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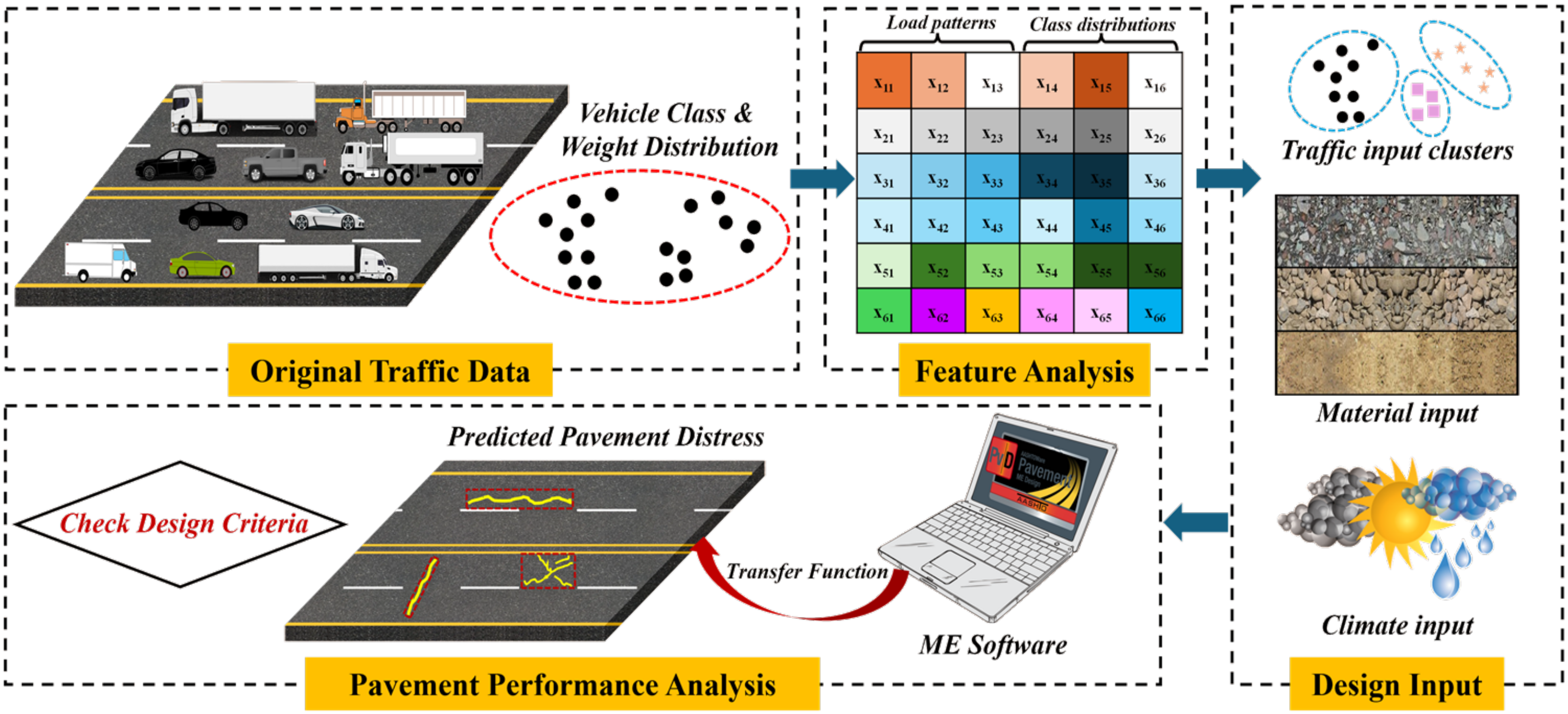

Traffic Data for Network Level Pavement Structural Assessment and Performance Grade Asphalt Selection

Research Final Report from University of Tennessee, Knoxville | Jingtao Zhong, Yangsong Gu, Kai Huang, Lee D. Han, Baoshan Huang | January 31, 2026

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THE UNIVERSITY OF TENNESSEE KNOXVILLE

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16. Abstract
Truck traffic is an important input for pavement design and analysis. Proper characterization of traffic patterns contributes to the design of reliable and cost-effective pavement structures. Axle load spectra obtained from the Long-Term Pavement Performance (LTPP) database, together with local Annual Average Daily Traffic (AADT) data from Tennessee, were analyzed to establish regional Level-2 traffic inputs for the Mechanistic-Empirical Pavement Design in Tennessee. Hierarchical clustering was performed to characterize the traffic patterns among the analyzed Weight-in-Motion (WIM) sites, followed by the sensitivity analysis to evaluate the impact of generated traffic inputs. Truck factors derived from National Cooperative Highway Research Program (NCHRP), LTPP Typical, LTPP Global, and cluster-based datasets were compared with TDOT default values. Results demonstrate that cluster-based level 2 provides the closest performance predictions compared with those from the site-specific level 1 data. TDOT's truck factors generally underestimate the structural number (SN) compared with the national datasets, whereas cluster-based local calibration tends to yield more conservative SN estimates for new pavement design. Additionally, the distribution of ESALs estimated from TDOT's default data was employed to classify traffic into four loading levels (standard, heavy, very heavy, and extreme) to support network-level binder selection. This classification attempts to provide a more rational basis for selecting Performance-graded (PG) asphalt binder consistent with expected loading conditions. The backcalculated SN values, derived by the estimated ESALs, serve as a valuable benchmark for evaluating required pavement structural capacity and supporting both new design and rehabilitation planning at the network level.

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Executive Summary

Accurate characterization of traffic loading is critical for reliable pavement design. The current TDOT Pavement Design Guide relies on default values for the estimation of Equivalent Single Axle Loads (ESALs) and truck factors developed more than a decade ago. While these defaults provide a consistent baseline, they may not adequately reflect current traffic conditions across Tennessee and could potentially lead to inaccurate pavement performance assessments and inadequate structural requirements. To address this issue, this project aimed to develop updated and regionally appropriate traffic inputs to enhance the reliability of pavement design and analysis in Tennessee.

In the absence of actual vehicle axle load data, data collected from Weigh-in-Motion (WIM) sites in Long-Term Pavement Performance (LTPP) database, combined with local vehicle counts, were analyzed to estimate regional Level-2 traffic inputs for the Mechanistic-Empirical Pavement Design Guide (MEPDG). Hierarchical clustering was performed to develop traffic clusters based on normalized axle load spectra (NALS) and vehicle class distribution (VCD). Furthermore, National Cooperative Highway Research Program (NCHRP), LTPP Typical, LTPP Global, and TDOT data were compared to calculating truck factors and structural number (SN), respectively.

This approach establishes a unified framework that integrates traffic characterization, binder selection, and network-level pavement performance evaluation to enhance the reliability of pavement design and asset management in Tennessee.

Key Findings

- Three clusters were developed using the hierarchical clustering algorithm to establish region-level traffic inputs for pavement design. The arithmetic mean across clusters was used to represent the statewide average, while cluster-specific data (level 2 traffic inputs) were employed to characterize axle load distribution and VCD patterns.
- The performance results based on cluster-specific level 2 data exhibit no significant difference from those obtained using the site-specific level 1 data for new flexible pavement and pavement overlay design. Root Mean Square Errors (RMSEs) of new pavement predictions for fatigue cracking, AC rutting, and IRI are 0.491%, 0.023 in., and 2.452 in./mile, respectively. For pavement overlay, RMSEs for fatigue cracking, AC rutting, and IRI are 0.011%, 0.027 in., and 1.5 in./mile, respectively.
- The calculated truck factors derived from NCHRP, LTPP Typical, LTPP Global, and clusters are compared with TDOT default values. While TDOT's truck factors generally underestimated the SN values compared with the national datasets, the cluster-based local results tended to overestimate SN and could produce more conservative estimates for new pavement design.
- The distribution of ESALs obtained from the TDOT default data can be used to categorize traffic into four levels (standard, heavy, very heavy, and extreme) for the development of network-level binder selection. This classification supports the selection of appropriate PG grades with expected loading conditions instead of grade bumping.
- The backcalculated SN values provide a valuable benchmark and a realistic reference for structural evaluation of both new pavement design and rehabilitation projects at the network level.

Key Recommendations

- Using the framework developed in this project, regional axle load datasets collected through continuous traffic monitoring (e.g., WIM) should be periodically updated to reflect evolving traffic conditions and to support calibration of local truck factors and load equivalency factors.
- It is recommended to use the generated traffic cluster data and inputs for pavement design and analysis, as they are more representative of Tennessee traffic conditions than nationwide default inputs and therefore better guide pavement design.
- It is suggested to combine temperature-based performance-graded (PG) binder selection with traffic loading levels. Four traffic levels (standard, heavy, very heavy, and extreme) are used for the development of network-level binder selection in accordance with regional climate and traffic conditions.
- The network-level backcalculated SN based on traffic level (ESALs) is recommended to be used as a reference for pavement structural evaluation and decision-making, supporting new pavement design, and prioritizing maintenance or rehabilitation planning at the network level.

Conclusion

This study provides TDOT with a network-level framework that improves the reliability of pavement design through incorporating locally derived truck factors, NALS, and SN benchmarks. By capturing Tennessee-specific traffic variability, the framework enables more accurate and consistent pavement design and network management decisions across the state. As more continuous traffic monitoring systems (e.g., WIM) are deployed, the resulting regional axle load datasets can be integrated into this framework to further strengthen the basis for performance-based roadway design and planning in Tennessee.

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Glossary of Key Terms and Acronyms

AADT: Annual Average Daily Traffic

AADTT: Annual Average Daily Truck Traffic

AASHTO: American Association of State Highway and Transportation Officials

AVC: Automatic Vehicle Classification

ESAL: Equivalent Single Axle Load

ETRIMS: Enhanced Tennessee Roadway Information Management System

FHWA: Federal Highway Administration

IRI: International Roughness Index

LEF: Load Equivalent Factor

LTPP: Long-Term Pavement Performance

MEPDG: Mechanistic-Empirical Pavement Design Guide

NCHRP: National Cooperative Highway Research Program

NALS: Normalized Axle Load Spectra

PG: Performance Grading

SN: Structural Number

TDOT: Tennessee Department of Transportation

TNTIMES: Tennessee Traffic Information Management and Evaluation System

TTC: Truck Traffic Classification

VCD: Vehicle Class Distribution

WIM: Weight-in-Motion

Chapter 1 Introduction

1.1 Problem Description

Traffic loading is one of the key inputs for the structural design and analysis of pavement structures using both the Association of State Highway and Transportation Officials (AASHTO) Guide for Pavement Design (1993) and the Mechanistic-Empirical Pavement Design Guide (MEPDG). The AASHTO design method uses the number of axle load repetitions in the design and analysis period in terms of equivalent single axle loads (ESALs), while the MEPDG requires proper traffic characterization to determine traffic parameters required as inputs for the pavement design process. Tennessee Department of Transportation (TDOT) simplifies the ESALs estimation procedures by using the 18-kip factor, which assumes the same truck factor and load equivalent factor (LEF). However, such factors are highly related to pavement structures, pavement categories, and traffic volume, which may affect the estimation accuracy of ESALs. The adjustment of LEF is needed by considering different pavement conditions. Also, accurate conversion of traffic data to the load spectra is needed in the MEPDG inputs for pavement design and analysis.

TDOT usually estimates the ESALs data at the project level based on traffic data from the radar detector. However, the traffic data, which is extrapolated to determine ESALs are not available for network-level analysis. Roadway traffic varies with time, lane direction, and roadway type. Additionally, the truck traffic may change over time due to the growing population and economic conditions. Hence, the default values recommended by design guidelines may not be suitable for traffic networks in Tennessee. A more sophisticated method is required to capture the traffic data-related factors in ESALs estimations and network-level analysis.

Additionally, a more detailed binder selection standard is needed with the establishment of a confident dataset of estimated ESALs to support a potential revision to TDOT PG asphalt binder selection standards at the network level.

1.2 Objectives of the Research

The objectives of the proposed study are to:

- Evaluate TDOT's approach to estimating daily ESALs.
- Develop a method to estimate network-level ESALs to determine funding needs and future rehabilitation projects.
- Incorporate estimated network-level ESALs into TDOT's binder selection.

1.3 Scope of Work

The scope of the research work includes:

- To complete a literature review on network-level ESALs estimation and PG binder selection, and to conduct a DOT survey on their ESALs estimation methods and specifications for PG binder selection.
- To collect traffic data from radar detectors, roadway inventory data from ETRIMS, and weather data.

- To evaluate and adjust TDOT's approach of estimating daily ESALs considering pavement structures, pavement categories, traffic, etc.
- To convert traffic data to load spectra for Mechanistic-Empirical pavement design.
- To develop a method to estimate network-level ESALs and incorporate estimated network-level ESALs into TDOT's binder selection.
- To make recommendations to TDOT specifications regarding estimation methods and PG binder selection.

Chapter 2 Literature Review

2.1 AASHTO pavement design

The American Association of State Highway and Transportation Officials (AASHTO) pavement design method originates from the AASHO Road Test conducted in the early 1960s, which served as the foundation for modern pavement design practices. The test aimed to quantify the damage caused by axle loads of varying magnitudes and configurations by converting them into an equivalent number of repetitions of a standard reference load, expressed by Equivalent Single Axle Load (ESAL). Truck traffic loading is used to calculate accumulated load-related damage [1].

Standard load is defined as an 18-kip (80 kN) single axle with dual tires and is considered to represent 1.0 ESAL, as illustrated in Figure 2-1. To enable practical application, the test results were used to develop empirical equations that express pavement damage in terms of load equivalency factors (LEFs). These LEFs vary by axle weight, axle configuration (e.g., single, tandem, tridem), pavement type (flexible or rigid), and other structural factors. The total ESAL for a vehicle is computed as the sum of the LEFs of all axle groups. LEFs are converted into truck factors to simplify the calculation.

Regression models were derived for flexible and rigid pavements, incorporating additional parameters such as the structural number, slab thickness, and terminal serviceability. These empirical equations remain a core component of the AASHTO pavement design methodology. AASHTO adopts the simplified Equivalent Single Axle Load (ESAL) concept to convert all truck axles into standardized loads for pavement design [2]. However, this experiment-based design method cannot accurately predict pavement distress due to various influencing factors, as pavement failure is influenced by the complex effects of climate conditions and traffic loading over time.

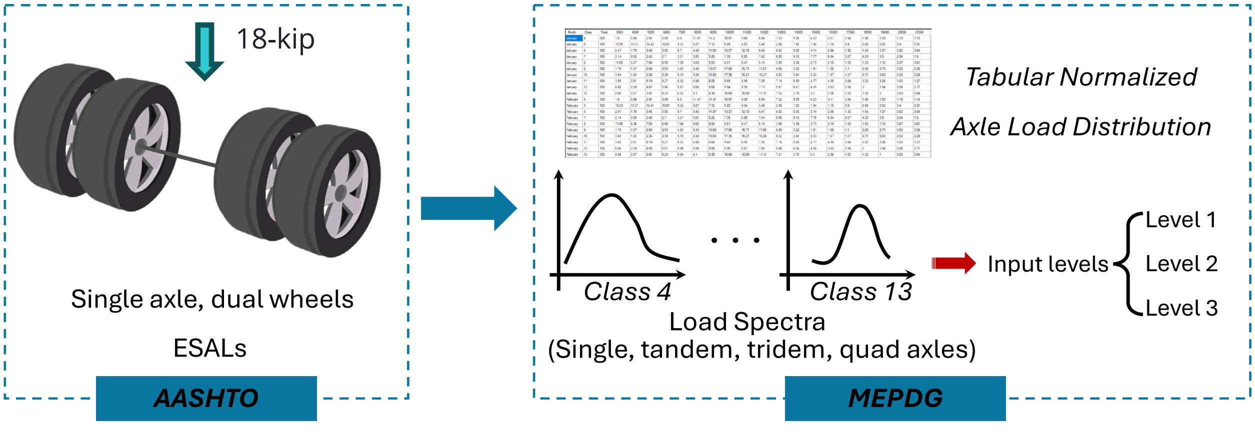


Figure 2-1 Quantification methods of traffic loading.

2.2 Mechanistic-Empirical pavement design

The use of ESALs limits the accuracy of performance analysis due to the simplified conversion method [3]. To address this limitation, the detailed characterization of traffic, including truck axle configuration and loading magnitudes, was used in the Mechanistic-Empirical Pavement Design

Guide (MEPDG), which provides a state-of-the-practice method for the design and analysis of the pavements [4, 5]. Unlike the AASHTO 1993 method, MEPDG does not rely on simplified ESALs or LEFs for calculation, enabling more accurate and detailed pavement performance predictions, as shown in Figure 2-1.

Pavement responses, such as stress, strain, and deflection (the mechanistic part), are combined with the traffic, climate, and materials properties to predict critical pavement distresses and smoothness (the empirical part with transfer function) over the design life. Collecting detailed data for predictions can be time-consuming. Therefore, MEPDG developed three hierarchical levels of inputs for analysis, including level 1: site-specific or project-specific data; level 2: statewide or regional data; and level 3: nationwide data. It is recognized that the level 1 traffic data should be used wherever available.

The traffic data includes traffic volume, volume adjustment factors, axle load spectra, and general traffic inputs (axle configuration, lateral wander, wheelbase). Since considering all traffic variables is computationally inefficient, it is crucial to identify the most representative variables. Studies have shown that axle load spectra and vehicle class distribution (VCD) are two key traffic inputs [6, 7]. The load spectra characterize the normalized frequency of load distribution of each axle across the load bins, developing the normalized axle load spectra (NALS) with the cumulative frequencies summing to 100 percent. Normalization is performed to establish a common basis, converting the data into proportions rather than absolute values [8]. Weight data are collected by specialized equipment such as Weight-in-Motion (WIM) stations. Based on the axle configuration of trucks, four types of load spectra are defined: single, tandem, tridem, and quad. Single and tandem NALS have been shown to significantly influence pavement performance [9]. VCD is defined as the percentage of trucks, classified according to the Federal Highway Administration (FHWA) from class 4 to class 13 [10] by axle type and distribution, as illustrated in Figure 2-2.

However, using Level 1 traffic data for all pavement designs is impractical due to the limited availability of WIM stations. Consequently, the commercially available AASHTOWare Pavement ME Design (PMED) software is utilized to analyze pavement performance, offering default input levels for design when site-specific data are unavailable. The truck traffic patterns vary significantly from site to site, and the nationwide default data from MEPDG cannot accurately reflect the specific pavement performance [11]. Therefore, researchers have investigated the development of level 2 traffic data for pavement design. Level 2 data provides an enhanced characterization of truck traffic patterns while minimizing the need for extensive data collection.

