Class 9 vehicles, respectively. It is observed from Fig. 5.4 that for single axles the distribution peaks around 11-kips axle loads, which is the expected range for Class 9 single axles (Tran and Hall, 2007). It can be observed from Fig. 5.5 that there are two distinct peaks for the tandem axle distribution: one between 10 and 16-kips, and the other between 26 and 34-kips.

Table 5.7 Single-Axle Load Spectra for 2007 of SHRP site 5021

Axle Load (lb)	VC4	VC5	VC6	VC7	VC8	VC9	VC10	VC11	VC12	VC13
3,000	0.00	9.94	0.23	1.28	4.53	0.57	0.13	0.00	0.00	0.00
4,000	0.00	34.91	0.90	1.88	14.18	2.40	1.06	0.83	10.33	0.55
5,000	0.00	24.51	1.87	2.02	20.19	3.63	1.76	3.95	30.37	3.37
6,000	0.11	13.73	5.48	4.15	19.74	3.15	2.55	8.99	11.35	7.38
7,000	0.65	4.59	7.15	5.11	10.11	1.90	3.10	8.49	3.79	7.06
8,000	23.14	3.62	9.61	3.59	9.67	5.93	8.06	10.98	10.20	11.57
9,000	14.71	2.24	13.15	9.32	6.61	14.38	14.09	13.96	10.39	16.03
10,000	17.05	2.15	23.64	16.45	5.73	31.97	29.29	16.89	6.72	19.04
11,000	13.01	1.18	14.35	11.74	2.94	19.30	22.24	8.04	2.67	10.79
12,000	12.45	0.96	10.75	13.57	2.03	7.54	11.22	8.15	3.16	7.55
13,000	5.87	0.50	5.09	7.11	1.23	1.67	3.29	5.58	2.67	4.94
14,000	5.19	0.45	3.71	9.76	0.89	1.65	1.39	5.41	2.70	3.25
15,000	2.78	0.39	1.78	6.00	0.70	1.74	0.83	3.80	2.37	2.24
16,000	1.72	0.23	0.98	3.33	0.38	1.32	0.29	2.41	1.24	1.27
17,000	1.42	0.20	0.76	2.36	0.32	1.22	0.35	1.35	0.85	1.45
18,000	0.75	0.11	0.35	0.00	0.18	0.64	0.16	0.54	0.52	0.92
19,000	0.46	0.07	0.12	0.94	0.17	0.46	0.06	0.41	0.37	0.88
20,000	0.24	0.03	0.04	0.00	0.10	0.22	0.13	0.13	0.21	0.53
21,000	0.21	0.03	0.03	1.39	0.10	0.16	0.00	0.03	0.06	0.48
22,000	0.09	0.02	0.00	0.00	0.07	0.06	0.00	0.04	0.02	0.17
23,000	0.08	0.02	0.00	0.00	0.06	0.04	0.00	0.01	0.02	0.26
24,000	0.03	0.01	0.00	0.00	0.03	0.02	0.00	0.00	0.00	0.09
25,000	0.00	0.02	0.00	0.00	0.02	0.02	0.00	0.01	0.00	0.10
26,000	0.02	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.09
27,000	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00
28,000	0.01	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
29,000	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
30,000	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31,000	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32,000	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33,000	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
34,000	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
35,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
36,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
37,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
38,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
39,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
40,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
41,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 5.8 Tandem-Axle Load Spectra for 2007 of SHRP site 5021

Axle Load (lb)	VC4	VC5	VC6	VC7	VC8	VC9	VC10	VC11	VC12	VC13
6,000	0.00	0.00	0.74	0.24	5.15	0.85	0.48	0.00	0.00	0.00
8,000	0.33	0.00	4.79	0.72	8.88	3.58	1.13	0.00	3.14	0.81
10,000	4.85	0.00	14.40	1.75	10.46	8.20	0.99	0.00	34.58	13.50
12,000	12.31	0.00	11.60	2.28	16.50	11.90	3.42	6.13	21.74	13.76
14,000	9.41	0.00	10.37	0.23	19.79	11.84	5.43	22.50	5.21	11.59
16,000	7.69	0.00	6.37	1.62	13.48	7.72	9.95	24.23	3.83	11.09
18,000	4.97	0.00	3.69	2.40	8.24	5.39	11.15	23.80	8.18	7.69
20,000	7.11	0.00	3.71	1.39	4.86	4.89	9.41	8.32	7.09	6.50
22,000	9.43	0.00	5.01	2.45	3.39	5.42	8.74	5.04	4.38	4.51
24,000	9.59	0.00	4.90	5.30	2.40	6.38	9.26	4.15	2.18	3.09
26,000	9.33	0.00	5.02	7.83	1.85	7.54	6.84	2.42	1.31	3.05
28,000	8.47	0.00	5.16	9.94	1.32	8.07	8.18	1.74	2.00	3.63
30,000	6.49	0.00	5.11	9.92	1.04	6.93	6.72	0.74	1.27	2.98
32,000	3.84	0.00	5.48	7.53	1.03	5.18	5.42	0.93	1.40	3.93
34,000	2.92	0.00	4.54	2.53	0.70	3.17	4.04	0.00	1.99	3.00
36,000	1.04	0.00	2.97	3.06	0.38	1.60	3.17	0.00	0.37	2.45
38,000	0.59	0.00	2.26	6.83	0.21	0.77	2.32	0.00	0.34	2.23
40,000	0.83	0.00	1.54	6.25	0.13	0.33	1.66	0.00	0.27	1.47
42,000	0.39	0.00	0.92	3.24	0.08	0.14	0.58	0.00	0.36	1.46
44,000	0.23	0.00	0.70	6.58	0.05	0.06	0.23	0.00	0.19	1.19
46,000	0.10	0.00	0.37	2.12	0.02	0.03	0.20	0.00	0.19	0.94
48,000	0.00	0.00	0.17	3.03	0.02	0.01	0.15	0.00	0.00	0.66
50,000	0.05	0.00	0.13	2.71	0.01	0.00	0.24	0.00	0.00	0.34
52,000	0.00	0.00	0.04	2.17	0.00	0.00	0.21	0.00	0.00	0.00
54,000	0.00	0.00	0.02	1.48	0.00	0.00	0.00	0.00	0.00	0.00
56,000	0.00	0.00	0.00	1.55	0.00	0.00	0.00	0.00	0.00	0.00
58,000	0.00	0.00	0.01	1.30	0.00	0.00	0.08	0.00	0.00	0.00
60,000	0.04	0.00	0.00	1.23	0.00	0.00	0.00	0.00	0.00	0.14
62,000	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.00
64,000	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.00	0.00	0.00
66,000	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.00	0.00	0.00
68,000	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00
70,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
72,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
74,000	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.00
76,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
78,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
80,000	0.00	0.00	0.00	0.62	0.00	0.00	0.00	0.00	0.00	0.00
82,000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

