Journal of Testing and Evaluation

doi:10.1520/JTE20190745 / Vol. 48 / No. 3 / 2020 / available online at www.astm.org

Lubinda F. Walubita,[1,2] Luis Fuentes,[2] Abu N. M. Faruk,[3] Julius J. Komba,[4] Adrianus Prakoso,[1] and Bhaven Naik[5]

Mechanistic-Empirical Compatible Traffic Data Generation: Portable Weigh-in-Motion versus Cluster Analysis

Manuscript received September 23, 2019; accepted for publication November 11, 2019; published online February 20, 2020. Issue published May 1, 2020.

[1] Texas A&M Transportation Institute (TTI), 1111 Rellis Pkwy., TAMU 3135, College Station, TX 77840, USA

[2] Department of Civil and Environmental Engineering, Universidad del Norte (UniNorte), Km 5 Via Puerto Colombia, Barranquilla 57, Colombia, https://orcid.org/0000-0002-7811-8821 (L.F.)

[3] Advanced Infrastructure Design, Inc., 1 Crossroads Dr., Hamilton, NJ 08691, USA

[4] Department of Transport Infrastructure Engineering, University of Pretoria/Council for Scientific and Industrial Research (CSIR), CSIR Smart Mobility, Meiring Naude St., Building 2C, Brummeria, Pretoria 0001, South Africa (Corresponding author), e-mail: jkomba@csir.co.za, https://orcid.org/0000-0002-8192-4170

[5] Department of Civil Engineering, Ohio University, Stocker Center 226, 1 Ohio University, Athens, OH 45701, USA

Reference

L. F. Walubita, L. Fuentes, A. N. M. Faruk, J. J. Komba, A. Prakoso, and B. Naik, "Mechanistic-Empirical Compatible Traffic Data Generation: Portable Weigh-in-Motion versus Cluster Analysis," *Journal of Testing and Evaluation* 48, no. 3 (May/June 2020): 2377–2392. https://doi.org/10.1520/JTE20190745

ABSTRACT

Axle load distribution factors (ALDFs) are used as one of the primary traffic data inputs for mechanistic-empirical (ME) pavement design methods for predicting the impact of varying traffic loads on pavement performance with a higher degree of accuracy than empirical methods that are solely based on equivalent single axle load (ESAL) concept. Ideally, to ensure optimal pavement structural design, site-specific traffic load spectra data—generated from weigh-in-motion (WIM) systems—should be used during the pavement design process. However, because of the limited number of available permanent WIM stations (in Texas, for example), it is not feasible to generate a statewide ALDFs database for each highway or project from permanent WIM data. In this study, two possible alternative methods, namely, the direct measurement using a portable WIM system and the cluster analysis technique, were explored for generating site-specific ME-compatible traffic data for a highway test section, namely, state highway (SH) 7 in Bryan District (Texas). The traffic data were then used for estimating pavement performance using a ME pavement design software, namely, the Texas Mechanistic-Empirical Thickness Design System (TxME). The TxME-predicted pavement performance (e.g., rutting) using the portable WIM-generated traffic input parameters closely matched with the actual field performance. Overall, the study findings indicated that the portable WIM (with proper installation and calibration) constitutes an effective means for rapidly collecting reliable site-specific ME-compatible traffic data.

Keywords

traffic load spectra, axle load distribution factors, weigh-in-motion, portable weigh-in-motion, cluster analysis, mechanistic-empirical, pavement design

Introduction

One of the key steps/processes in the analysis and design of pavements is the ability to characterize traffic correctly. The development of the Mechanistic-Empirical Pavement Design Guide under the National Cooperative Highway Research Program Project 1-37[1] and its subsequent adoption in mechanistic-empirical (ME) pavement design software packages, such as the "AASHTOWare Pavement ME design," has vastly changed the traffic characterization requirements for pavement design, specifically, the use of traffic weight distributions in place of single-point loads. That is, traditional pavement design methods, e.g., the AASHTO 1993, utilized 18-kips (~80-kN) equivalent single axle loads (ESALs) for establishing pavement layer thicknesses, whereas the current ME pavement design systems require the axle load distributions for each axle type for both new and rehabilitation pavement design processes. In addition, the pavement design methods need to be calibrated to local conditions. In Texas, a prototype ME pavement design software has recently been developed, namely, the Texas Mechanistic-Empirical Flexible Pavement Design System (TxME),[2] thus necessitating an effort to generate ME-compatible traffic input parameters for the Texas highways.