Several studies have explored using the arithmetic average of collected traffic data to represent regional truck traffic characteristics. Swan et al. generated regional traffic inputs and found that the pavement performance predicted by the generated inputs varies significantly from those by the MEPDG default data [12]. Tran et al. observed a notable difference in pavement performance predictions using the statewide and MEPDG default NALS [13]. Smith et al. established the statewide traffic input and evaluated the normalized difference between the established data and the default data [14]. They recommended using the nationwide NALS instead of MEPDG default values, while keeping other traffic parameters from the default for pavement design. However, the statewide arithmetic average did not consider the variations between different sites, failing to accurately capture comprehensive local traffic patterns. To address this limitation, cluster-based analysis algorithms have been utilized to identify the similarities between different sites and develop region-based traffic inputs instead of relying solely on the statewide traffic data [15].

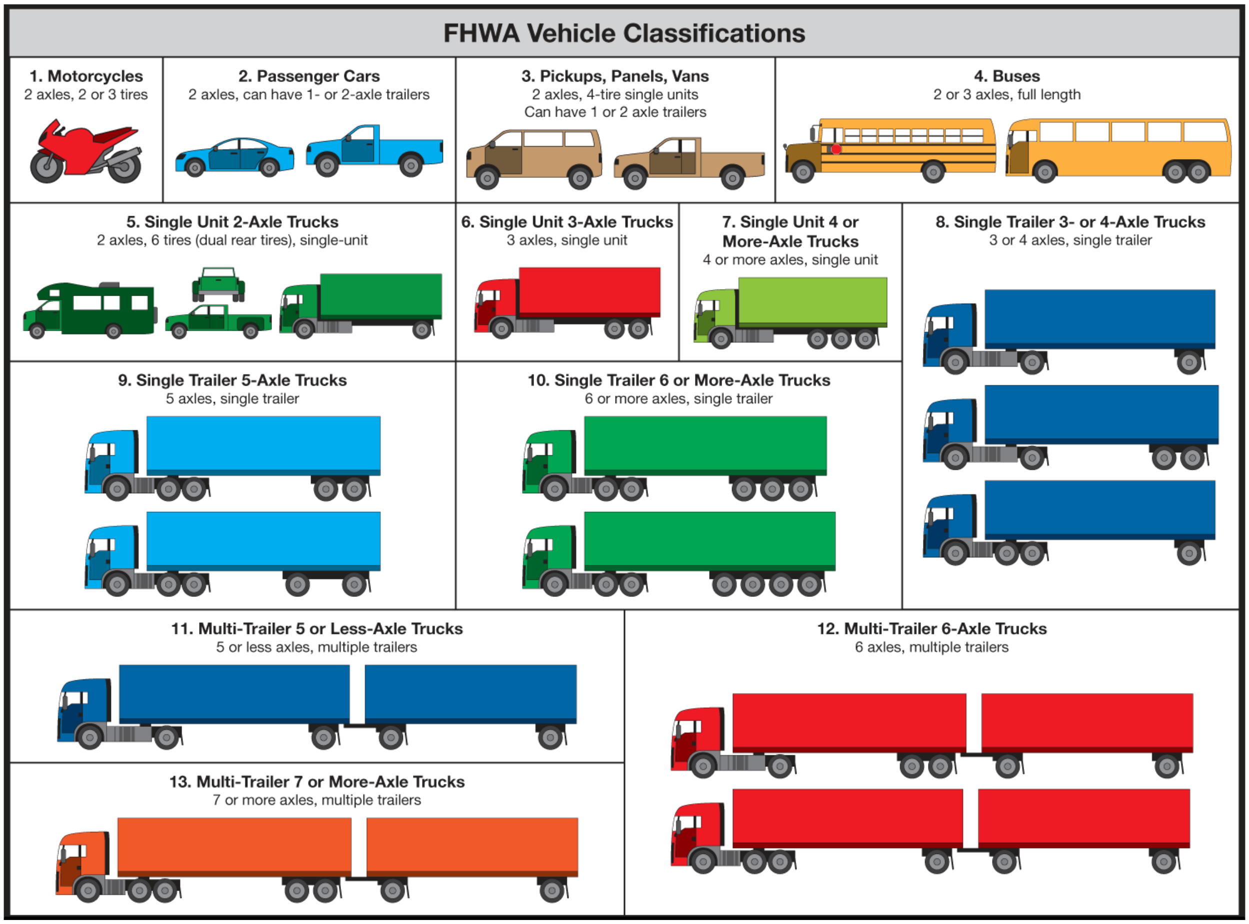


Figure 2-2 FHWA vehicle classification [16].

Sayyady et al. generated representative truck traffic patterns via the hierarchical clustering analysis and evaluated the accuracy of the proposed methods through MEPDG damage-based analysis [17]. Ishak et al. grouped the WIM sites using the sum of squared differences (SSD) as the metric for clustering comparison [18]. Their study demonstrated that the developed region-based NALS is significantly different from the MEPDG default values. Abbas et al. compared the clustered and MEPDG default NALS for pavement performance prediction [7]. They found that the MEPDG default tends to underestimate the pavement service life. Although previous studies have attempted to develop cluster-based data for the implementation of MEPDG [19], different traffic attributes have been classified, leading to varying performance results. Lu et al. performed the cluster analysis on tandem axle load, considering the functional classification of roads [20]. Jasim et al. conducted the clustering algorithm on single, tandem, and tridem axle loads to perform the damage-based sensitivity analysis for pavement performance prediction [4]. However, previous studies focused on either NALS or VCD for separate performance comparisons. Hasan et al. explored various combinations of clustered VCD and NALS to compare the predicted pavement performance, but developing the optimal combination is time-consuming [6]. Additionally, semi-rigid pavements have rarely been investigated using MEPDG-based damage analysis. It is important to analyze comprehensive pavement structures for further evaluation.

2.3 Binder selection method

The traditional approach to asphalt binder specification was formalized in the Superior Performing Asphalt Pavements (Superpave) system in AASHTO M 320 [21]. Grading designations are related to the average seven-day maximum pavement design temperature and the minimum pavement design temperature. In this system, high-temperature binder grading was based on the expected pavement temperature and adjusted for traffic loading through a process known as grade bumping. This was typically done by increasing the binder test temperature while maintaining the same specification limits, regardless of actual in-service thermal conditions. While this approach provided a standardized way to account for increased loading demands, it often resulted in the selection of stiffer binders that were never subjected to such extreme temperatures in the field. This discrepancy was particularly problematic for polymer-modified binders, whose rheological properties can be highly sensitive to temperature and stress conditions. As traffic volumes and loading scenarios have become more complex, the limitations of this temperature-based grade bumping approach have become increasingly evident, prompting the development of more realistic, stress-based binder evaluation methods.

In contrast, the MSCR (Multiple Stress Creep Recovery) specification redefines grade bumping by evaluating binder performance at the actual environmental temperature expected in the field, as expressed in AASHTO M332 [22]. It incorporates traffic-induced stress through the non-recoverable creep compliance (J_{nr}) parameter, allowing for stress-level-specific classifications. This shift enables more realistic and performance-oriented binder evaluation, especially under heavy or slow-moving traffic conditions. ESALs are used to classify traffic levels for the MSCR test requirements of PG binder in AASHTO M332 specifications. Based on different EASLs, traffic levels are divided into 4 levels (S, H, V, and E), which represent standard, heavy, very heavy, and extremely heavy traffic levels. As shown in Table 2-1, creep compliance and elastic recovery replacement (% replacement) are specified for asphalt binder selection based on different traffic levels.

Table 2-1 Binder selection based on different traffic levels [22].

Category	*Traffic level*	*Jnr value (kPa^{-1})*	*% Recovery*
Standard (S)	< 10 million ESALs and standard traffic loading	< 4.5	~
Heavy (H)	10-30 million ESALs or slow moving traffic loading	< 2.0	⩾ 30%
Very Heavy (V)	> 30 million ESALs or standard traffic loading	< 1.0	⩾ 55%
Extreme (E)	> 30 million ESALs and standard traffic loading	< 0.5	⩾ 75%

Chapter 3 Methodology

3.1 Data collection and processing

Traffic data were obtained from two major databases: the Tennessee Traffic Information Management and Evaluation System (TNTIMES) and the Enhanced Tennessee Roadway Information Management System (ETRIMS). The average annual daily traffic (AADT) and traffic growth rates were primarily derived from these two sources to characterize long-term and spatial variations in traffic demand across Tennessee's state routes and highways. Specifically, ETRIMS provides averaged segment-level AADT values aggregated from count stations, allowing consistent estimation of vehicle exposure along each analyzed segment. Meanwhile, TNTIMES offers complementary historical traffic count records and regional growth trends. Together, these datasets support a comprehensive assessment of traffic loading and demand evolution.

TDOT currently lacks automatic vehicle classification (AVC) and WIM stations, with WIM sensor deployment anticipated in 2025. Therefore, the data obtained from Long-Term Pavement Performance (LTPP) was used to develop level 2 statewide traffic inputs in Tennessee. As shown in Figure 3-1, there are 9 WIM sites in Tennessee with complete axle load spectra (ALS), VCD, and Annual Average Daily Truck Traffic (AADTT) that could be used for analysis. The functional class for site 600 is classified as a rural principal arterial-interstate, whereas the remaining ones are rural principal arterial-other category. The NALS were obtained from the SDR37-TRF_MEPDG_AX_DIST LTPP file. Additionally, the VCD, growth function, and growth rate were from SDR37-MEPDG_INPUTS of LTPP data.

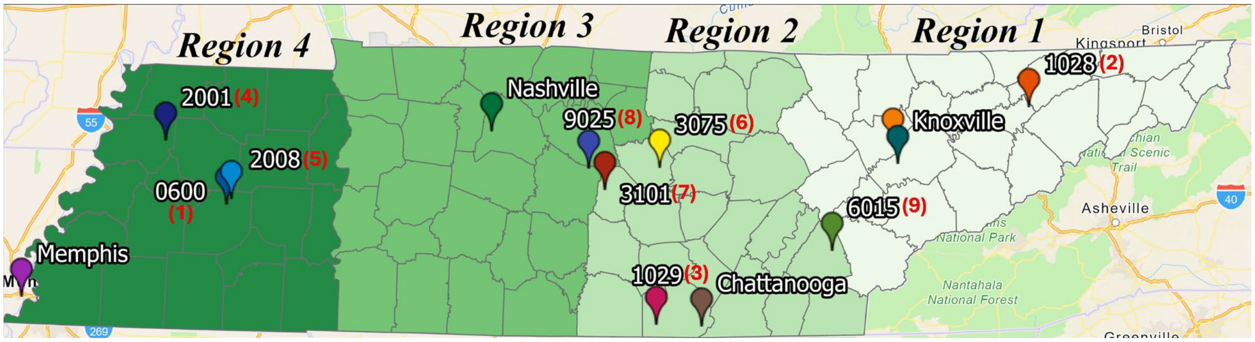


Figure 3-1 Long-term pavement performance weigh-in-motion sites in Tennessee.

The single and tandem NALS were analyzed for their significant influence on pavement performance. For some sites lacking sufficient monthly NALS data for specific vehicle classes, averages from other months were used to address the missing data. The data from AASHTOWare PMED software was used for comparison and investigation of the local application in Tennessee. The software includes five NALS as input for a level 3 default distribution, named National Cooperative Highway Research Program (NCHRP) 1-37A, Heavy, Typical, Light, and Global axle load distribution, respectively. The NCHRP 1-37A is recommended for highways with a higher percentage of overloaded trucks and serves as the default value for MEPDG. The NALS data obtained from the LTPP database were converted to align with the specific load ranges required by the MEPDG.

3.2 Mechanistic-Empirical pavement design in Tennessee

To develop cluster-based traffic data for pavement design, a four-step framework is proposed in Figure 2: (1) traffic data collection, (2) feature analysis, (3) input selection, and (4) pavement performance analysis. In the first step, traffic data—including VCD and NALS—were collected from the LTPP database to construct a feature matrix for pattern characterization. The second step involved performing feature analysis to extract meaningful characteristics from the collected data, enabling the differentiation of regional traffic patterns. Based on these traffic features, the third step determined the design inputs by integrating traffic clusters with material and climate information, which were then used in the AASHTOWare PMED software. In the final step, pavement performance was analyzed using ME software, where predicted distresses and smoothness were evaluated to ensure that the clustered inputs met the design requirements.

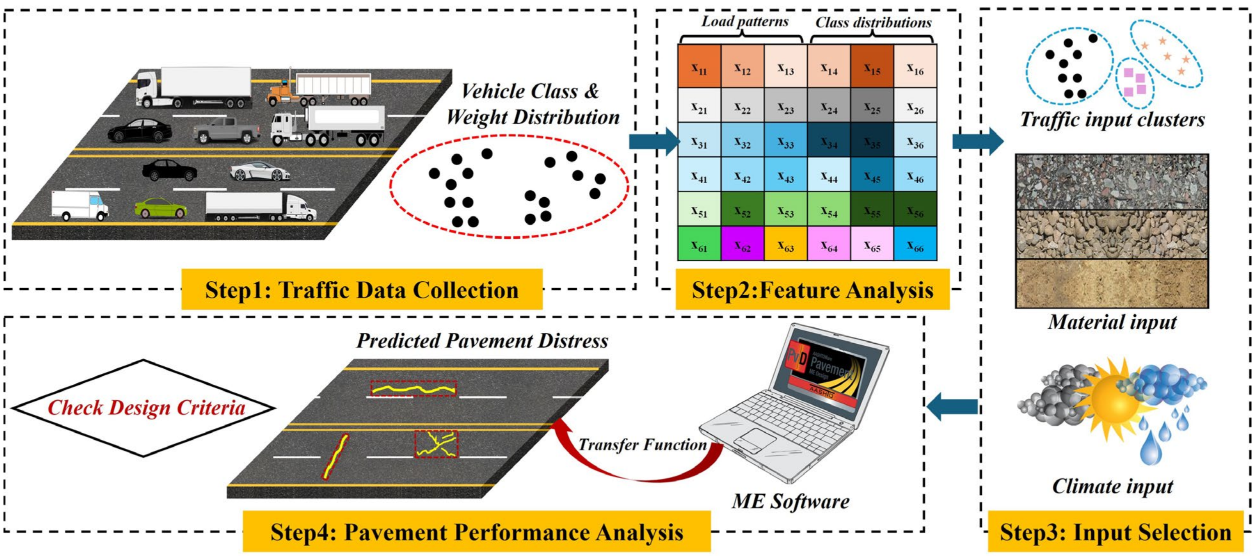


Figure 3-2 Flowchart of Mechanistic-Empirical pavement design implementation.

3.2.1 Optimal clusters for characterizing traffic patterns

An appropriate number of clusters contributes to the computational efficiency of data analysis. An exhaustive search was used to find the appropriate clusters to characterize the traffic patterns among those WIM sites. In K-means clustering, distance metrics are used to quantify differences between data points, serving as a basis for identifying significant distinctions among analyzed data, which is expressed by Equation (3-1):

$$D(x_i) = \arg\min_{r} (x_i - \mu_r)^2 \tag{3-1}$$

$$SSE_r = \sum_{i=1}^{n_r} \left(x_i - \mu_r\right)^2 \tag{3-2}$$

$$SSE_{total} = \sum_{r=1}^{k} SSE_r \tag{3-3}$$

where μ_r is the centroid, x_i is the ith sample in the dataset. Euclidean distance is used as the loss function to minimize the within-cluster sum of squares (SSE). The SSE is calculated in the k clusters, and the elbow method is used to determine the optimal number of clusters k, formulated by Equation (3-2) and (3-3). The elbow point is the cutoff point selected as the optimal number of clusters, which means adding another cluster does not improve the model further to reduce computation. There are 9 sites, and the SSEs were calculated from cluster 1 to cluster 9 to find the optimal values. SSE is calculated based on the feature matrix from the WIM sites. In our research, the feature matrix consists of the NALS and VCD, which are flattened as the vector shown in Equation (3-4):

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & \cdots & \cdots & x_{1n} \\ \cdot & x_{22} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{n1} & x_{n2} & \cdots & \cdots & \cdots & x_{nn} \end{bmatrix} \tag{3-4}$$

where the row is the number of samples, and the column is the features of each sample. Normalized single axle load spectra (39 load bins), normalized tandem axle load spectra (39 load bins), and VCD (10 classes) were jointly incorporated as the features for the analysis, including a total of 88 features for each WIM site.

3.2.2 Hierarchical clustering algorithm

Similarly, the distance within WIM sites for clustering is formulated by Equation (3-5):

$$d_{ij} = \left\| x_i - x_j \right\|_r = \left\{ \sum_{k=1}^{n} \left| x_{ik} - x_{jk} \right|^r \right\}^{1/r} \tag{3-5}$$

where i and j are two samples, k is the first feature, n is the total number of features, and r is the user-defined parameter, which is defined as Euclidean distance to evaluate the similarity and was set to 2 in this study.

3.3 Impact of traffic inputs on pavement performance

3.3.1 MEPDG calculation

To evaluate the sensitivity of cluster-generated NALS on pavement performance, typical pavement structures (flexible, semi-rigid, and rigid) in Tennessee were chosen to run the AASHTOWare PMED software for comparison. Eight traffic scenarios — LTPP-Global, LTPP-Typical, NCHRP, cluster 1, cluster 2, cluster 3, Statewide average, and site-specific data — were considered to investigate their impact on pavement performance, respectively. Cluster data represent level 2 inputs, while site-specific data corresponds to level 1 inputs. A Comparison with site-specific WIM data is conducted to assess the accuracy of cluster-generated traffic inputs.

The climate and material inputs were obtained from the LTPP and the default values provided by the AASHTOWare PMED software. The North American Regional Reanalysis (NARR) climate data was obtained from the LTPP database and incorporated into the software as the representative climate data for analysis. For the material inputs, the gradation of soil and unbound materials was sourced from SDR37-MATERIAL_TEST in LTPP to determine the AASHTO soil classification. PG 64-22 asphalt binder was selected for all HMA layers. Other material inputs, such as modulus and Poisson's ratio, were kept as default values, as the primary objective was to assess the impacts of different levels of traffic inputs.

The axle configuration, lateral wander, wheelbase, monthly adjustment factor (MAF), and hourly adjustment factor (HAF) were maintained constant using the default values from the software due to the unavailability of local data. These parameters were found to have minimal impact on predicted pavement performance [12]. The specific AADTT was obtained from the LTPP-derived data. The new pavement and pavement overlay design were compared and analyzed using the generated traffic scenarios. One month (typically 30 days) is defined as the basic unit for evaluating incremental damage. AASHTOWare PMED (version 2.6.2.2) predicts the performance in terms of critical pavement distress and smoothness to determine the optimal traffic input parameters. Figure 3-3 presents the typical pavement structures in Tennessee, which include semi-rigid, flexible, and rigid pavements, to comprehensively analyze the impacts of the generated traffic inputs. The unbound aggregate base was assumed to have a thickness of 2 in., as required by the prediction models. The pavement design criteria are listed in Table 3-1.