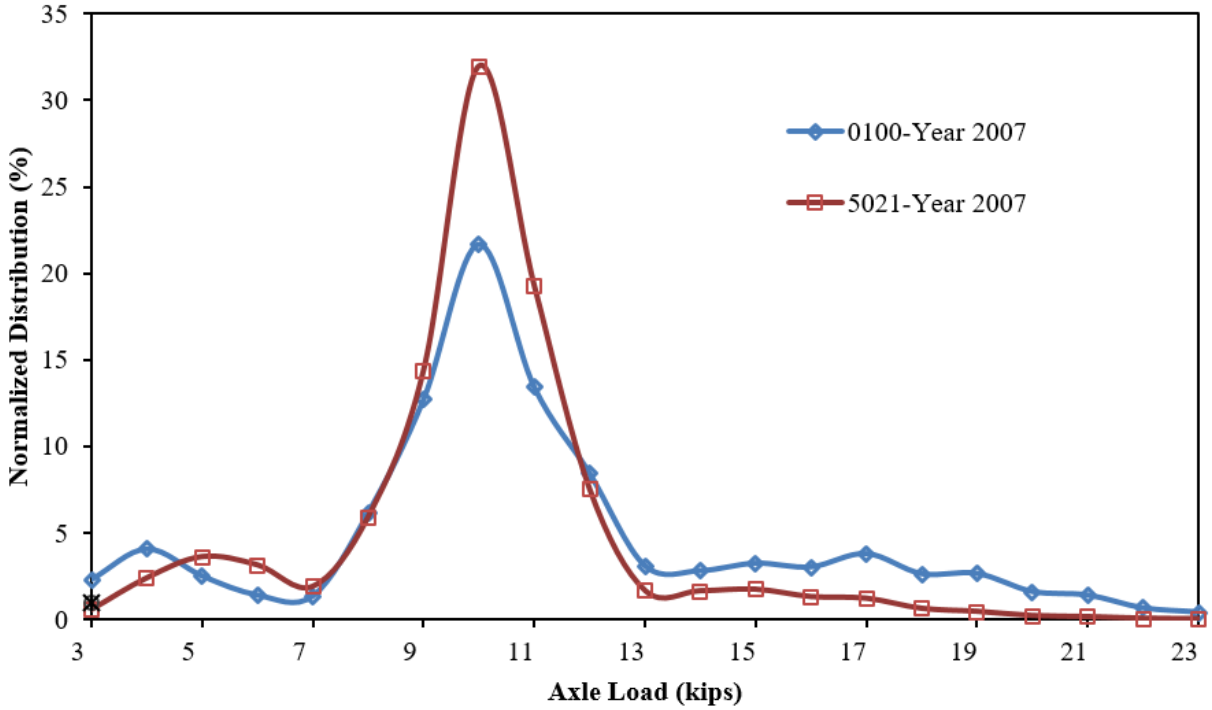


Fig. 5.4 Class-9 Single Axle Load Spectra for SHRP sites 0100 and 5021

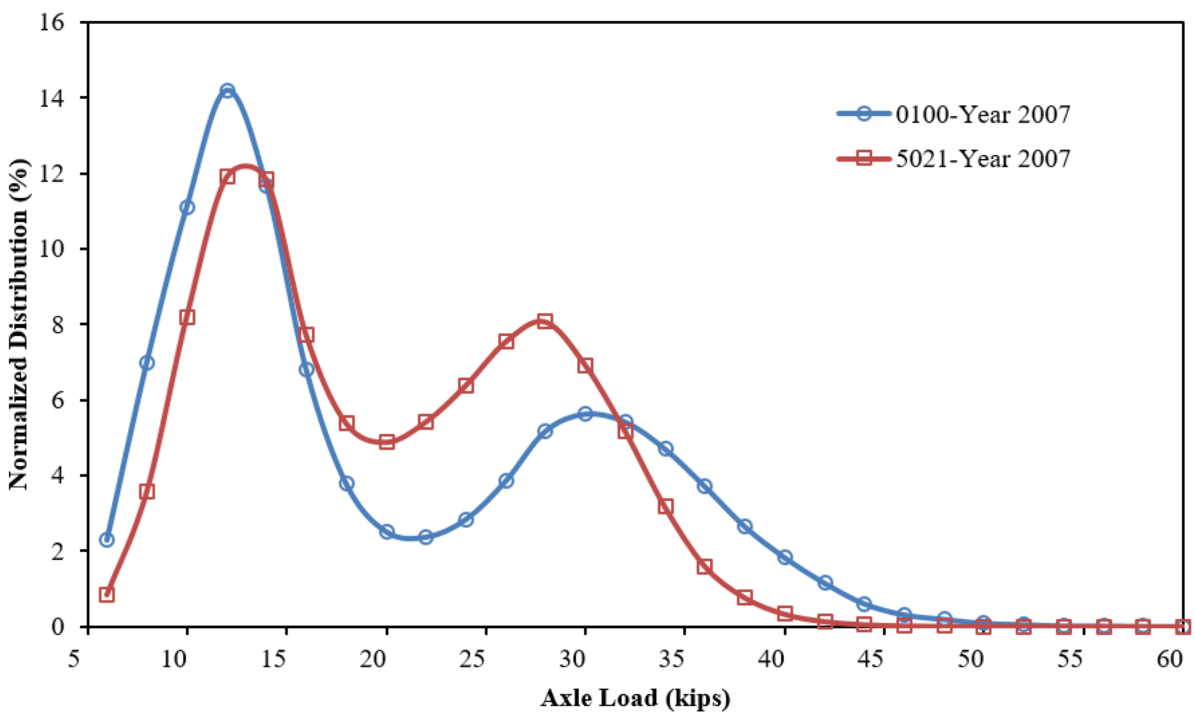


Fig. 5.5 Class-9 Tandem Axle Load Spectra for SHRP sites 0100 and 5021

6. MATERIAL DATA IN OKLAHOMA FOR PAVEMENT ME DESIGN

6.1 Introduction

Good quality materials data are essential for efficient pavement design using MEPDG. Throughout the years, ODOT and OkTC has sponsored multiple projects in producing these data. Among these data, particular area of interest is focused on three types of valuable materials input for flexible pavements: resilient modulus (Mr) data for natural subgrade, stabilized subgrade, and aggregate base materials; dynamic modulus data for asphalt mixes, and dynamic shear modulus and phase angle data for asphalt binders. Through this project, the research team has investigated the available data for (1) the resilient modulus of Oklahoma subgrade materials, and (2) dynamic modulus of asphalt mixes along with phase angle data of asphalt binders, and also performed the quality check of those data sets. In addition, software interfaces have been developed for users to retrieve material inputs for the AASHTOWare Pavement ME Design software.

6.2 Resilient Modulus Data

6.2.1 Natural Subgrade

The ODOT database on the natural subgrade's resilient modulus is an extensive one which consists of over 10,000 resilient modulus values. Geographical locations of the sampling sites for the Mr database of natural subgrade materials are shown in Fig. 6.1. The database included the resilient modulus values