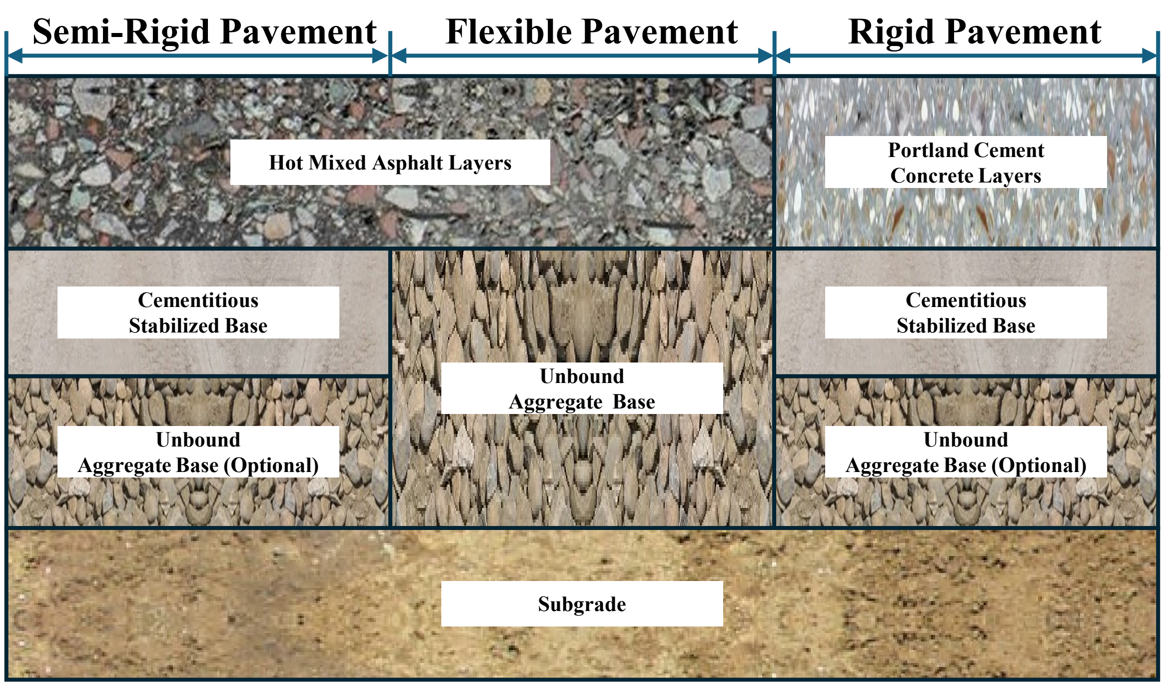


Figure 3-3 Typical pavement structures in Tennessee.

Table 3-1 Design criteria for pavement design [23].

Design criteria limit			
Rigid Pavement		*Flexible Pavement*	
Reliability	90%	Reliability	90%
Operational speed (mph)	60	Operational speed (mph)	60
Terminal IRI (in./mile)	172	Terminal IRI (in./mile)	172
JPCP transverse cracking (percent slabs)	15	AC total fatigue cracking (% lane area)	25
Mean joint faulting (in)	0.12	Permanent deformation (Asphalt concrete only, in.)	0.25
		Permanent deformation (total pavement, in.)	0.75

3.3.2 AASHTO calculation

3.3.2.1 Calculation of truck factor

The LEF was calculated based on AASHTO 1993 for flexible pavement, expressed by Equation (3-6), (3-7), and (3-8):

$$\log\left[\frac{W_{t_x}}{W_{t_{18}}}\right] = \log\left[\frac{1}{LEF}\right] = 4.79\log_{10}\frac{18+1}{L_x+L_2} + 4.33\log_{10}L_2 + \frac{G_t}{\beta_x} - \frac{G_t}{\beta_{18}} \tag{3-6}$$

$$G_t = \log_{10}\left(\frac{4.2-p_t}{4.2-1.5}\right) \tag{3-7}$$

$$\beta_x = 0.40 + \frac{0.081\left(L_x+L_2\right)^{3.23}}{(SN+1)^{5.19}\,L_2^{3.23}} \tag{3-8}$$

where W_{tx} is the number of applications of given axle, W_{t18} represents the number of standard axle passes (single 18-kip axle), L_x means load in kips of axle group, L_2 is the axle code (1 for single axle, 2 for tandem axles, 3 for tridem axles, and 4 for quad axles), β_{18} represents value of β_x when Lx = 18 and L_2 = 1, P_t is the terminal serviceability and SN is the structure number.

In this research, SN=5 and P_t=2.5 were selected to calculate the LEF, then the truck factor of each vehicle class is formulated by Equation (3-9):

$$TruckFactor_k = \sum_{b=1}^{4}\sum_{a=1}^{n}\left(APT_{k,b}\right)\left(NALS_{k,b,a}\right)\left(LEF_{b,a}\right) \tag{3-9}$$

where:

$TruckFactor_k$ is the truck factor for vehicle class k;
$APT_{k,b}$ means axles per truck for vehicle class k and axle type b (single, tandem, tridem, and quad types);
$NALS_{k,b,a}$ shows normalized load spectra for vehicle class k, axle type b, and load bin a;
$LEF_{b,a}$: load equivalent factor for axle type b and load bin a.
Since TDOT adopts the combination of classes, the weighted truck factor is averaged by the vehicle classification distribution (VCD), calculated by Equation (3-10):

$$AvgTruckFactor = \frac{\sum_{k=i}^{j} (VCD_k)(TruckFactor_k)}{\sum_{k=i}^{j} (VCD_k)} \tag{3-10}$$

3.3.2.2 Back-calculation of SN

To intuitively demonstrate the influence of varying truck factors on pavement structural design, each truck factor was used to compute the corresponding ESAL based on Equation (3-11) and (3-12). Subsequently, the structural number (SN) was back-calculated from the ESAL values to quantify the required pavement strength using Equation (3-13).

$$ESAL = \sum_{k=4}^{13} (AADT)_0 (T_k)(T_{fk})(G)(D)(L)(365)(Y) \tag{3-11}$$

$$Total\ growth\ factor = (G)(Y) = \frac{(1+r)^Y - 1}{r} \tag{3-12}$$

$$\log_{10}(ESAL) = Z_R S_0 + 9.36 \times \log_{10}(SN+1) - 0.20 + \frac{\log_{10}\left(\frac{\Delta PSI}{4.2-1.5}\right)}{0.40 + \frac{1094}{(SN+1)^{5.19}}} + 2.32 \times \log_{10} M_R - 8.07 \tag{3-13}$$

where Z_R is the reliability factor, S_0 is the standard deviation, and M_R is the resilient modulus.

The relative inputs for the calculation of ESAL and SN are listed in Table 3-3. The M_R was estimated from the California Bearing Ratio (CBR) from TDOT using the empirical correlation in Equation (3-14).

$$M_R = \begin{cases} 1,500 \times CBR, & 4 \le CBR \le 10 \\ 15,000, & CBR > 10 \end{cases} \tag{3-14}$$

Table 3-2 Reliability and standard deviation for flexible pavement [24].

Route Classification	*Pavement Reliability*	Z_R	S_0
Interstate	95%	-1.645	0.45
Controlled Access State Route	95%	-1.645	0.45
State Routes	90%	-1.282	0.45
Off System Arterial	85%	-1.037	0.45
Temporary Traffic Lane	85%	-1.037	0.45
Off System Minor	80%	-0.841	0.45

Table 3-3 Back-calculation input.

Input	*Values*
Initial Serviceability	4.2
Terminal serviceability	2.5
Reliability level	varies
Overall standard deviation	varies
Roadbed soil resilient modulus (psi)	varies
Design life (years)	20
No. of lanes in design direction	varies
Two-way AADTT	varies
Percent of all trucks in design lane	varies
Percent of trucks in design direction	varies
Traffic volume growth	varies

Chapter 4 Results and Discussion

This chapter presents the results of collected traffic data to update the truck factor and develop appropriate traffic inputs for MEPDG implementation in Tennessee. Traffic patterns are identified using clustering algorithms to be used for different traffic scenarios. NALS is established based on clustered traffic characteristics and evaluated by the AASHTOWare PMED software for sensitivity analysis. Additionally, the network-level ESALs and SN are illustrated for asphalt binder selection and pavement design analysis. Detailed results and discussion are described in the following sections.

4.1 Clustering algorithms

As shown in Figure 4-1, the optimal clusters are determined with the elbow criterion. The elbow criterion refers to the point in the graph where the rate of decrease in SSE begins to slow down significantly. This point forms an elbow shape in Figure 4-1. The elbow point, identified through the analysis of the gradient of SSE reduction, is considered the best balance between the number of clusters and the SSE. Adding more clusters beyond this point does not result in a significant reduction in SSE in Figure 4-1(a), making it computationally inefficient to further increase the number of clusters.

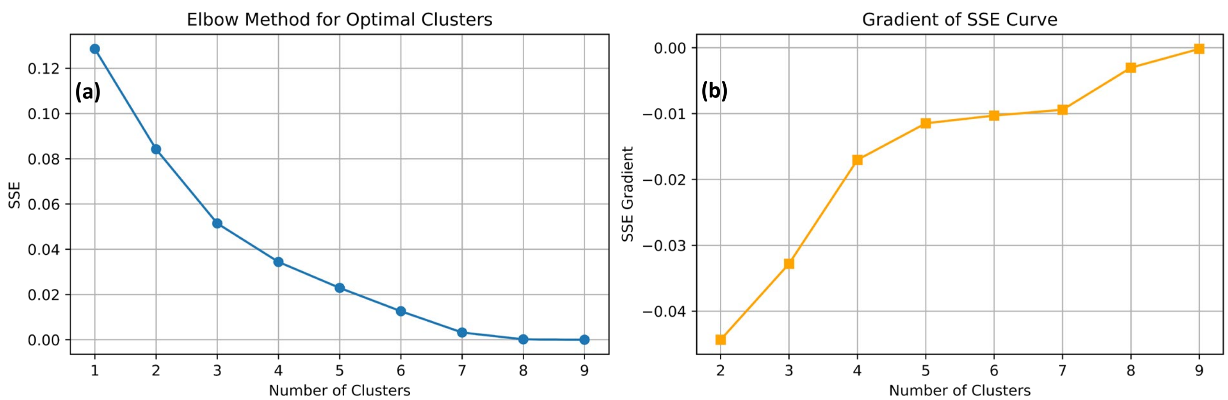


Figure 4-1 Determination of the optimal number of clusters.

The gradients for each cluster number are calculated using Equation (4-1), which represents the difference in SSE values between adjacent cluster counts.

$$G_i = \frac{SSE_i - SSE_{i-1}}{i-(i-1)} = SSE_i - SSE_{i-1},\ i \geq 2 \qquad (4\text{-}1)$$

As shown in Figure 4-1(b), this gradient quantifies the rate of change in SSE across different cluster numbers. The most significant changes in the SSE gradient occur between 2 to 3 clusters (0.01578) and 3 to 4 clusters (0.00555). These two points exhibit the steepest decline, suggesting that 3 clusters option is the optimal choice by elbow criteria, as it marks the point where the reduction in SSE begins to slow significantly.

A total of 9 WIM sites were used to perform clustering analysis. The WIM sites are annotated as 1 (site 600), 2 (site 1028), 3 (site 1029), 4 (site 2001), 5 (site 2008), 6 (site 3075), 7 (site 3101), 8 (site 9025), and 9 (site 6015), respectively. The Euclidean distance between different sites is listed in

Table 4-1, representing the pairwise distance. This matrix is useful for determining the degree of similarity between WIM sites.

Table 4-1 Euclidean distance matrix between WIM sites.

Site	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	0	0.159	0.196	0.181	0.156	0.264	0.214	0.213	0.134
2	0.159	0	0.121	0.133	0.078	0.223	0.159	0.160	0.117
3	0.196	0.121	0	0.205	0.141	0.151	0.172	0.175	0.138
4	0.181	0.133	0.205	0	0.133	0.290	0.181	0.177	0.162
5	0.156	0.078	0.141	0.133	0	0.234	0.154	0.154	0.154
6	0.264	0.223	0.151	0.290	0.234	0	0.252	0.257	0.205
7	0.214	0.159	0.172	0.181	0.154	0.252	0	0.018	0.168
8	0.213	0.160	0.175	0.177	0.154	0.257	0.018	0	0.169
9	0.134	1. 0.117	0.138	0.162	0.154	0.205	0.168	0.169	0

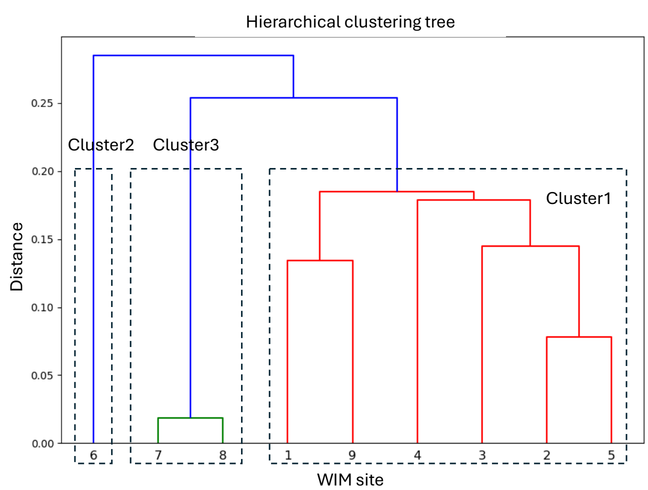


Figure 4-2 Cluster tree for the WIM sites.

The criterion for aggregating the sites is based on the minimum distance between samples from Table 4-1, where the smallest distance between 2 and 5 is aggregated first, and the hierarchical clustering is followed by the relative distances. In hierarchical clustering, data points (WIM sites) are initially treated as individual clusters. The algorithm then repeatedly merges the clusters that have the smallest distance, based on the distance matrix, until all the sites are combined into a single cluster or until a desired number of clusters is reached. The final 3 clusters are shown in Figure 4-2. The figure demonstrates a bottom-up approach, where WIM sites are merged iteratively based on their pairwise similarity until only three final clusters remain. Cluster 1 consists of WIM sites 1, 2, 3, 4, 5, and 9. These sites are grouped based on their similar traffic patterns. The red lines represent the merging of sites, indicating that these WIM sites are relatively similar in terms of the clustering criteria. The hierarchical merging shows that sites 2 and 5 are grouped first, followed by other combinations until the final cluster is formed. Cluster 2 consists of WIM sites 6 and 7, depicted by the green lines. This cluster has the smallest clustering distance compared to other clusters, indicating that sites 6 and 7 have highly similar traffic characteristics.

Additionally, compared with the geographic location in Figure 3-1, there is no significant correlation between geographic information and cluster assignments, which is consistent with the previous research [4].

4.2 Developed normalized axle load spectra

The NALS, based on 3 clusters, were utilized to develop level 2 traffic inputs, which include both statewide average (cluster average) and cluster-specific data. The arithmetic average was used to represent the statewide average traffic input. The AASHTOWare PMED software used for ME design provides two different defaults for axle load spectra: NCHRP 1-37A default by NCHRP project and LTPP default collected by Specific Pavement Studies (SPS), with four levels (global, heavy, typical, and light). Figure 4-3 presents the cluster-based and default nationwide NALS.

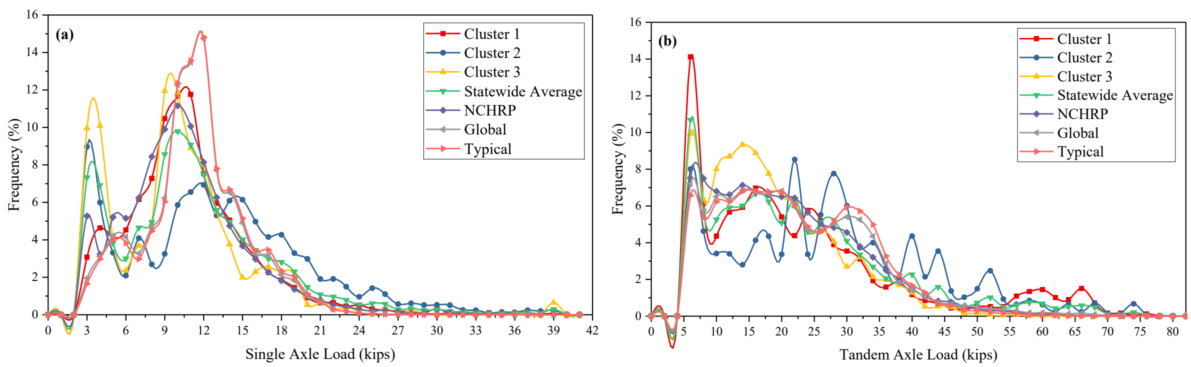


Figure 4-3 Developed NALS based on different levels. (a) Single axle load spectra (b) Tandem axle load spectra

As for single axle load spectra in Figure 4-3(a), the LTPP global and typical data show a similar distribution over the single axle load, with a higher percentage of loads concentrated at around 12 kips. The spectrum of cluster 1 closely resembles that of NCHRP default data, with a peak around 10 kips. Cluster 2 displays a more uniform distribution across the load bins without obvious peaks compared with other spectra. Cluster 3 presents two distinct peaks, one at 4 kips and another at 9 kips, respectively, which could correspond to the weight distribution of empty trucks and fully loaded trucks. It is noted that similar distribution trends with different peak values are observed for single axles. In terms of tandem axle load distribution in Figure 4-3(b), there are typically two peaks for this traffic pattern. The majority of clusters exhibit a higher percentage at 6 kips, followed by the second peak at approximately 15 kips. Cluster 2 presents a higher percentage from 20 to 30 kips, which is different from the single axle load distribution of cluster 2.

Additionally, another important traffic input is the VCD. There are 17 truck traffic classifications (TTCs) provided by AASHTOWare PMED software for pavement design [25]. The frequency distribution of VCD by developed hierarchical clusters is compared with the default values in

Figure 4-4. As shown in Figure 4-4(a), the predominant trucks for cluster 1 are class 9. For cluster 2 and cluster 3, the predominant truck is class 5, with a moderate amount of class 9 trucks. The cluster average has a slightly greater proportion of class 9 compared to the individual clusters. Consequently, the VCD from ME default values is compared with the generated clusters in Figure 4-4(b), (c), and (d). The distribution patterns of cluster 1 are close to those of TTC2, with a higher percentage of class 9 trucks. Cluster 2 and cluster 3 are compared with TTC12 and TTC9, respectively. Figure 4-4 illustrates that the generated vehicle distribution aligns with the default values.