from a wide range of soil series (B and C horizon) prevalent in Oklahoma. In addition, the database also included different types of soils comprising of clay, sand and silt mostly obtained by the "In-place Soil Survey" and "Shoulder Soil Survey" from ODOT projects. The quality control review of the resilient modulus data from the unbound natural subgrade have been carefully checked by working closely with ODOT engineers. The QC process divides the resilient moduli data into three classifications: a) Good, b) Bad, and c) Questionable data. This database can be further sorted out based on the county, soil series, soil types, ODOT divisions etc.

These data after QC process are then included in the Prep-ME software so that ODOT engineers can call the data from a unified Mr database.

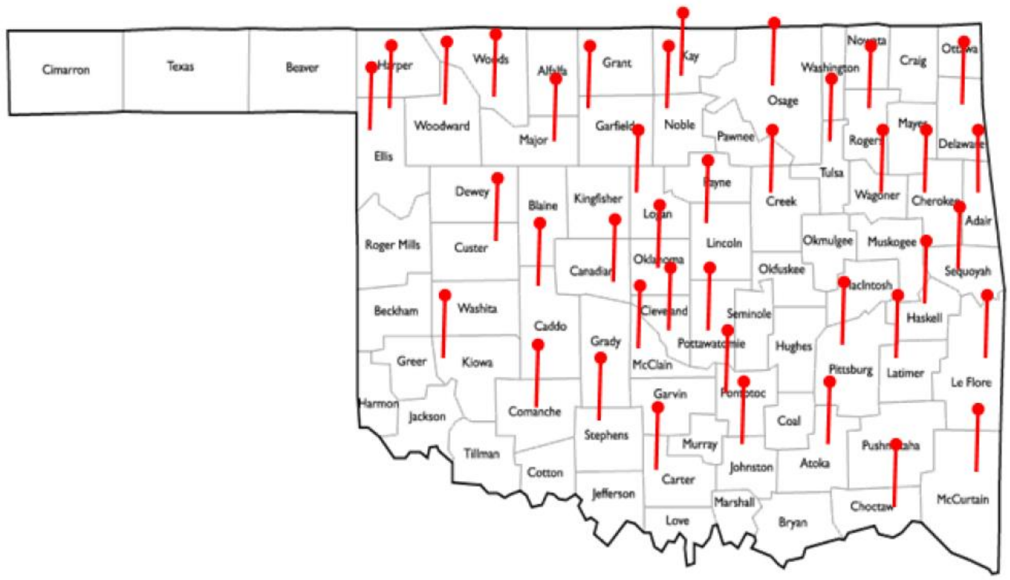


Fig. 6.1 Location of M_R sampling sites (Hossain et al., 2011)

6.2.2 Stabilized Subgrade

The ODOT Mr database for the stabilized subgrade consists of soils from four different soil series: Carnasaw series (C-soil; 39 samples), (2) Port series (P-soil: 35 samples), (3) Kingfisher series (K-soil: 31 samples), and (4) Vernon series (V-soil: 34 samples). These soils were classified as A-4 (P-soil), A-6 (K- and V-soil), and A-7-6 (C-soil), as shown in Fig. 6.2. Each soil series were mixed with three different stabilizing materials commonly used in Oklahoma: hydrated lime (0%, 3%, 6%, 9% by dry soil unit weight), Class C fly ash (0%, 5%, 10%, and 15% by dry soil unit weight), and Cement Kiln Dust (CKD) (0%, 5%, 10%, and 15% by dry soil unit weight).

Details regarding the stabilization and discussions on the effects of stabilizing agents have been reported in Hossain et al. (2011) and Solanki et al. (2010). It was observed that stabilizing the soil increased their Mr values significantly. For example, 3% lime increased the Mr values of P-, K-, V-, and C-soils approximately by 435%, 1,647%, 914%, and 123%, respectively. Although the addition of stabilizing agents increased the Mr values from the unstabilized cases, a reduction in Mr values were observed beyond a certain percentage of lime. For example, K-soil specimens stabilized with 9% lime showed a 28% decrease in Mr values as compared to specimens stabilized with 6% lime (Solanki et al., 2010). In case of CFA, 15% additive showed a maximum increase in Mr values of approximately 983%, 1,449%, 1,203%, and 215% for P-, K-, V- and C-soil, respectively, as compared to raw soil. Similar to CFA, 15% CKD showed the maximum increase in Mr values for all four soil types. With 15% CKD, the Mr values increased as much as 1,963%, 2,998%, 2,001%, and 691% for P-, K-, V-, and C-soil, respectively (Hossain et al., 2011). Fig. 6.3 shows the variation of Mr values with different soil and additive types.

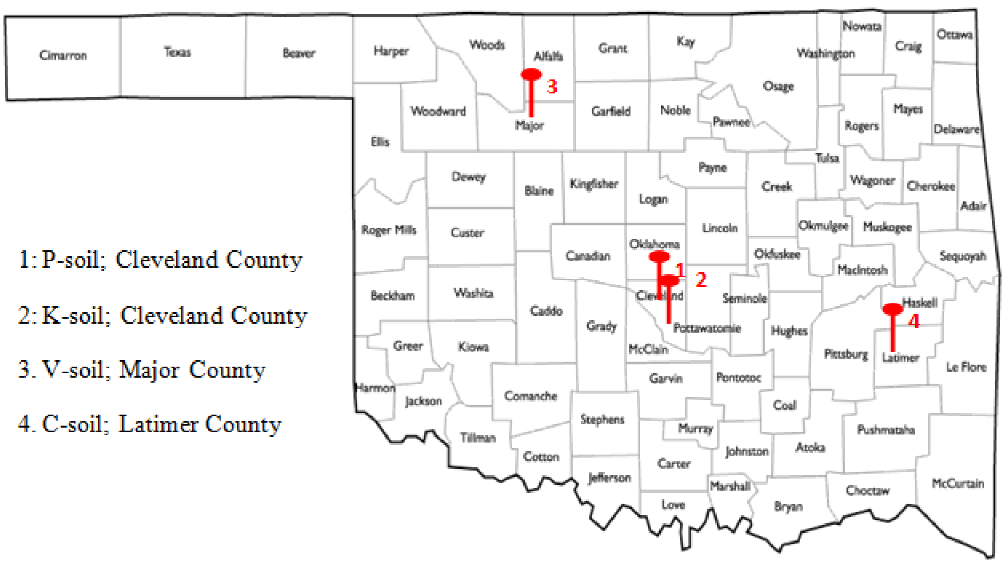


Fig. 6.2 Location Map of Stabilized Subgrade Source Sites

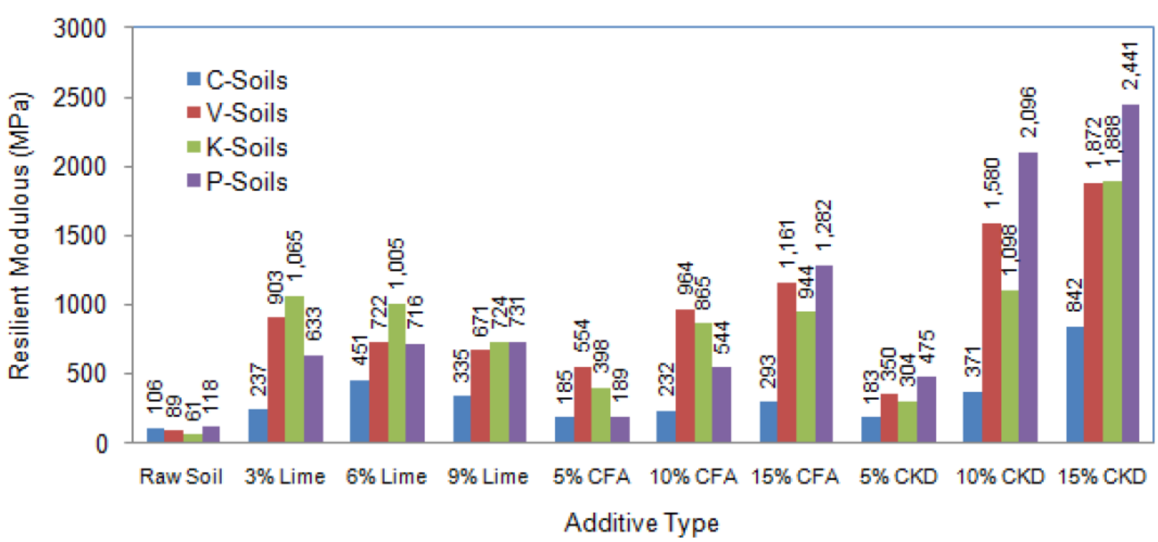


Fig. 6.3 Variation of M_R values with Soil and Additive Type (σ_d = 6 psi, σ_3 = 4 psi) (Hossain et al., 2011)

6.2.3 Aggregate Base

A total of 105 samples from two commonly used aggregates (limestone and sandstone) were tested to develop the Mr database for aggregate base materials in Oklahoma (Hossain et al., 2011). Limestone aggregates were obtained from Meridian quarries in Marshal County, and from Richard Spurs quarries in Comanche County; whereas Sandstone aggregates were from Sawyer quarry in Choctaw County, as shown in Fig. 6.4.