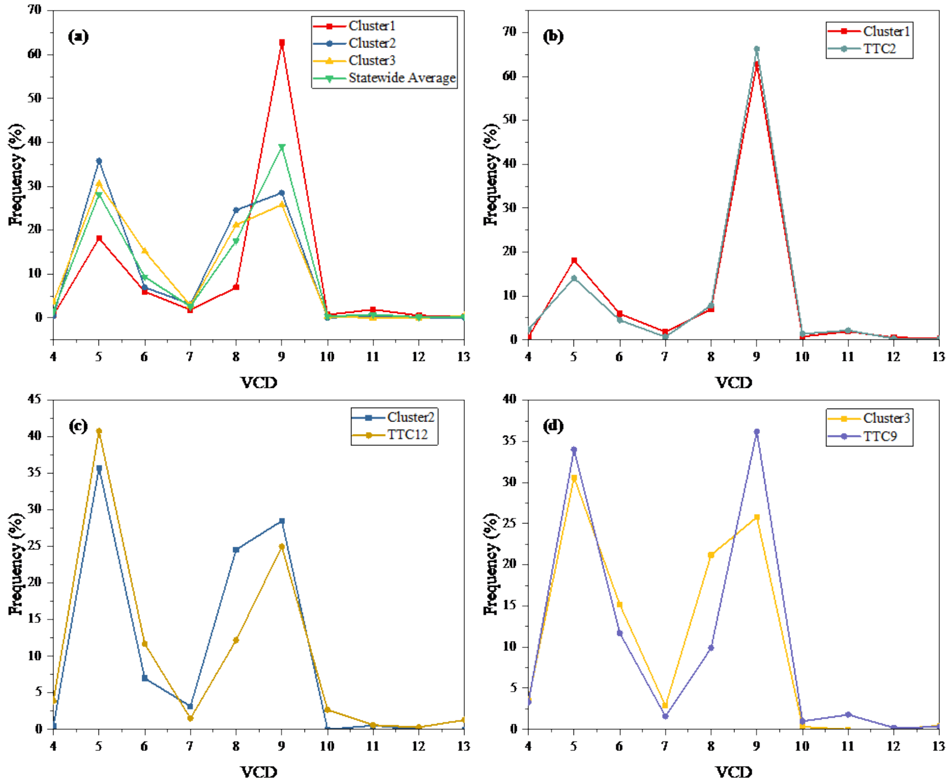


Figure 4-4 Vehicle class distribution of clusters.

Due to the predominance of class 5 and class 9 vehicles in generated clusters, the single and tandem axle load spectra for class 5 and class 9 are presented in Figure 4-5. Cluster 3 spectra for class 5 axle load shows two peaks, which closely correspond to those observed in Figure 4-3, while other axle load bins with the greatest frequency present consistent patterns. Class 5 tandem axle aggregates at 7 kips and does not distribute over the heavy load bins, which is typical for class 5 vehicles in Figure 4-5(c). In contrast, there is a greater proportion of class 9 tandem axles distributed between 10 and 50 kips. The generated level 2 traffic inputs were used to analyze pavement performance and determine the most appropriate regional values for design applications.

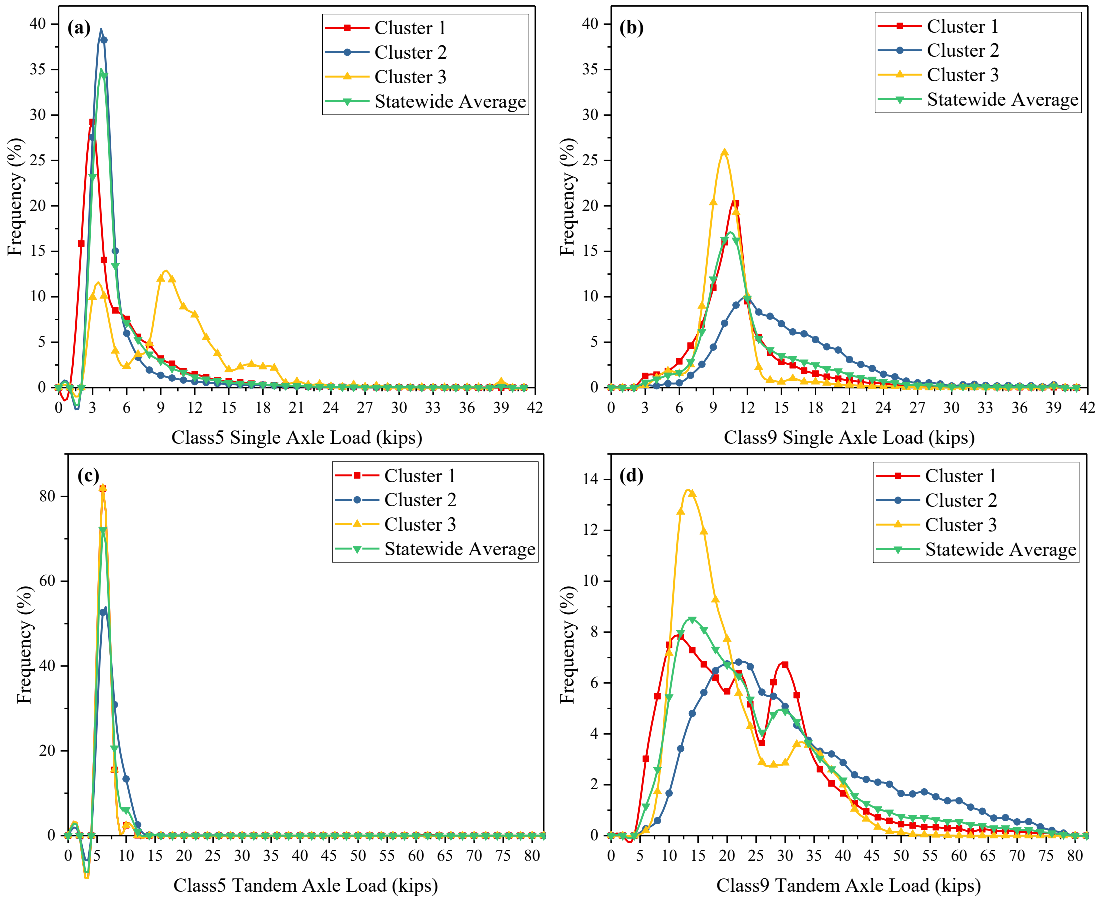


Figure 4-5 Single and tandem ALS for class5 and class9.

4.3 Impact of traffic inputs on pavement performance

4.3.1 Rigid pavement performance analysis

Figure 4-6 presents the performance of new pavement over 20 years at WIM site 600, which was analyzed as Jointed Plain Concrete Pavement (JPCP, rigid pavement). The thickness of the surface slab and cemented treated base are 9 and 6 in., respectively, and the subgrade is classified as A-2-6 for analysis. The JPCP transverse cracking for all traffic scenarios is less than 1%, and it is not displayed in Figure 4-6. The traffic patterns of site 600 belong to cluster 1, and the performance was compared with other scenarios. IRI is 152.02 in./mile and 158.41 in./mile for site-specific and cluster 1 data, respectively. Cluster-based data and default data predict higher IRI values than the site-specific case. The predicted IRI remains within acceptable limits after 20 years, without exceeding the limit. However, the critical pavement distress is the joint faulting, as shown in Figure 4-6. The service years vary significantly based on mean joint faulting. Based on the design limit, the service years are 17.17, 14.90, 19.42, 18.02, 17.92, and 18 for cluster 1, statewide average, site-specific, NCHRP, LTPP Global, and LTPP Typical scenarios, respectively. The predicted service years from cluster 1, NCHRP, and LTPP default data show no statistically significant differences. Cluster 1 data tends to overestimate the distress of rigid pavement compared to the site-specific data. Either the NCHRP or the LTPP default values can be used to predict the performance of the new rigid pavement effectively.

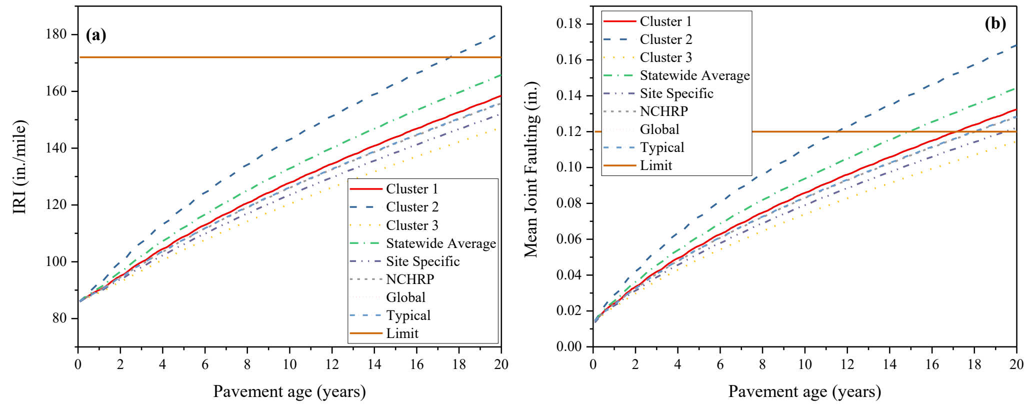


Figure 4-6 New rigid pavement performance.

In addition to the new pavement design, a pavement overlay design was performed on the rigid pavement. A total of 4.4 in. thickness of HMA was used as an overlay for site 600, and the design limits were the same as those for flexible pavements. Figure 4-7 compares the performance of the asphalt concrete (AC) overlay placed over the rigid pavement. The IRI of the overlay shows a similar trend to that of the new rigid pavement. The statewide average traffic input overestimates the IRI distress. All the traffic inputs predict the same fatigue cracking performance, as the underlying Portland cement concrete (PCC) layer provides adequate structural support. However, the analyzed overlay suffers from premature damage due to AC rutting, with all the traffic inputs failing within approximately 2 years due to excessive deformation (namely, 0.5 years for cluster analysis and 2 years for site-specific data). The measured rut depth from the LTPP database is 5 mm (0.2 in.) after two years, and it demonstrates that the overlay rutting is the critical response for overlay design. Therefore, it is recommended to use the LTPP default (Global or Typical data) to analyze the structure of the new rigid pavement and overlay placed on the rigid pavement in Tennessee.

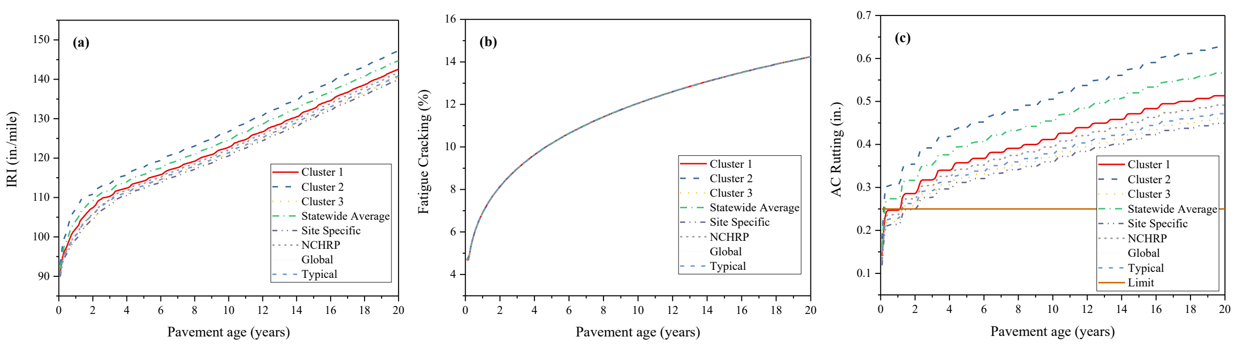


Figure 4-7 Rigid pavement overlay performance.

4.3.2 Semi-rigid pavement performance analysis

Figure 4-8 shows the WIM site 2008 of the Semi-rigid pavement without the aggregate subbase layer. The pavement structure consists of 11.6 in. HMA layer, 9.3 in. cement-treated base (CTB) layer, supported by the A-4 subgrade. However, the assumed 2 in. drainage layer is required for the computation in AASHTOWare PMED software, as the reflection cracking was derived based on the aggregate subbase layer [19]. The design criteria are listed in Table 3-1, and IRI, as an indicator of smoothness and functional distress, has been considered in the analysis.

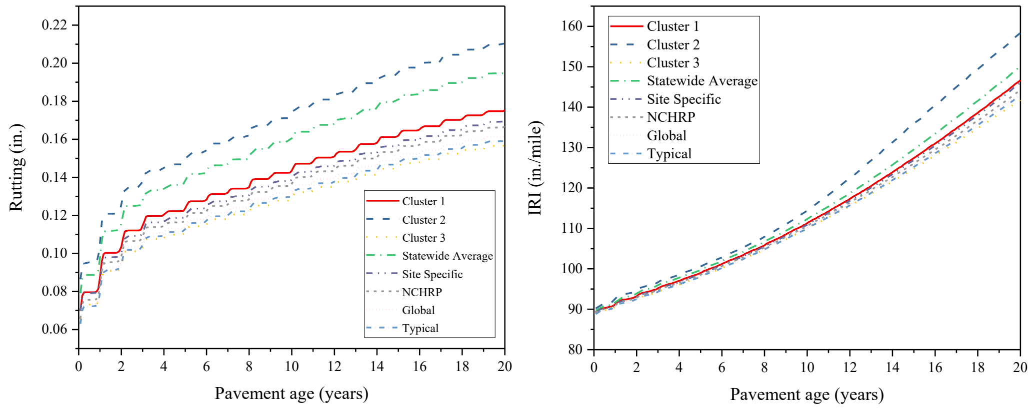
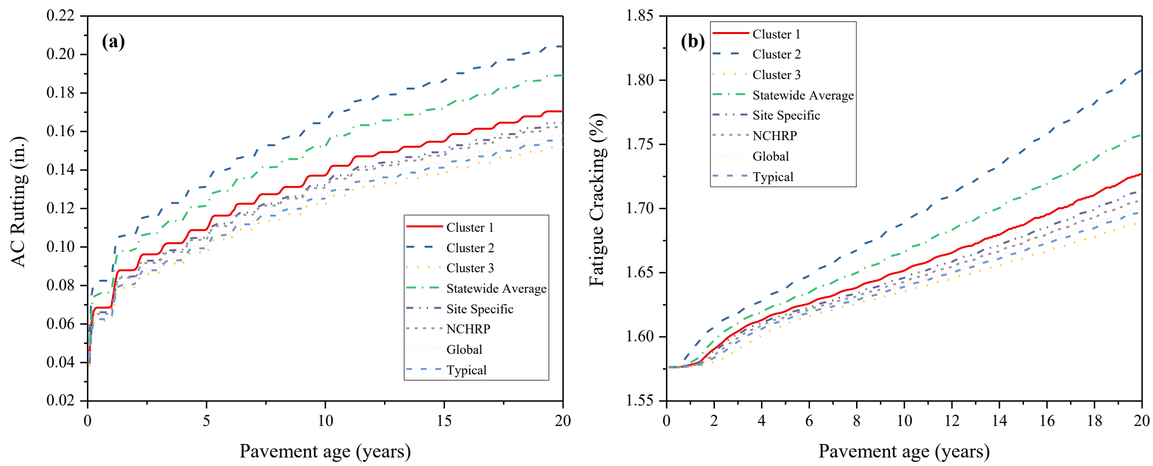


Figure 4-8 Pavement performance at site 2008.

The predicted fatigue cracking is less than 0.6% and therefore not plotted here. In the MEPDG framework, bottom-up fatigue cracking is modeled as the accumulation of tensile damage at the bottom of the asphalt concrete layer under repeated traffic loading. For thin asphalt pavements, higher tensile strains at the bottom of the asphalt layer under traffic loading make bottom-up fatigue damage more likely. The fatigue cracking is negligible for the thick analyzed scenario here[4]. The traffic input of the analyzed semi-rigid pavement is classified as cluster 1, and the distress trend in Figure 4-8 shows that the prediction using cluster 1 exhibits no significant difference from that using the level 1 data for both rutting and IRI. The cluster generates the closest prediction compared with the level 1 site-specific data.

Additionally, the overlay performance of the semi-rigid pavement is compared with other traffic inputs in Figure 4-9. The 1.5 in. AC overlay was constructed after 16 years of service at the site 2008, as recorded from the LTPP maintenance history. The corresponding pavement critical distresses and smoothness are presented in Figure 4-9. From Figure 4-9(a), (b), and (c), it is evident that cluster 1 continues to provide predictions that are equivalent to those obtained using level 1 traffic input.



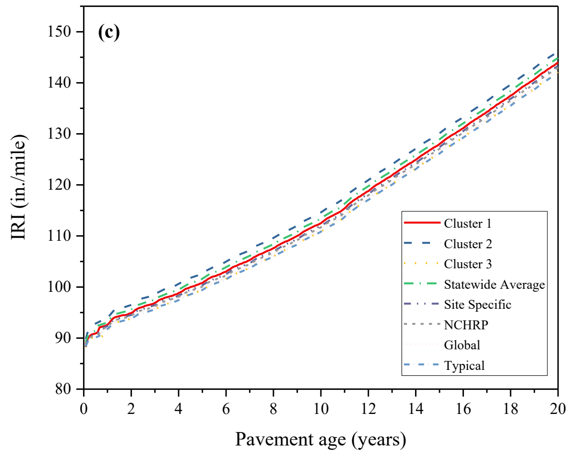


Figure 4-9 Performance on the overlay placed over the semi-rigid pavement.

4.3.3 Conventional flexible pavement performance

The conventional flexible pavement in Tennessee typically consists of asphalt concrete (AC) surface and binder layers placed over unbound aggregate base layers, with a total AC thickness generally less than 6 in., according to typical TDOT design practice and layer thickness requirements [24]. WIM Site 9025, belonging to cluster 3, was used for comparison. The thicknesses of the HMA and unbound base layers were 5 in. and 9.2 in., respectively, for new pavement, and 1.5 in. for the HMA overlay used in the analysis. The performances of the new and overlay analysis are shown in Figure 4-10 and Figure 4-11. The results demonstrate that the level 2 cluster data yield performance predictions equivalent to those from level 1 site-specific data for the conventional flexible pavement. The NCHRP default and LTPP data overestimate the pavement rutting and IRI, while there is no significant difference for LTPP Global and Typical data. The new pavement and overlay exhibit similar deterioration trends for both AC rutting and IRI over the design years. It is indicated that the cluster-generated level 2 data provides the closest performance prediction compared to level 1 site-specific data for both flexible pavement and flexible pavement overlay design. The cluster-generated truck traffic data can be used for pavement design and analysis when the site-specific data is unavailable.

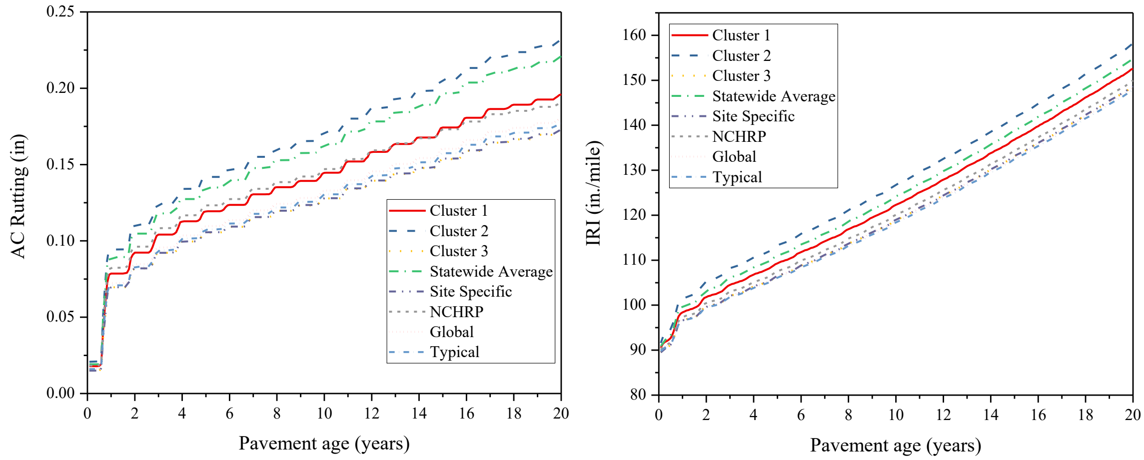


Figure 4-10 Performance of new conventional flexible pavement.

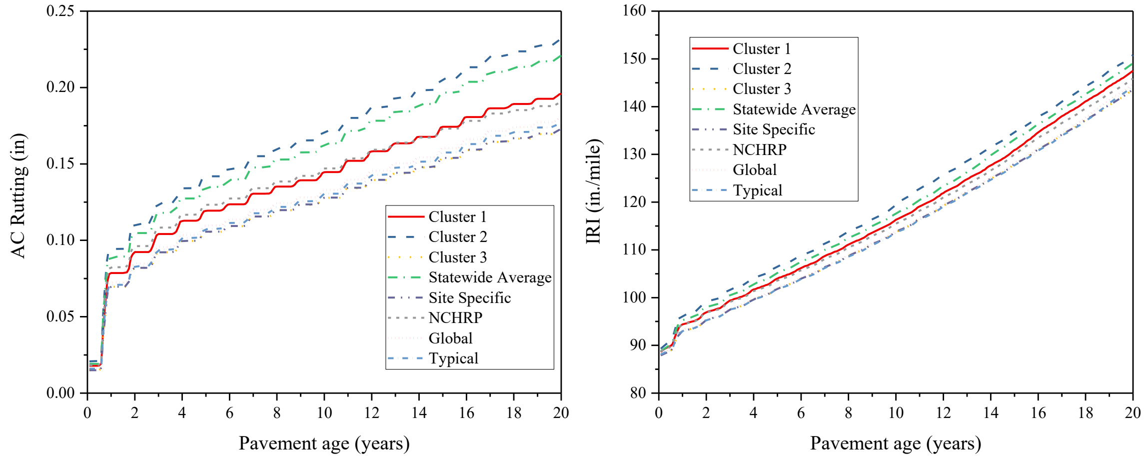


Figure 4-11 Overlay performance of conventional flexible pavement.

4.3.4 Overall performance of the WIM site

The predicted pavement performances of 8 WIM sites with flexible pavement structures (excluding site 600, which is the rigid pavement) after 20 years are compared in Figure 4-12, Figure 4-13, and Figure 4-14. There are two overlapping points in Figure 4-12 with similar performance, thereby presenting 7 points. The Root Mean Square Error (RMSE) is the metric to determine the accuracy of the traffic input: level 1 (site-specific), level 2 (clusters), and level 3 (NCHRP default values). Figure 4-12 compares the new pavement fatigue cracking performance using level 2 and level 3 inputs against level 1 data. The accuracy of different traffic inputs is considered equivalent if the observed points fall along the red line. The level 2 inputs include both the statewide average and the corresponding cluster-based input data. The RMSEs of NCHRP default, statewide average, and clusters are 1.029%, 1.973%, and 0.491%, respectively. The statewide average data yield the highest deviations in predicting fatigue cracking, as it tends to overestimate the pavement fatigue cracking. In contrast, the cluster-based input demonstrates the greatest accuracy for prediction with the lowest RMSE. However, though the NCHRP-based level presents lower RMSE than statewide average data, it tends to underestimate the pavement fatigue damage, as indicated by a greater number of points falling below the red line.

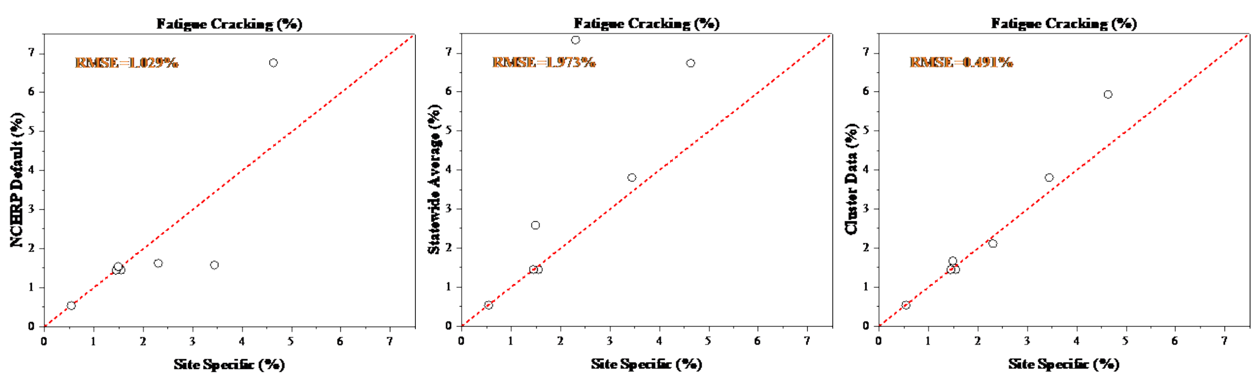


Figure 4-12 New pavement fatigue cracking performance via different traffic input.

Similar observations are found in Figure 4-13 for predicting AC rutting. The RMSEs for level 3, level 2 statewide average, and level 2 cluster are 0.024in., 0.037in., and 0.023in., respectively. The cluster-based input performs similarly to the level 3 data in terms of rut depth. The RMSEs are

3.057 in./mile, 6.130 in./mile, and 2.452 in./mile for IRI, as shown in Figure 4-14. The design threshold for pavement AC rutting is 0.25 in., and several observed points have reached the design limits while predicted fatigue cracking and IRI remain acceptable over the design years with a 90% reliability.

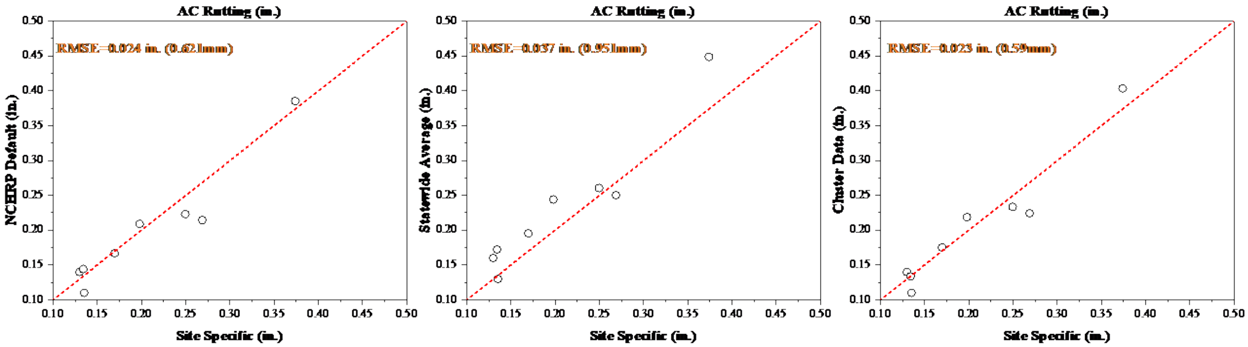


Figure 4-13 New pavement rutting performance via different traffic input.

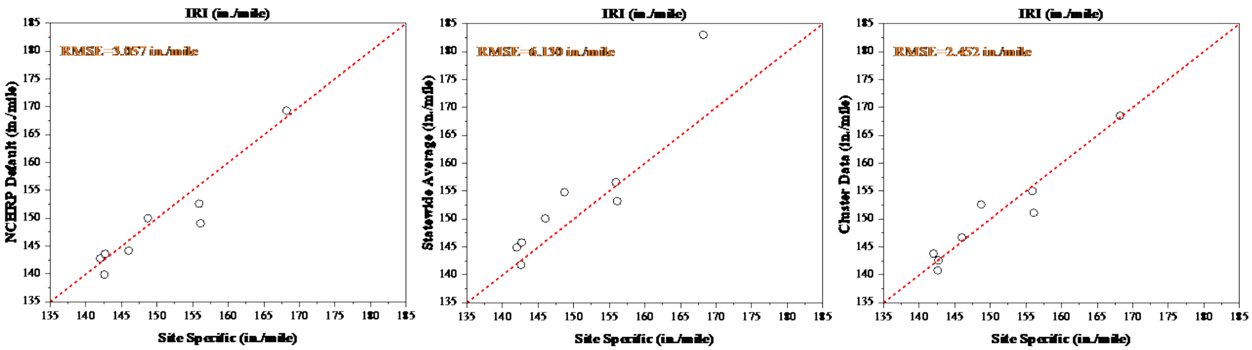


Figure 4-14 New pavement IRI performance via different traffic input.

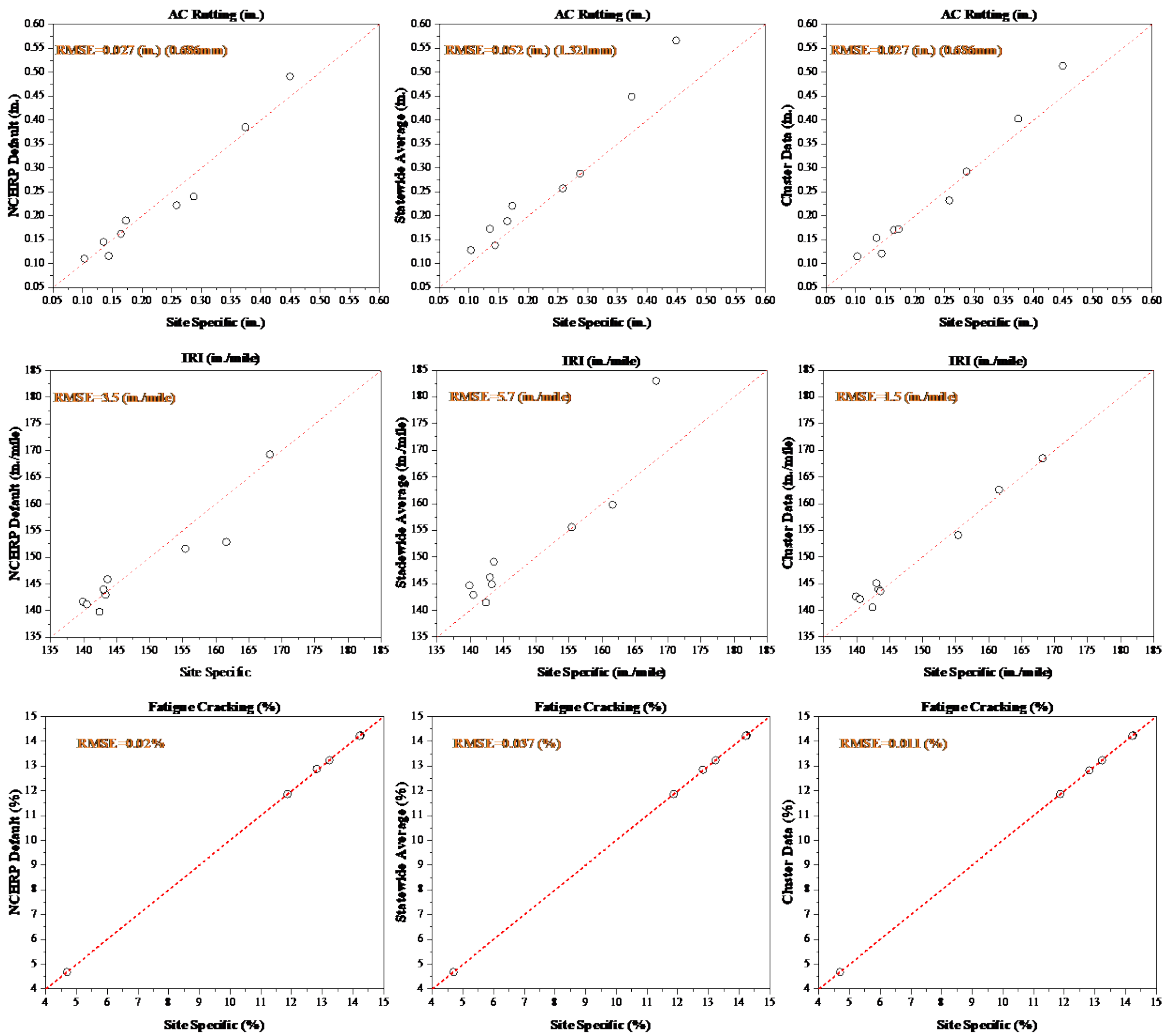


Figure 4-15 Performance of overlay via different traffic input.

The overall AC overlay performance is presented in Figure 4-15. The performance of AC overlays is controlled by AC rutting, fatigue cracking, and IRI. Therefore, 9 WIM sites were compared, including site 600 (where an AC overlay was placed over the rigid pavement). Similar observations are found from the overlay performance compared with the new pavement. As shown in Figure 4-15, the RMSEs for predicting rutting are 0.027 in. (0.686mm), 0.052 in. (1.321mm), and 0.027 in. (0.686mm) for level 3, level 2 (statewide), and level 2 (cluster), respectively. Additionally, the rutting remains a critical distress indicator, since some observed points present greater rut depths. Level 2 (cluster) has the smallest RMSE of 1.5 in./mile for predicting IRI among the three traffic inputs, while the statewide average leads to the greatest error for RMSE. It indicates that the cluster-based traffic data is more reliable for both new and overlay pavement design. The predictions of fatigue cracking of the three inputs are similar, and the fatigue cracking is still not the critical pavement distress with a threshold of 25%. The observation is consistent with the findings for the new pavement design.

4.3.5 Impacts on SN calculations

Figure 4-16 and Figure 4-17 compare the SN calculated using different truck factor sources against site-specific SNs, which serve as the reference. Points falling below the red diagonal line indicate underestimation, while points above reflect overestimation. In Figure 4-16, the SN values derived from national datasets—NCHRP, LTPP Typical, and LTPP Global, tend to underestimate the actual structural requirements. Among them, NCHRP performs best (RMSE = 0.356), followed by LTPP Typical (0.425) and LTPP Global (0.468). In Figure 4-17, the use of locally calibrated truck factors results in different trends. TDOT's truck factors slightly underestimate the SN values, similar to national datasets, as most points lie below the diagonal (RMSE = 0.353). In contrast, the cluster-based data tends to overestimate SN values while providing a more conservative design. Overall, these comparisons demonstrate that site-specific or regionally calibrated truck factors are essential for improving pavement design accuracy, as national and statewide averages can either underestimate or overestimate actual pavement strength.

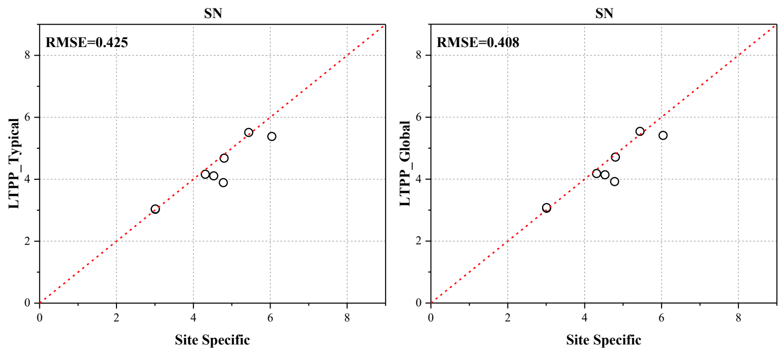


Figure 4-16 SN calculation with nation-wide NCHRP and LTPP data.

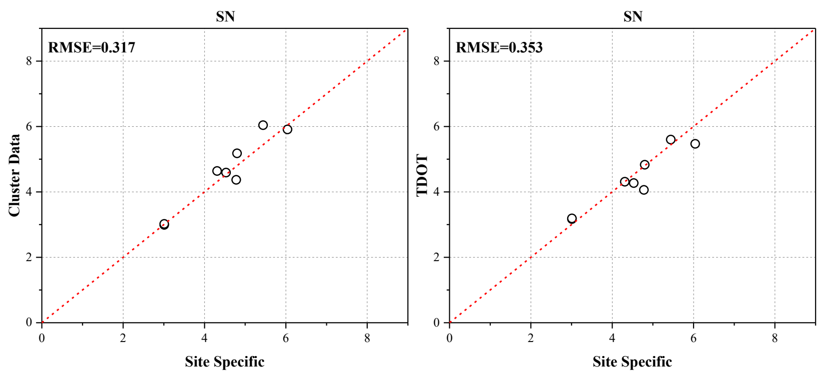


Figure 4-17 SN calculation with cluster and site-specific data.

4.4 Truck factor based on different ALS data

The NALS were derived from the NCHRP data, LTPP data, and the developed cluster. Based on the default number of axles per vehicle in Table 4-2, Table 4-3 to Table 4-8 present the calculation of the truck factor for different axle load inputs by different vehicle classes and load types. The total truck factor is calculated by Equation (3-9) with the axle configuration for each vehicle class.

Table 4-2 NCHRP Default Number of Axles per Vehicle.

Vehicle Class	Single axles per vehicle	Tandem axles per vehicle	Tridem axles per vehicle	Quad axles per vehicle
4	1.62	0.39	0.00	0.00
5	2.00	0.00	0.00	0.00
6	1.02	0.99	0.00	0.00
7	1.00	0.26	0.83	0.00
8	2.38	0.67	0.00	0.00
9	1.13	1.93	0.00	0.00
10	1.19	1.09	0.89	0.00
11	4.29	0.26	0.06	0.00
12	3.52	1.14	0.06	0.00
13	2.15	2.13	0.35	0.00

Table 4-3 Truck factor calculated from NCHRP data.

Vehicle class	Truck factor					VCD (%)
	Single	Tandem	Tridem	Quad	Total	
Class4	0.34	0.29	0.17	0.06	0.66	3.30
Class5	0.14	0.18	0.63	0.23	0.28	34.00
Class6	0.28	0.42	0.66	0.24	0.70	11.70
Class7	0.63	0.85	0.93	0.33	1.63	1.60
Class8	0.24	0.16	0.83	0.30	0.68	9.90
Class9	0.19	0.46	0.09	0.03	1.11	36.20
Class10	0.20	0.61	0.37	0.13	1.23	1.00
Class11	0.36	0.35	0.17	0.06	1.66	1.80
Class12	0.28	0.36	0.54	0.19	1.43	0.20
Class13	0.28	0.68	0.95	0.35	2.39	0.30

Table 4-4 Truck factor from LTPP Typical data.