Default Mr values for limestone and sandstone aggregates are calculated using the average material constants obtained from regression modeling and are presented in Table 6.1. These Mr values can be used as Level 3 input in the MEPDG analysis and design. It was observed that the predicted typical Mr values obtained from different models are in agreement with each other, and the variations of Mr values among different models were within 4%. However, all of these models would result in conservative designs compared to the MEPDG recommended typical values. In general, limestone aggregate showed higher (51%) Mr values than those of sandstone aggregate. This could be due to the fact that Richard Spurs or Meridian limestone aggregate contained bigger size particles with higher interlocking potential than Sawyer sandstone aggregates. According to the AASHTO T 145 specifications, all these aggregates are classified as A-2-4.

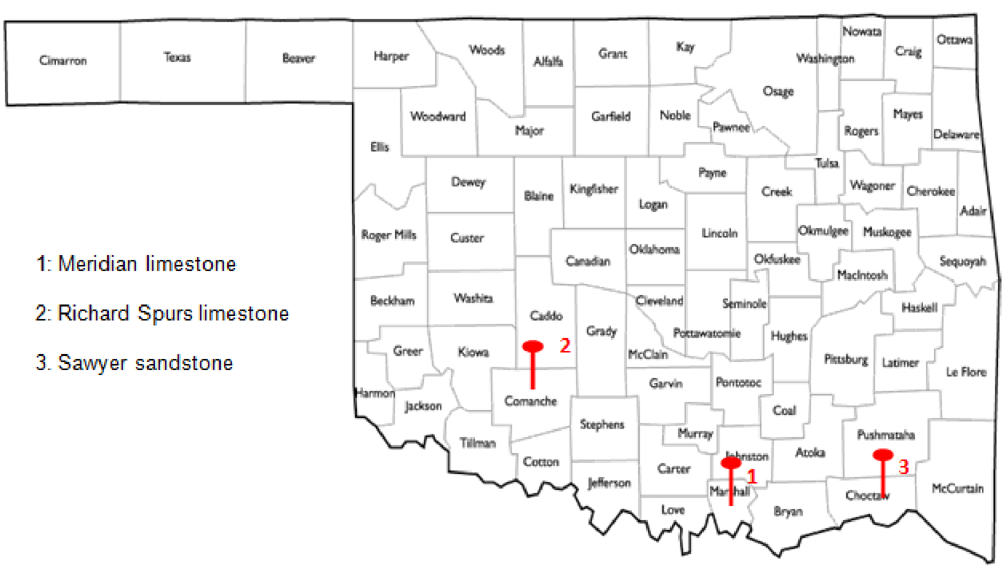


Fig. 6.4 Location Map of Base Aggregate Source Sites.

Table 6.1 Recommended Mr Values for Tested Oklahoma Aggregates

Aggregate Source and Type	AASHTO Classification	MEPDG Default, ksi (MPa)	Estimated from Model 2, ksi (MPa)	Estimated from Model 3, ksi (MPa)	Estimated from Model 4, ksi, (MPa)
Meridian & RS Limestone	A-2-4	32.0 (220.63)	14.1 (97.42)	14.3 (98.40)	14.2 (98.03)
Sawyer sandstone	A-2-4	(32.0) (220.63)	9.0 (62.35)	9.4 (65.12)	9.3 (64.03)

6.3 Dynamic Modulus Data

6.3.1 Asphalt Binder

Literature review was performed to search for the existing test information regarding the asphalt binders. Dynamic Shear Modulus (G*) and Phase Angle (δ) values are required as Level 1 input for the asphalt binder in the AASTOWare software. A report titled "Development of Flexible Pavement Database for Local Calibration of MEPDG (SPR 2209), June (2011) (Hossain et al., 2011)" was particularly helpful in finding the data on the asphalt binders. Three different Performance Grade (PG) binders are typically used in Oklahoma: PG 64-22, PG 70-28, and PG 76-28. In the referenced study (Hossain et al., 2011), these three types of binder were collected from three different refineries in Oklahoma: NuStar from Catoosa, Valero from Ardmore, and Asphalt Terminal and Transportation (ATT) from Muskogee. Superpave binder test protocol (AASTO T315) were followed to determine the G* and δ of these binders. Table 6.2 presents the G* and δ values for these three different types of binder at various testing temperatures.

Table 6.2 MEPDG Level 1 Inputs of Asphalt Binders

Binder Type	Testing Temp. (°C)	NuStar @ Catoosa: G* (kPa)	NuStar @ Catoosa: δ (deg)	Valero @ Ardmore: G* (kPa)	Valero @ Ardmore: δ (deg)	ATT @ Muskogee: G* (kPa)	ATT @ Muskogee: δ (deg)
PG64-22	54.4	9.28	80.63	10.32	78.70	13.80	81.20
PG64-22	46.1	32.47	76.10	34.20	73.60	48.99	76.90
PG64-22	43.3	46.98	74.70	56.52	71.00	75.55	74.80
PG64-22	29.4	344.36	63.77	402.11	63.70	407.86	66.60
PG64-22	21.1	1030.38	60.77	1869.11	45.50	911.32	48.30
PG64-22	12.7	4870.00	55.90	4574.00	48.80	8606.19	50.80
PG64-22	4.4	18300.00	53.30	23778.84	47.00	19848.75	49.60
PG70-28	54.4	12.14	65.70	15.54	49.40	12.20	63.30
PG70-28	46.1	28.31	64.60	32.92	51.30	31.80	63.80
PG70-28	43.3	40.56	64.20	44.01	51.90	46.27	64.10
PG70-28	29.4	268.41	60.80	229.39	54.20	333.00	63.50
PG70-28	21.1	1061.36	54.40	861.58	49.20	1720.00	52.00
PG70-28	12.7	4040.00	52.20	3796.25	49.10	4155.00	50.60
PG70-28	4.4	15200.00	50.40	13875.00	48.10	14528.50	48.40
PG76-28	54.4	13.93	59.40	14.09	50.30	12.64	59.90
PG76-28	46.1	33.39	59.40	30.03	51.90	30.79	61.30
PG76-28	43.3	47.15	59.40	40.47	52.40	44.05	62.00
PG76-28	29.4	274.68	58.80	181.40	56.60	322.22	62.90
PG76-28	21.1	1025.48	52.70	548.47	58.10	1478.04	53.30
PG76-28	12.7	5010.00	53.80	3287.20	47.50	5823.44	52.30
PG76-28	4.4	17800.00	51.80	13726.25	46.50	20450.98	46.00

6.3.2 Asphalt Mix

The dynamic modulus (E*) of hot-mix asphalt (HMA) is one of the key parameters used to evaluate both rutting and fatigue cracking distresses in the MEPDG. Many state agencies, including ODOT, have conducted comprehensive dynamic modulus laboratory testing based on state local materials and mix design specifications.