Vehicle class	Truck factor					VCD (%)
	Single	Tandem	Tridem	Quad	Total	
Class4	0.32	0.51	0.00	0.00	0.72	3.30
Class5	0.07	0.00	0.00	0.00	0.14	34.00
Class6	0.28	0.23	0.00	0.00	0.52	11.70
Class7	0.69	0.96	0.52	0.44	1.38	1.60
Class8	0.19	0.09	0.00	0.00	0.52	9.90
Class9	0.22	0.36	0.00	0.00	0.94	36.20
Class10	0.19	0.52	0.26	0.23	1.03	1.00
Class11	0.32	0.00	0.00	0.00	1.36	1.80

Class12	0.20	0.11	0.00	0.00	0.84	0.20
Class13	0.29	0.94	1.08	0.61	3.00	0.30

Table 4-5 Truck factor from LTPP Global data.

Vehicle class	*Truck factor*					*VCD (%)*
	Single	Tandem	Tridem	Quad	Total	
Class4	0.32	0.50	0.00	0.00	0.71	3.30
Class5	0.07	0.00	0.00	0.00	0.14	34.00
Class6	0.27	0.29	0.00	0.00	0.57	11.70
Class7	0.54	1.78	0.83	0.44	1.70	1.60
Class8	0.21	0.14	0.00	0.00	0.59	9.90
Class9	0.22	0.38	0.00	0.00	0.98	36.20
Class10	0.19	0.51	0.33	0.23	1.08	1.00
Class11	0.30	0.00	0.00	0.00	1.29	1.80
Class12	0.20	0.11	0.00	0.00	0.84	0.20
Class13	0.34	0.85	1.01	0.46	2.91	0.30

Table 4-6 Truck factor from Cluster 1 data.

Vehicle class	*Truck factor*					*VCD (%)*
	Single	Tandem	Tridem	Quad	Total	
Class4	0.59	0.63	0.00	0.00	1.20	0.75
Class5	0.11	0.02	0.00	0.00	0.21	16.72
Class6	0.50	0.80	0.00	0.00	1.30	5.64
Class7	0.49	7.75	2.12	0.40	4.27	1.59
Class8	0.42	0.35	0.00	0.00	1.23	7.01
Class9	0.34	0.78	0.17	0.47	1.90	64.44
Class10	0.22	0.85	0.43	0.15	1.57	0.74
Class11	0.61	0.37	0.00	0.00	2.72	2.28
Class12	0.45	0.25	0.15	0.00	1.86	0.59
Class13	0.27	1.57	0.00	0.51	3.91	0.24

Table 4-7 Truck factor from Cluster 2 data.

Vehicle class	*Truck factor*					*VCD (%)*
	Single	Tandem	Tridem	Quad	Total	
Class4	1.82	1.86	0.00	0.00	3.67	0.46
Class5	0.08	0.00	0.00	0.00	0.16	35.78
Class6	1.44	2.63	0.00	0.00	4.07	6.99
Class7	1.43	1.16	2.94	0.00	4.17	3.16
Class8	0.56	0.46	0.00	0.00	1.63	24.57
Class9	1.02	2.06	0.00	0.00	5.13	28.50
Class10	0.76	2.72	0.27	0.00	4.11	0.00
Class11	1.41	0.00	0.00	0.00	6.03	0.54

Class12	0.11	0.36	0.00	0.00	0.79	0.00
Class13	0.79	2.56	0.45	0.27	7.33	0.00

Table 4-8 Truck factor from Cluster 3 data.

Vehicle class	*Truck factor*					*VCD (%)*
	Single	Tandem	Tridem	Quad	Total	
Class4	0.26	0.18	0.00	0.00	0.49	0.75
Class5	0.06	0.00	0.00	0.00	0.13	16.72
Class6	0.26	0.40	0.00	0.00	0.66	5.64
Class7	0.61	0.61	1.04	0.00	1.63	1.59
Class8	0.08	0.10	0.00	0.00	0.25	7.01
Class9	0.19	0.37	0.00	0.00	0.94	64.44
Class10	1.75	0.40	0.12	0.00	2.63	0.74
Class11	0.17	0.00	0.00	0.00	0.73	2.28
Class12	0.09	0.12	0.05	0.00	0.47	0.59
Class13	0.42	0.61	2.43	0.28	3.04	0.24

4.5 Development of network-level ESAL distribution in Tennessee

Table 4-9 and

Table 4-10 present the 18-kip factor (truck factor) from TDOT used for the calculation of ESALs. The truck factor in Table 4-9 is used for Urban and Rural Interstate routes. Other types of highways adopt the truck factor in

Table 4-10.

Table 4-9 Truck factor for Urban and Rural Interstate routes [24].

Vehicle Type (Vehicle category)		*Flexible (18-kip factor)*	*Rigid (18-kip factor)*
Passenger Cars and motorcycles (Class 1-2)		0.001	0.001
Pick-up, Panel, Van (Class 3)		0.004	0.005
Single Unit	Buses (Class 4)	0.300	0.300
	2-axle, 6 tire (Class 5)	0.170	0.170
	3-axle or more (Class 6-7)	0.700	1.000
Comb.	4-axle (Class 8)	0.700	0.780
	5 axle or more (Class 9-13)	1.100	1.780

Table 4-10 Truck factor for other routes.

Vehicle Type (Vehicle category)		*Flexible (18-kip factor)*	*Rigid (18-kip factor)*
Passenger Cars and motorcycles (Class 1-2)		0.001	0.001
Pick-up, Panel, Van (Class 3)		0.004	0.004
Single Unit	Buses (Class 4)	0.300	0.300
	2-axle, 6 tire (Class 5)	0.260	0.260
	3-axle or more (Class 6-7)	1.000	1.500

Comb.	4-axle (Class 8)	0.640	0.800
	5 axle or more (Class 9-13)	1.200	1.900

Figure 4-18 presents the distribution of pavement design temperatures derived from the LTPP Binder Program across the United States [26], representing the climatic basis for Performance-Grading (PG) asphalt binder selection. Figure 4-18(a) illustrates the distribution of high pavement temperatures at 98% reliability, which governs rutting resistance and binder stiffness. Figure 4-18(b) shows the corresponding low pavement temperatures, which control the binder's thermal cracking susceptibility at cold conditions. Tennessee is characterized by high pavement temperatures ranging approximately from 58 °C to 64 °C and low pavement temperatures from -22 °C to -16 °C. Therefore, PG 64-22 is adopted as the baseline binder grade in Tennessee, ensuring adequate resistance to both rutting and thermal cracking.

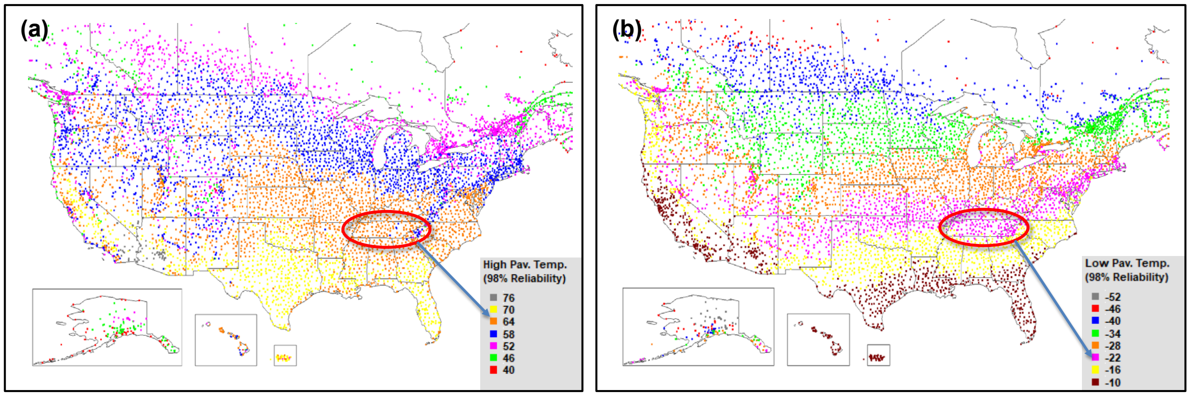


Figure 4-18 Pavement temperature distribution from LTPP binder program (a) high temperature; (b) low temperature.

Figure 4-19 illustrates the network-level distribution of ESALs across Tennessee, which was computed based on the statewide traffic data. The resulting ESAL map provides an initial estimate of the structural loading demand over the 20-year design life for each pavement segment.

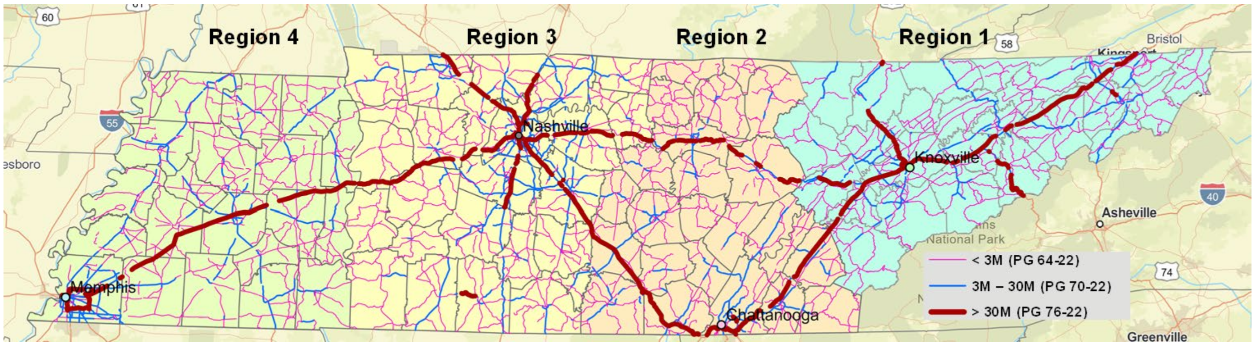


Figure 4-19 Network-level ESALs in Tennessee

However, according to TDOT specifications, the selection of PG asphalt binders is not only determined by the calculated ESALs. As summarized in Table 4-11, TDOT specifies that all Interstate highways require PG 76-22 binders, regardless of the ESALs. Based on this requirement, the network-level PG binder selection was adjusted accordingly, as shown in Figure 4-20.

Table 4-11 Performance Grade Asphalt.

Accumulated ESALs over Design Life	*Performance Grade Asphalt*
30,000,000+ or All Interstates	PG 76-22
3,000,000 to 29,999,999	PG 70-22
<3,000,000	PG 64-22

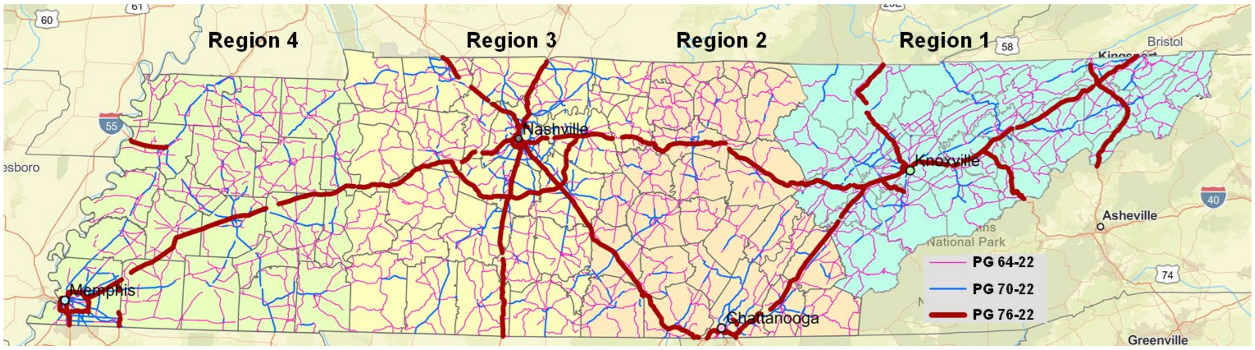


Figure 4-20 ESALs distribution adjusted by TDOT specification

4.6 Development of network-level SN distribution in Tennessee

As illustrated in Figure 4-21, the distribution of CBR values varies noticeably among the four regions. Overall, Region 4 exhibits the highest median and greater variability in CBR. CBR is used to calculate the M_R for SN. Figure 4-22 and Figure 4-23 present the distribution of the backcalculated SN across different functional highway classes across Tennessee. As shown in Figure 4-22, interstate highways exhibit the highest SN values (typically above 5), reflecting the thicker structural layers designed to accommodate heavy traffic. In contrast, collectors and minor arterials display lower SN values (mostly between 2 and 4), consistent with their lighter traffic volumes and reduced design reliability.

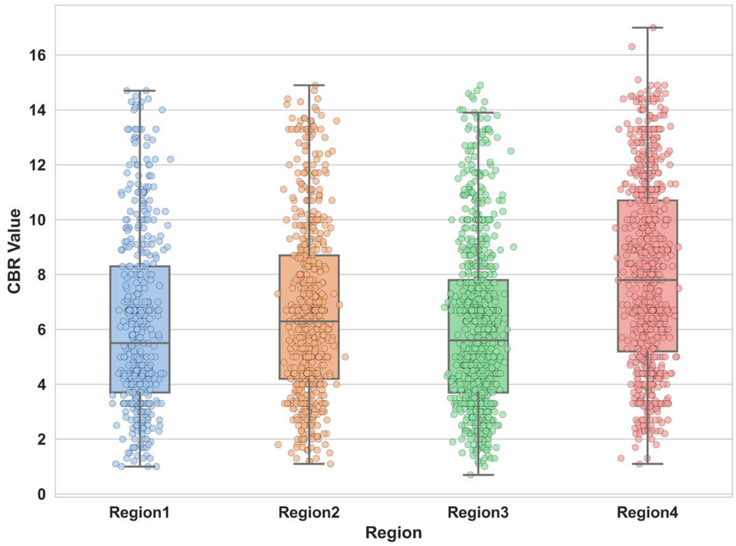


Figure 4-21 CBR distribution by regions

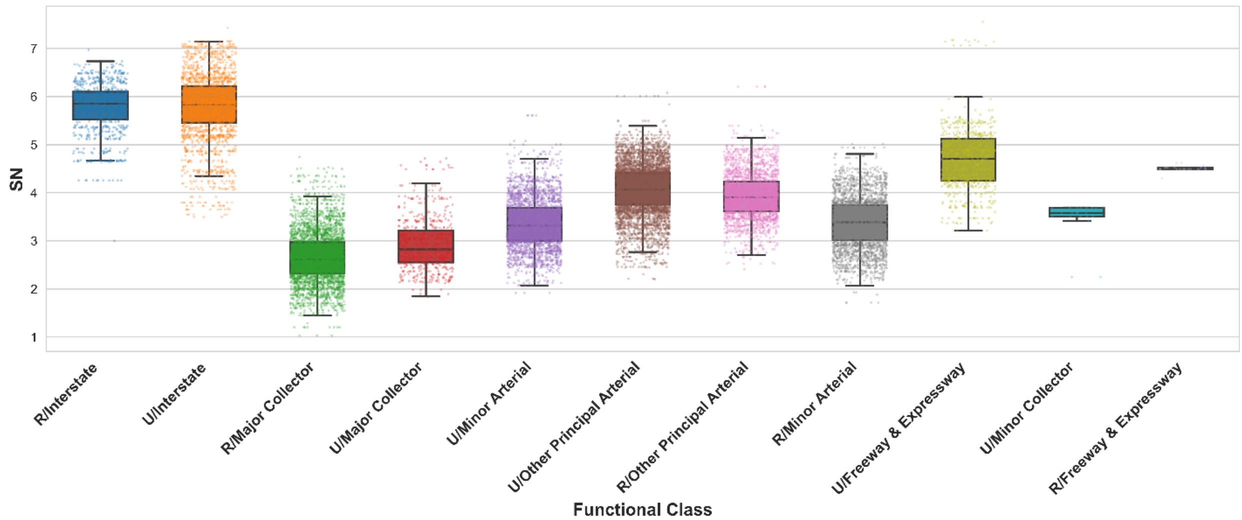


Figure 4-22 SN distribution for different functional highways

Figure 4-23 illustrates the network-level distribution of the backcalculated SN across Tennessee. Higher SN values, generally exceeding 5.5, are concentrated along major interstate corridors such as I-40, I-24, and I-75, reflecting the thicker structural layers required to sustain heavy truck traffic and high reliability levels. The spatial pattern highlights the regional variability in pavement structural capacity. Moreover, the backcalculated SN values can serve as a reference benchmark for structural evaluation by comparing them with SNs derived from Falling Weight Deflectometer (FWD) or Traffic Speed Deflectometer (TSD) measurements for maintenance and rehabilitation planning.

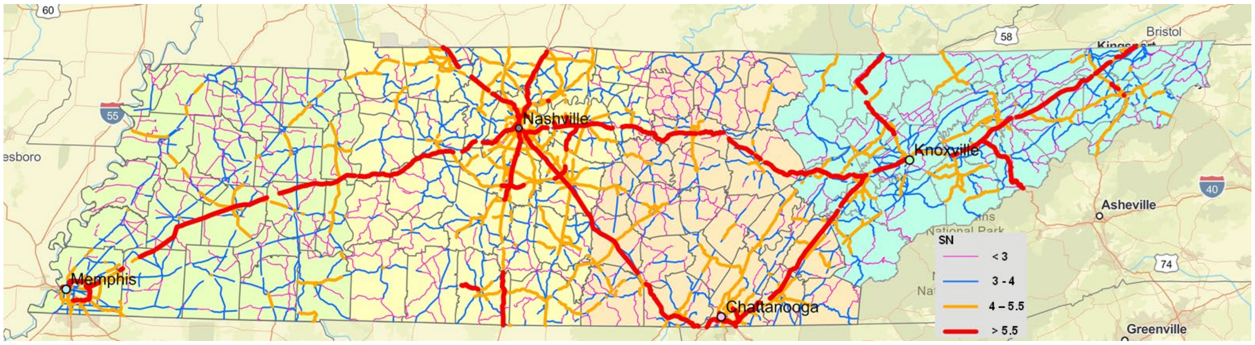


Figure 4-23 Network-level SN distribution in Tennessee.

4.7 Benefits of the findings

The findings of this study offer significant value to TDOT's pavement design and management practices. By developing regional truck factors and ALS from Tennessee WIM sites, the research provides data-driven insights that directly enhance the reliability of AASHTO 1993 and MEPDG. The proposed regional Level 2 traffic inputs, derived from hierarchical clustering, capture the variability in Tennessee's truck loading conditions rather than relying on generalized national defaults.

The updated cluster-specific data and recalculated SN values offer a more accurate reflection of local pavement performance, supporting more realistic predictions of fatigue cracking, rutting, and IRI development. These findings ensure that pavement design and rehabilitation decisions are grounded in Tennessee-specific conditions, leading to longer service life and a more cost-effective allocation of TDOT's maintenance resources.

Furthermore, the classification of ESALs into four traffic loading levels creates a clear framework for binder selection and structural design, thereby improving consistency and enhancing the long-term durability of the roadway network.

4.8 Implementation potential and limitations

The proposed framework has practical potential for statewide implementation within TDOT's pavement design and asset management systems. By integrating the updated regional traffic factors and cluster-based spectra into MEPDG software or AASHTO 1993 workflows, the Department can achieve more reliable pavement performance predictions and improved design performance across Tennessee. The back-calculated SN values are useful for project-level and network-level pavement rehabilitation analyses.

In terms of implementation challenges, the primary consideration involves maintaining an updated WIM dataset and ensuring consistent data quality across regions. Continued data collection and WIM maintenance will be essential to keep the regional calibration updated.

Chapter 5 Conclusion

Axle load spectra obtained from the LTPP database, together with local AADT data from Tennessee, were analyzed to establish regional Level-2 traffic inputs for Mechanistic-Empirical Pavement Design. NALS and VCD were combined as the features for cluster analysis. Hierarchical clustering was applied to classify the WIM sites into representative traffic clusters based on NALS and VCD. The three clusters of traffic patterns were developed and compared with the NCHRP, LTPP nationwide data, and site-specific data to determine the suitable traffic inputs for pavement design and analysis. In addition, datasets from NCHRP, LTPP Typical, LTPP Global, and TDOT were evaluated and compared to derive regional truck factors for ESAL estimation and corresponding SN calculation. This research provides a framework for Tennessee to establish the local traffic inputs for pavement design and provide actionable network-level asphalt binder selection and network-level SN values as a reference benchmark. The conclusions are drawn as follows:

- The single and tandem axle load spectra with VCD were formulated into the feature matrix with 88 dimensions to effectively characterize the traffic patterns among WIM sites in Tennessee. Three clusters were developed via the hierarchical clustering algorithm to develop region-level traffic inputs for pavement design. Regional level 2 traffic inputs were derived from the clustering results. The arithmetic mean across clusters was used to represent the statewide average. Axle load distribution and VCD patterns can be characterized by cluster-specific data (level 2 traffic inputs).
- The cluster-specific level 2 data yield performance results showing no significant difference from those obtained using the site-specific level 1 data for new flexible pavement and pavement overlay design. RMSEs of new pavement predictions for fatigue cracking, AC rutting, and IRI are 0.491%, 0.023in., and 2.452 in./mile for 8 WIM sites. For pavement overlay, RMSEs for fatigue cracking, AC rutting, and IRI are 0.011%, 0.027in., and 1.5 in./mile for 9 WIM sites. It is recommended to use the generated cluster data for pavement design and analysis instead of using the nationwide default inputs.
- The calculated truck factors derived from NCHRP, LTPP Typical, LTPP Global, and clusters are compared with TDOT default values. While TDOT's truck factors generally underestimated the SN values compared with the national datasets, the cluster-based local results tended to overestimate SN to produce more conservative estimates for new pavement design. It is suggested to continue collecting regional axle load data and update the truck factor accordingly using this framework for more reliable pavement design and rehabilitation analysis.
- The distribution of ESALs obtained from the TDOT default data can be used to categorize traffic into four levels (standard, heavy, very heavy, and extreme) for the development of network-level binder selection. This classification supports the selection of appropriate PG grades with expected loading conditions instead of grade bumping.
- The backcalculated SN values provide a valuable benchmark and a reasonable reference for structural evaluation of both new pavement design and rehabilitation projects at the network level.
- With the continued deployment of WIM sites in Tennessee, the framework developed in this study can be applied to newly collected traffic data to produce more representative

and realistic estimates of ESAL and SN, thereby enhancing the reliability of pavement design and rehabilitation analyses.

In summary, this study provides TDOT with a network-level framework for developing Level 2 traffic inputs and SN benchmarks to enhance the reliability of pavement design. Although the findings are based on limited set of LTPP data, they offer a practical foundation for statewide application. The research team is collaborating with TDOT to refine and update traffic inputs as more WIM systems are deployed and more data become available. Integrating cluster-based inputs into MEPDG workflows, together with sustained and consistent traffic monitoring, is expected to further improve accuracy. Future work should expand WIM coverage and incorporate additional traffic characteristics for feature extraction and classification. Overall, the framework supports a more reliable and adaptive pavement design and network-level pavement management in Tennessee.

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Appendices

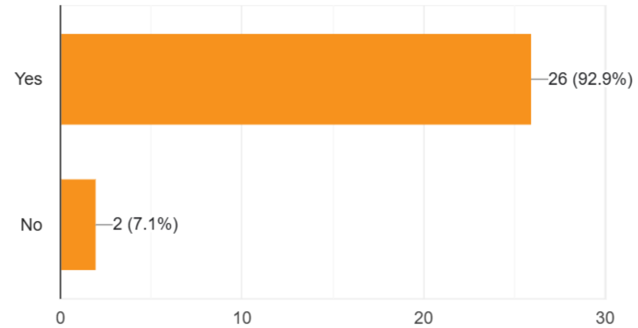
Appendix A: DOT Survey Summary

Through an online survey of the State and Provincial Departments of Transportation (DOTs), the survey was sent to 50 states in the US, and 28 responses were received. This summary is based on the responses of the following states: Hawaii (HI), Wyoming (WY), Connecticut (CT), Ohio (OH), Delaware (DE), Colorado (CO), Utah (UT), Indiana (IN), Kentucky (KY), New York (NY), Oregon (OR), Minnesota (MN), West Virginia (WV), North Carolina (NC), Maryland (MD), Illinois (IL), Alabama (AL), Georgia (GA), Texas (TX), Florida (FL), Virginia (VA), Louisiana (LA), Iowa (IA), New Jersey (NJ), Missouri (MO), Mississippi (MS), Arizona (AZ), and North Dakota (ND).

This questionnaire is prepared by the University of Tennessee, Knoxville (UTK), intending to update the truck factor based on Weigh-in-Motion (WIM) data for pavement design and binder selection. This goal will be achieved through the development of a practical method to determine the Equivalent Single Axle Load (ESAL). The research will convert the traffic data into load spectra and consider different pavement structures, functions, condition to calculate and update the truck factors for the estimation of network-level ESALs, incorporating estimated network-level ESALs into TDOT's binder selection.

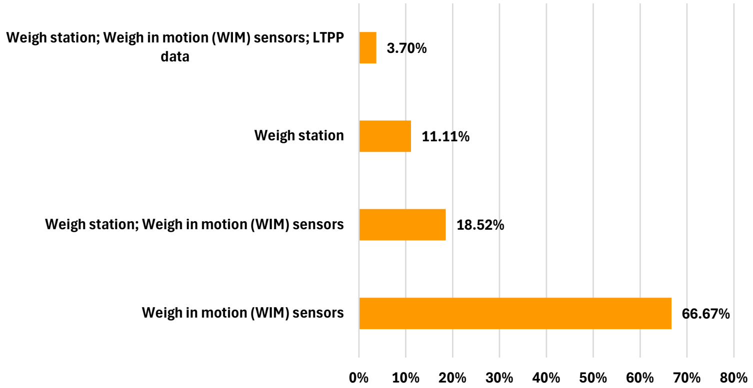
According to the responses, 92.9% of states classify vehicles by axle type and axle load. 78.6% of states use WIM to collect axle load data. 64.3% of states use AASHTO1993 for pavement design. The following are the details of the survey:

(1) Do you classify vehicles by axle type and axle load in your state?



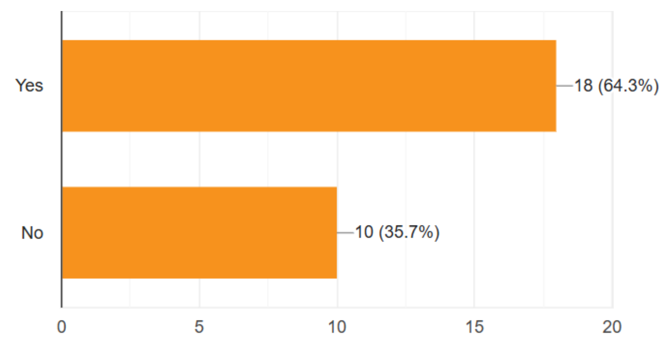
Note: A majority of states (92.9%) classify vehicles by axle type and axle load.

(2) How do you measure the axle load in your state?



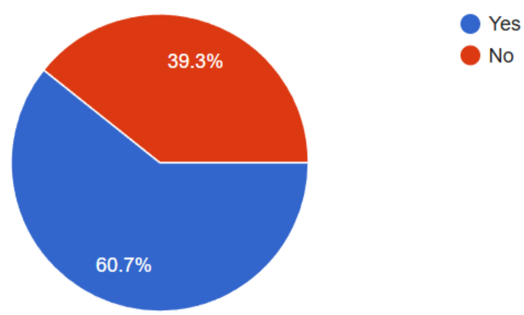
Note: A majority of states (88.89%) use WIM to collect the axle load data, with one state no longer using WIM after the data collection. 22.22% of states will use both weight station and WIM for data collection. LTPP data is also utilized for some states.

(3) Do you use the load equivalent factor (LEF) developed by AASHTO 1993 in your state?



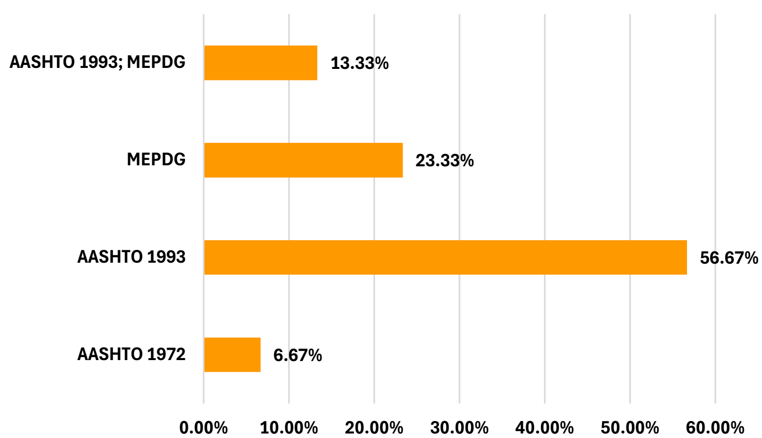
Note: 64.3% of states use AASHTO1993 to calculate the LEF.

(4) Do you use the truck factor to replace the load equivalent factor (LEF) for simplified calculation?



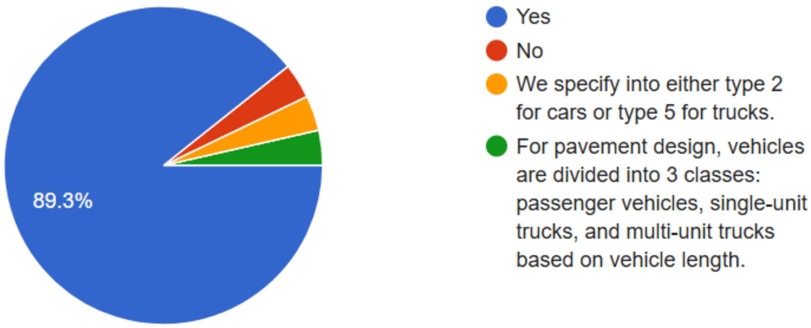
Note: 60.7% of states convert the LEF into a truck factor for simplified calculation since the only requirement is the classification of vehicles.

(5) What is your current pavement design guide in your state?



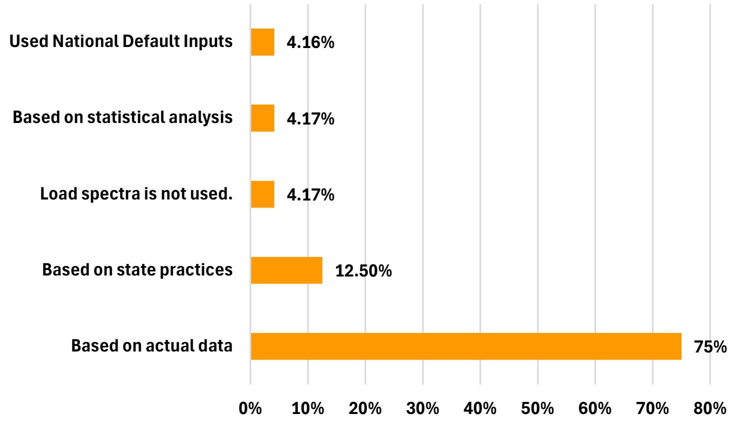
Note: A majority of states are still using AASHTO for pavement design. 13.33% of states use both AASHTO 1993 and MEPDG, where AASHTO is for flexible pavement design, and MEPDG is for rigid pavement design.

(6) Do you classify vehicles according to FHWA guidelines into 13 types of vehicles in your state?



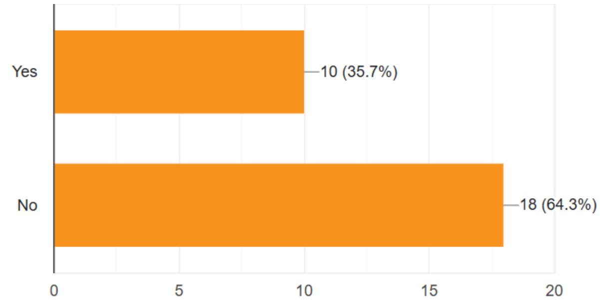
Note: 89.3% of states classify vehicles into 13 types of vehicles, while some states classify them into 2 or three categories for simplification.

(7) How did you get the axle load spectra in your state?



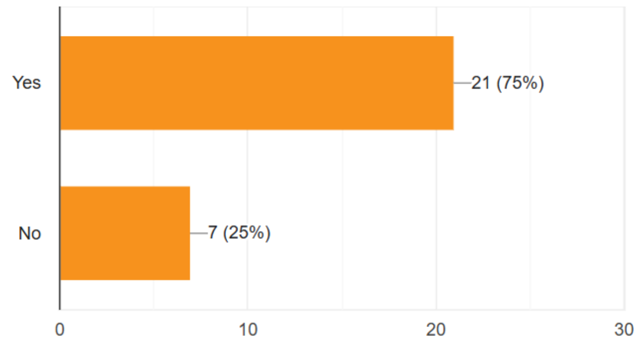
Note: 75% of states develop the axle load spectra based on actual data, while 12.5% of states use the state practice/experience. 4.16% states use the national default as input.

(8) If you are using truck factor, do you use the same truck factor for different regions (state route/interstate) in your state?



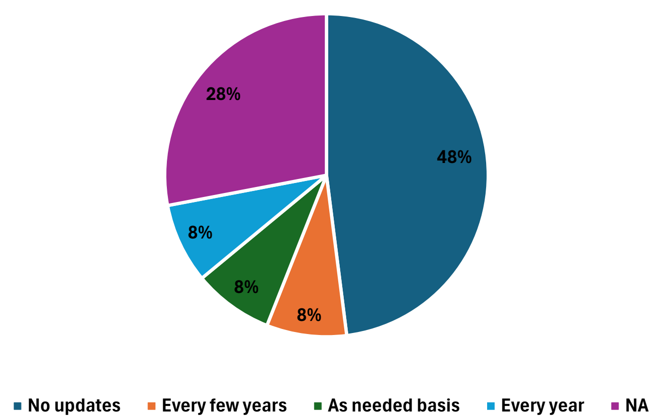
Note: 64.3% of states apply different truck factors into pavement design.

(9) Do you consider ESAL into asphalt binder selection (e.g. use PG 64E-22 for extreme heavy traffic level instead of PG64-22)?



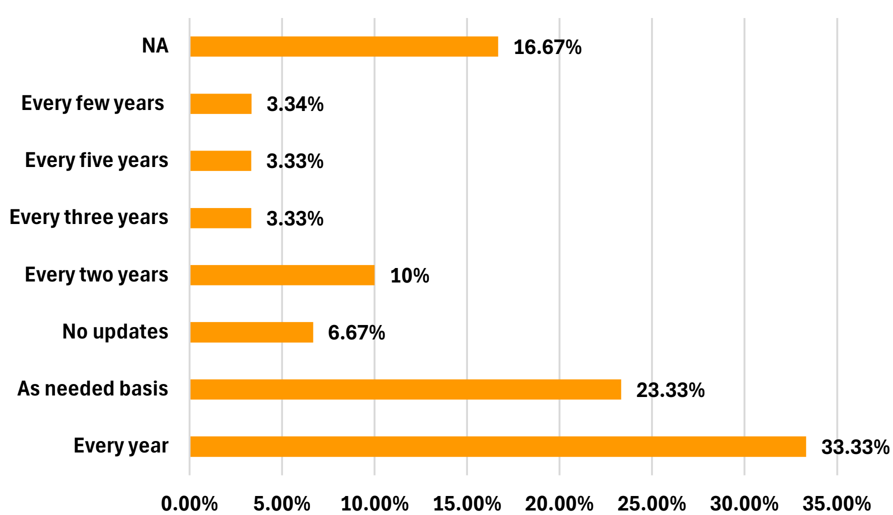
Note: 75% of states take the ESAL levels into asphalt performance grade selection.

(10) How often do you update the truck factor?



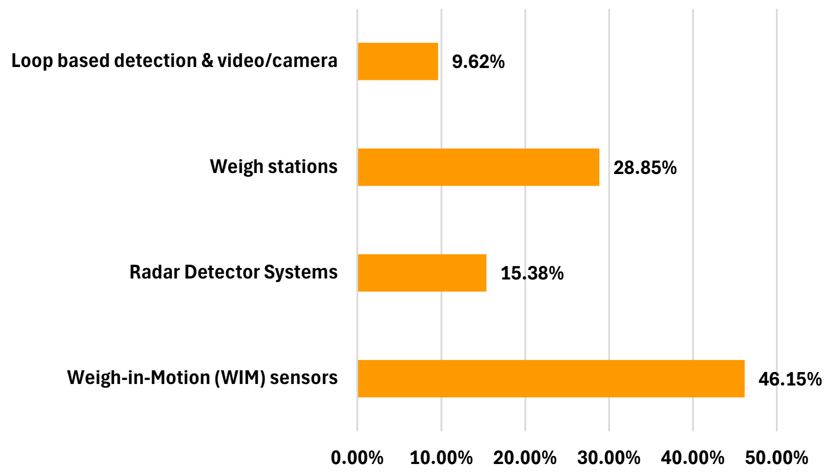
Note: 48% of states do not update the truck factors, while some states will update periodically or as needed.

(11) How often do you update the traffic growth rate?