Dynamic modulus values for the mixes were measured in the laboratory in accordance with AASHTO TP62 specifications. Tests were performed using a mechanical testing system (MTS) equipped with a servo-hydraulic testing system. The test specimen was placed in an environmental chamber and allowed to reach equilibrium to the specified testing temperature ±0.5oC. The specimen temperature was monitored using a dummy specimen with a thermocouple mounted at the center. Two linear variable differential transducers (LVDTs) were mounted on the specimen at 100 mm gauge length. Two friction reducing end treatment or teflon papers were placed between the specimen and loading platens. A sinusoidal axial compressive load was applied to the specimen without impact in a cyclic manner. The test was conducted on each specimen at four different temperatures: 4, 21, 40, and 55^{0}C, starting from the lowest temperature and going to the highest temperature. For each temperature level, the test was conducted at different loading frequencies from the highest to the lowest: 25, 10, 5, 1, 0.5, and 0.1 Hz. Prior to testing, the specimen was conditioned by applying 200 cycles of load at a frequency of 25 Hz. The load magnitude was adjusted based on the material stiffness, temperature, and frequency to keep the strain response within 50-150 micro-strains (Tran and Hall, 2006). The data was recorded for the last 5 cycles of each sequence. Dynamic modulus values were calculated for combinations of temperatures and frequencies. Thereafter, the master curves were constructed using the principle of time-temperature superposition and approach developed by Bonaquist et al. (2005). The amount of shifting at each temperature required to form the master curve describes the temperature dependency of the material. First, a standard reference temperature is selected (i.e., 21°C), and then data at various temperatures are shifted with respect to time until the curves merge into a single smooth function.

Fig. 6.5 shows a general master curves developed for S3 and S4 mixes in Oklahoma. It can be seen that the mix (S3) has a higher dynamic modulus values compared to the top layer mix (S4) for different combinations of temperature and frequency. These master curves are required to estimate the dynamic modulus values for both the mixes at wide range of temperature encountered in the field.

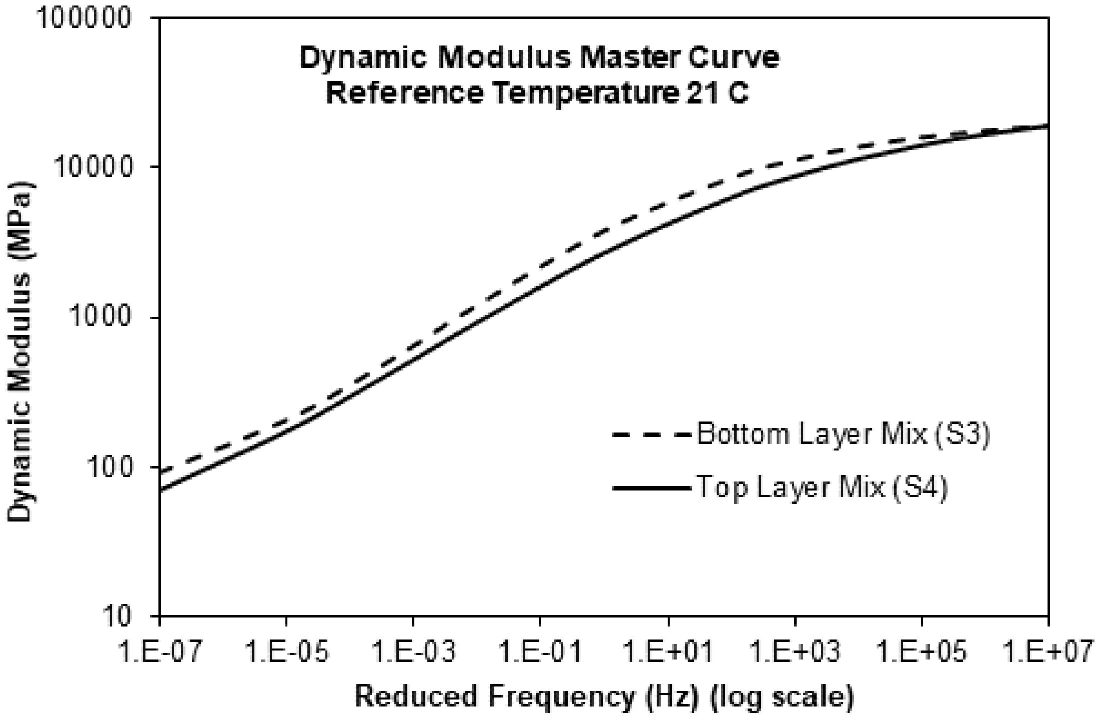


Fig. 6.5 Dynamic Modulus Master Curve for Top (Surface) S4 Mix and Bottom (Base) S3 Mix

6.4 Prep-ME Software Implementation

In the Prep-ME software, two features have been developed to integrate material data sets in the database. Firstly, the extensive ODOT resilient modulus database for the natural subgrade after manual quality checks are populated into the Prep-ME database, and software interface is customized for the data sets, as shown in Fig. 6.6. The Prep-ME software can retrieve resilient modulus data of natural subgrade soils based on site name, soil series, and soil classification (either USCS or AASHTO method). It is noted that the data for stabilized soils and base aggregates are not implemented in the Prep-ME since the numbers of available samples are very limited.