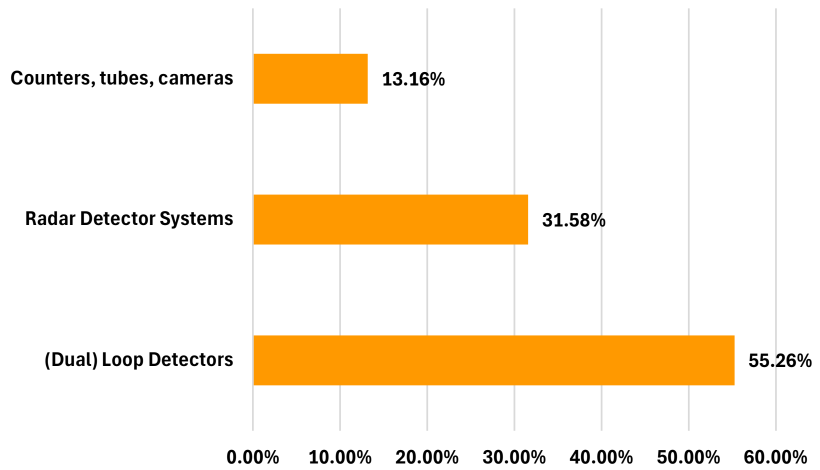
Note: 33.33% of states will update the traffic growth rate every year, and 23.33% of states will update as needed.

(12) Which of the following traffic detectors are deployed on your state freeway?



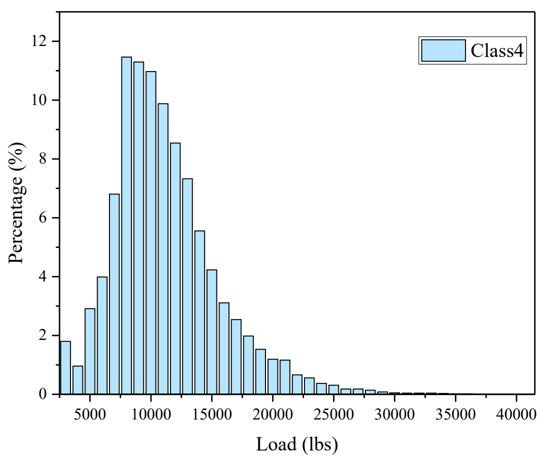
Note: WIM sensors are the most commonly used tools for data collection on the state highway.

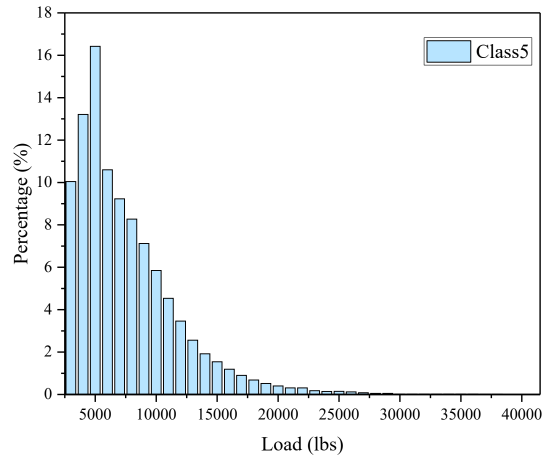
(13) Which of the following traffic detectors are deployed in your state local routes (e.g., intersections, arterial routes)?

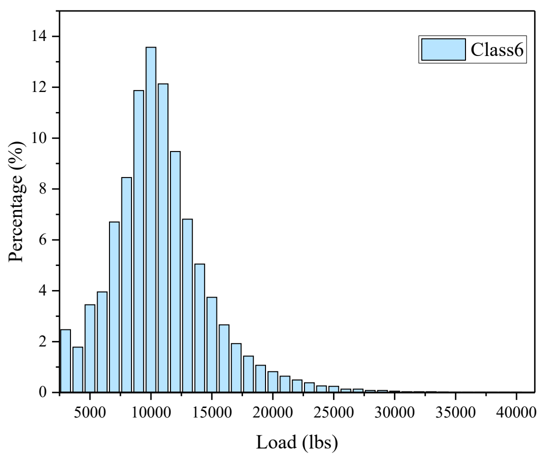


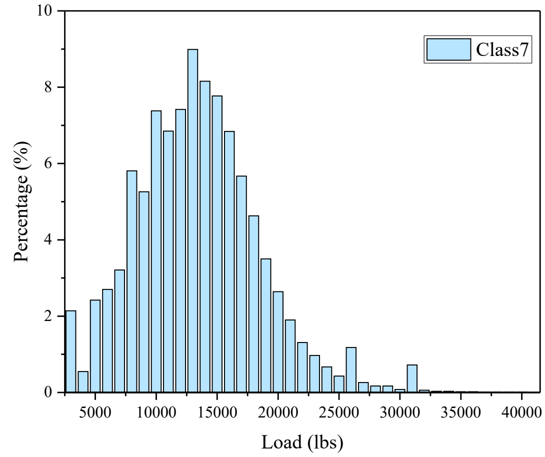
Note: Loop detectors are frequently used on the state highway.

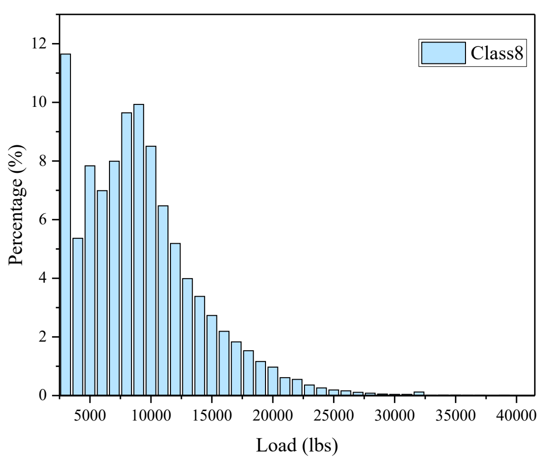
Appendix B: Additional Figures

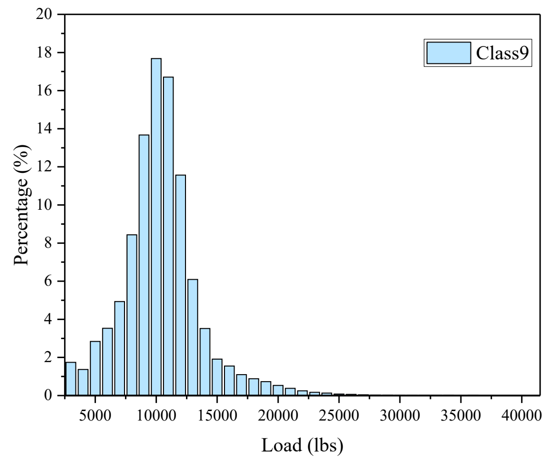












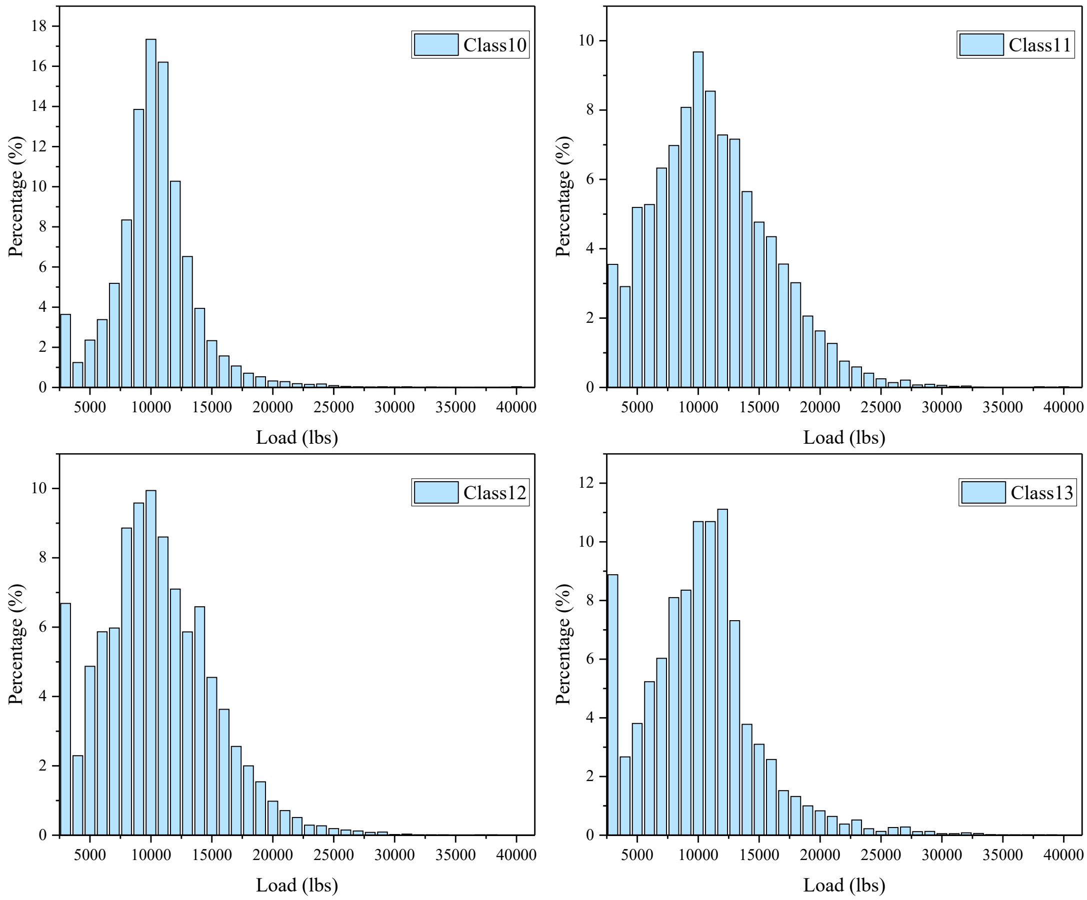
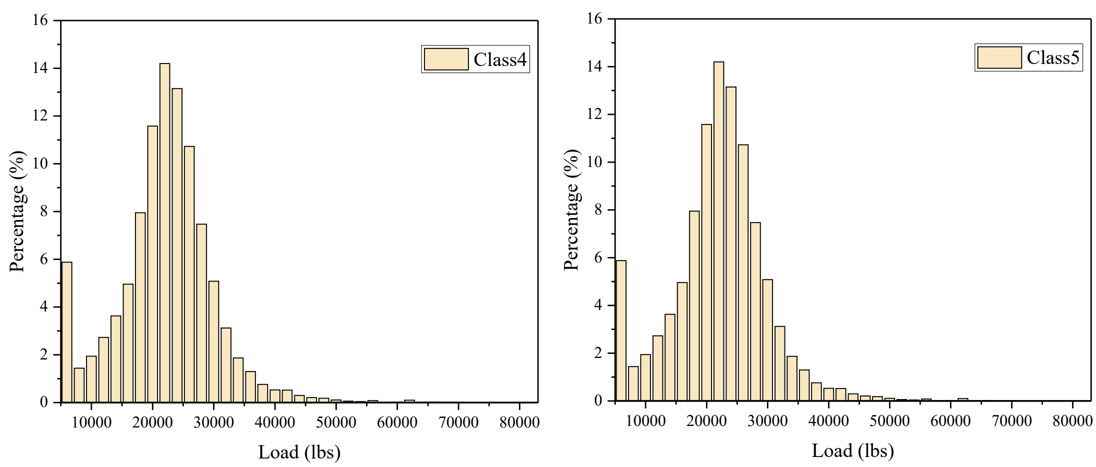
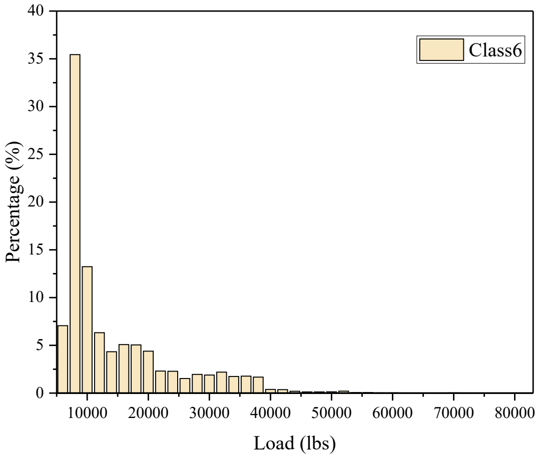
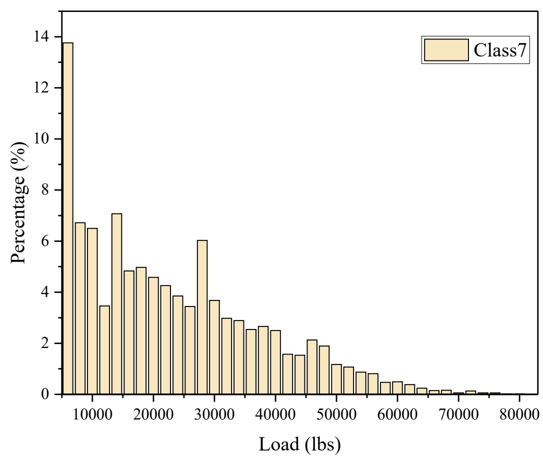
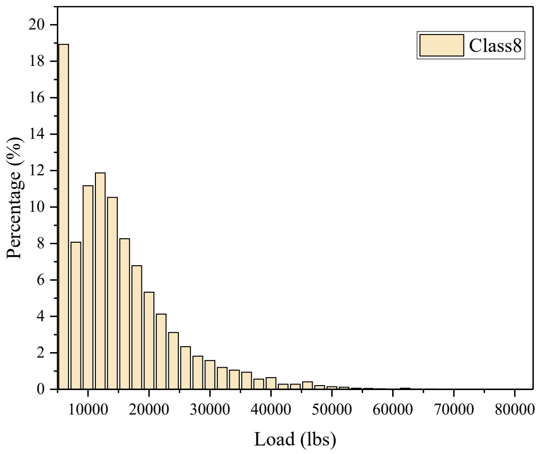
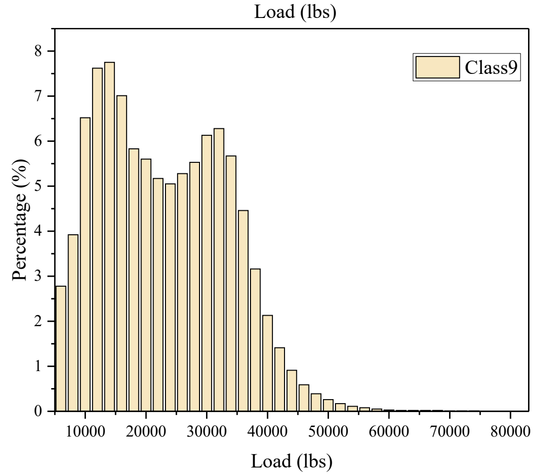
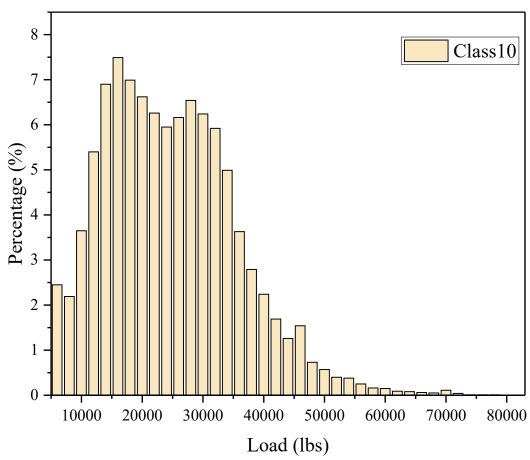
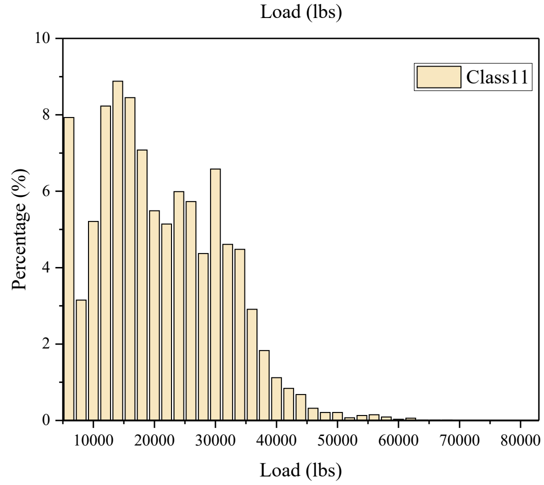


Figure B-1 Single axle load spectra from NCHRP default data.




Class6
Percentage (%)
Load (lbs)
0 5 10 15 20 25 30 35 40
10000 20000 30000 40000 50000 60000 70000 80000

Class7
Percentage (%)
Load (lbs)
0 2 4 6 8 10 12 14
10000 20000 30000 40000 50000 60000 70000 80000

Class8
Percentage (%)
Load (lbs)
0 2 4 6 8 10 12 14 16 18 20
10000 20000 30000 40000 50000 60000 70000 80000

Class9
Percentage (%)
Load (lbs)
0 1 2 3 4 5 6 7 8
10000 20000 30000 40000 50000 60000 70000 80000

Class10
Percentage (%)
Load (lbs)
0 1 2 3 4 5 6 7 8
10000 20000 30000 40000 50000 60000 70000 80000

Class11
Percentage (%)
Load (lbs)
0 2 4 6 8 10
10000 20000 30000 40000 50000 60000 70000 80000

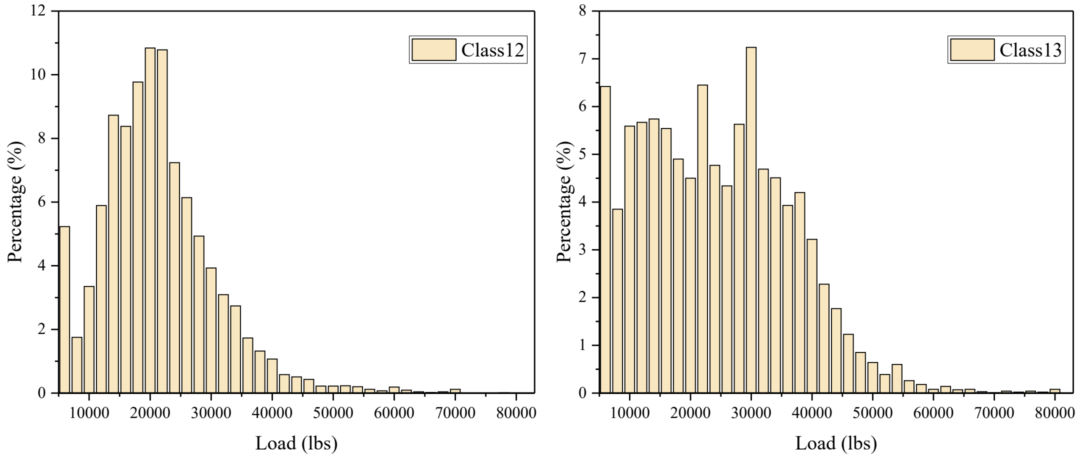


Figure B-2 Tandem axle load spectra from NCHRP default data.