Secondly, the currently available dynamic modulus testing data in Oklahoma are populated into the Prep-ME database. The Prep-ME software can retrieve dynamic modulus data based on binder grade, air void level, mix type, and refinery (Fig. 6.7). Users can not only view the retrieved testing data for dynamic modulus, asphalt binder properties, and mix design, but also export the data for directly importing into the Pavement ME Design software.

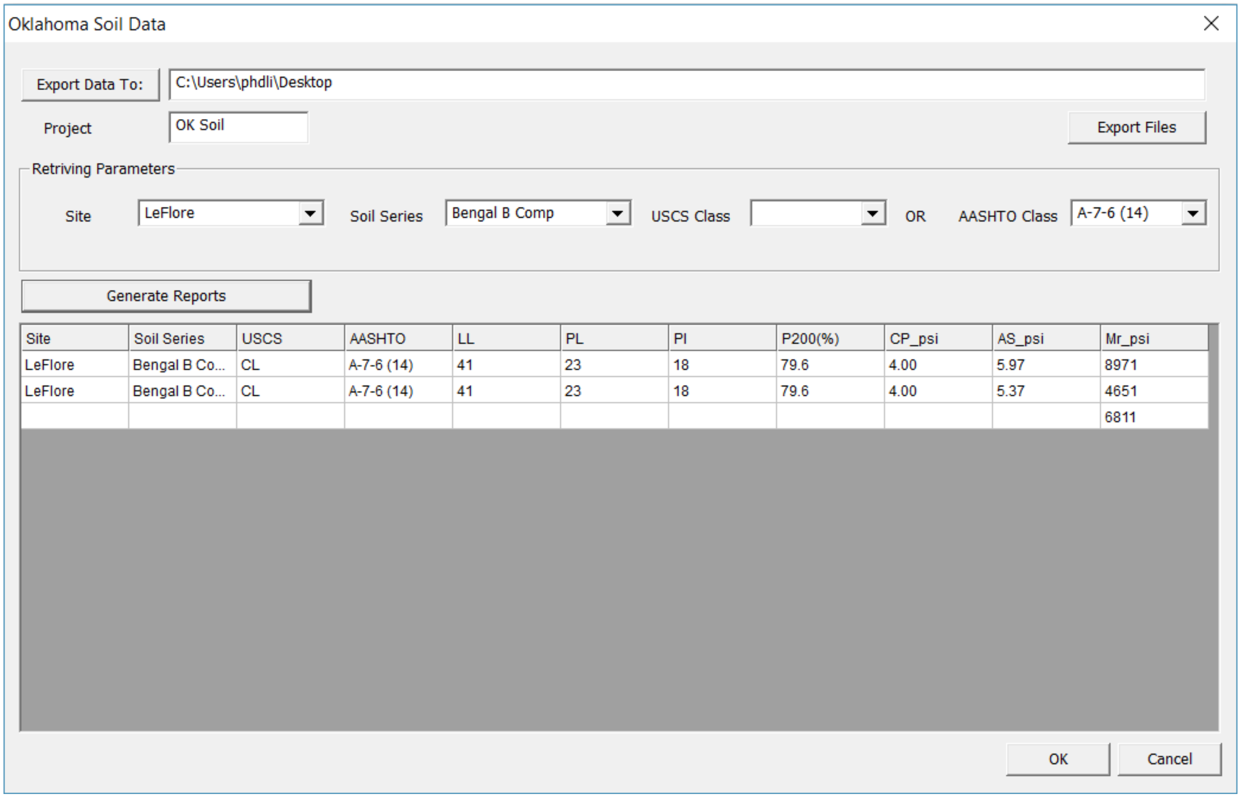
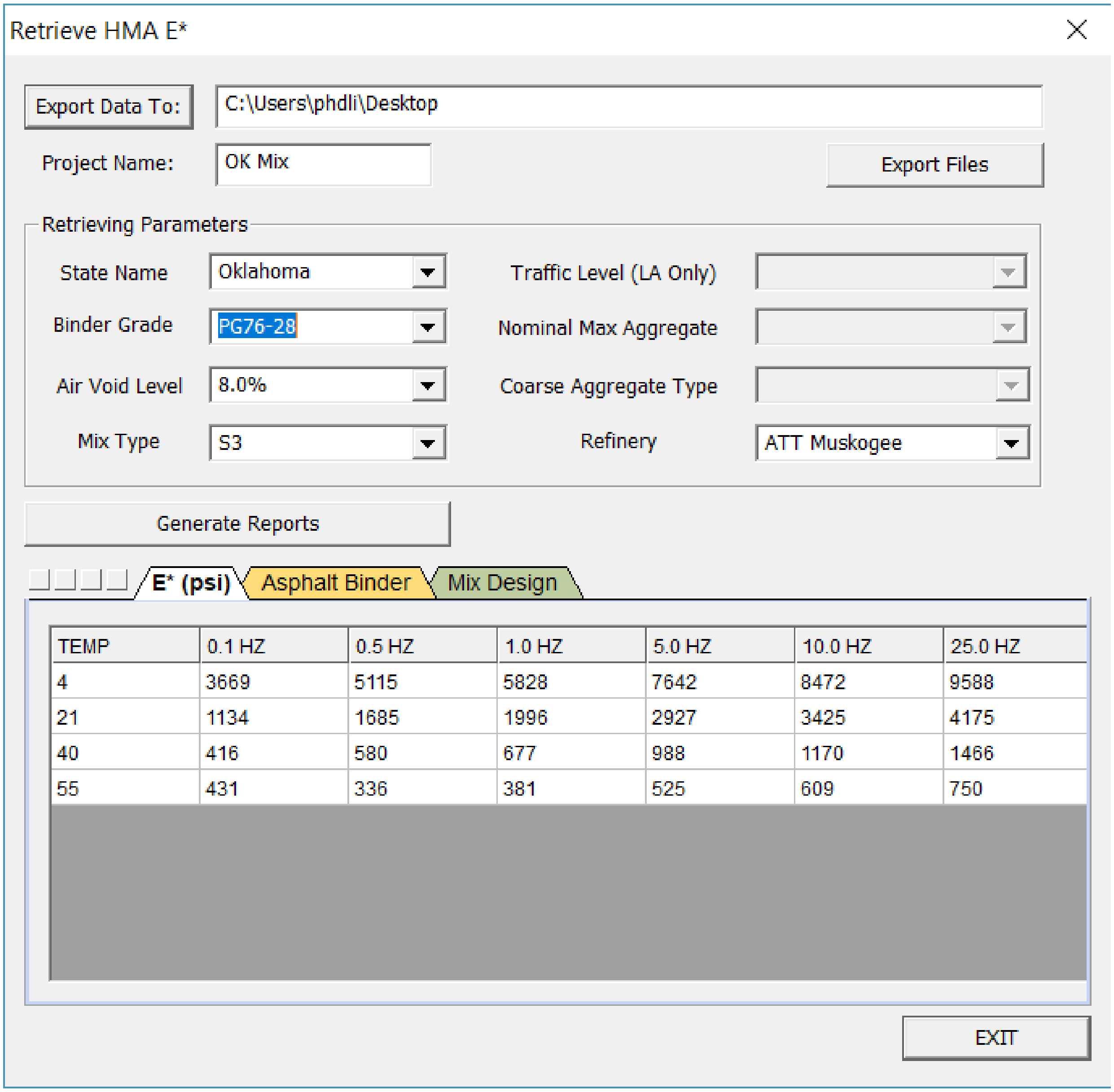


Fig. 6.6 Retrieving Oklahoma Soil Resilient Modulus Data



TEMP	0.1 HZ	0.5 HZ	1.0 HZ	5.0 HZ	10.0 HZ	25.0 HZ
4	3669	5115	5828	7642	8472	9588
21	1134	1685	1996	2927	3425	4175
40	416	580	677	988	1170	1466
55	431	336	381	525	609	750

Fig. 6.7 Retrieving Oklahoma Dynamic Modulus (E*) Data

7. CONCLUSIONS

The Mechanistic Empirical Pavement Design Guide (MEPDG), later named as DARWin-ME and Pavement ME Design, proposes a more rational approach to characterizing traffic loading spectrum and material properties. The objective of this research is to develop WIM QC metrics and associated software interfaces that ODOT can use to assess and improve WIM data quality, and generate site-specific (Level 1), region-specific (Level 2), and statewide average (Level 3) traffic inputs that are required for the Pavement ME Design in Oklahoma.

Five years of WIM data (2008 to 2012) and three years of AVC data (2013-2016) are acquired from ODOT, which are converted into the TMG data format and exported into the Prep-ME SQL database. Statewide WIM data check is performed by utilizing the Prep-ME software to examine the traffic data quality for each station by year, by direction and by lane via various data check operations, such as automated check, manually accept/reject, replacing, daily sampling. The data passed the semi-automated data checks with the aid of Prep-ME software are then utilized for the generation of three Levels of traffic inputs for Pavement ME Design. For Level 1 input, site-specific traffic data “By Direction” or “By Station” can be prepared in Prep-ME. Level 2 input level is developed in Prep-ME based on four clustering parameters: the rural or urban classification, function class of highway, average daily truck traffic volume (AADT) and ratio of single unit and multiple unit trucks (SU/MU). In addition, the TTC approach, simplified TTC approach, and "Flexible Clustering" method are maintained in Prep-ME for Oklahoma users for design of low volume roads, or to apply local engineering judgment and select WIM sites with similar traffic patterns for traffic data preparation for Pavement ME Design. For Level 3 input, three methods are provided in Prep-ME: State Average, LTPP-5(004) and Pavement ME Default.

Secondly, available material data in Oklahoma are investigated and integrated in the Prep-ME software to generate Level 1 and Level 2 material inputs for DARWin-ME. In particular, extensive amount of resilient modulus data for unbound natural subgrade soils with over 10,000 records have been manually checked for data quality. In addition, the AASTO T315 Superpave binder testing data of three types of asphalt binders typically used in Oklahoma: PG 64-22, PG 70-28, and PG 76-28 from three different refineries (NuStar from Catoosa, Valero from Ardmore, and Asphalt Terminal and Transportation (ATT) from Muskogee), and the dynamic modulus values for Oklahoma S3 and S4 mixes measured in accordance with AASHTO TP62 are populated into the Prep-ME database. Two software features have been developed in Prep-ME to retrieve (1) resilient modulus data of natural subgrade soils based on site name, soil series, and soil classification (either USCS or AASHTO method), and (2) dynamic modulus data based on binder grade, air void level, mix type, and refinery for directly importing into the Pavement ME Design software.

The default inputs provided in DARWin-ME were developed based on national-level data and may not work for a particular state or a site. Therefore, development of traffic and material inputs are helpful in the design and in predicting pavement performance accurately. This project is expecting not only to benefit state traffic data collection engineers in conducting an effective QC check on traffic data collected, but also to help state pavement design engineers to analyze and prepare traffic loading data collected through WIM for Pavement ME design. The productivities of the above operations can be improved tremendously.

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LIST OF DELIVERABLES

Besides this final report, the following items are delivered as the appendices of this project:

- Appendix A Prep-ME Installation Guideline.
- Appendix B Prep-ME Software User Manual (customized for this project with new developed modules);
- Appendix C Statewide WIM Data Check Results;