In ME pavement designs, traffic loading is one of the key parameters and main influencing factors for pavement distress prediction.[3] A typical ME pavement design system uses a hierarchical approach (Level 1 to Level 3) for the traffic inputs. Level 1 (site specific), Level 2 (state/regional specific), and Level 3 (national/default) indicate a good, modest, and poor knowledge/accuracy of past and future traffic characteristics, respectively. For example, the TxME[2] uses a two-level traffic data input scheme, in which Level 1 represents site-specific measured traffic data (i.e., highest accuracy and reliability level) and Level 2 represents the state default traffic data. Many researchers have reported that utilization of default (Level 3) traffic input parameters may, at times, result in inconsistent and inaccurate pavement designs/analyses.[4–8] This makes sense, in that traffic conditions at the local level can be significantly different from the national (or default) expectation and can potentially influence the pavement design and, ultimately, the performance of the designed pavement structure.

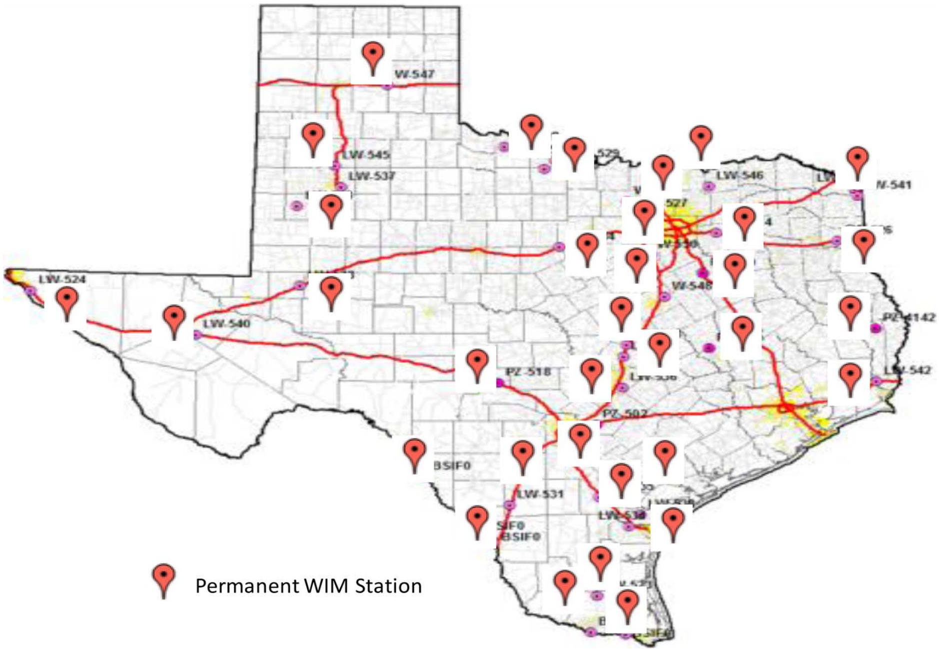
A study by Haider et al.[9] indicated an alternative means of generating state-specific (Level 2) traffic data by using clustering analysis (Level 2A) and grouping roads by similar attributes (Level 2B) to substitute for site-specific (Level 1) traffic data. Another study by Sauber et al.[10] showed that there were significant differences in pavement performance when default (Level-3) traffic data are used instead of site-specific (Level 1) traffic data. Therefore, site-specific (Level 1) traffic input parameters are deemed vital and more accurate for successful implementation and optimization of the ME pavement designs. It is thus recommended to always use site-specific (Level 1) traffic data whenever available.[4]

In Texas, traffic data (axle load spectra) for pavement design and performance prediction purposes are traditionally directly measured using permanent weigh-in-motion (WIM) stations. However, high installation and maintenance costs associated with these permanent WIM stations dictate that their deployment is mostly limited to major highways with high traffic volumes. For example, as at the time of writing this article (May 2019), the Texas Department of Transportation (TxDOT) had about 41 operational permanent WIM locations within the state, as illustrated in **figure 1**, the majority of which are on the interstate network. Therefore, alternative/supplementary methods need to be explored for generating site-specific ME-compatible traffic data for highway locations that lack permanent WIM stations.

With the aforementioned background, the objective of this study was to explore alternative methods for generating site-specific ME-compatible traffic data (axle load spectra) to supplement the permanent WIM stations. These alternate/supplementary methods include (a) direct measurement using portable WIM systems and (b) estimation of the axle load spectra data using cluster analysis techniques. To achieve the aforementioned objective, the following tasks were undertaken using an in-service field test section located on state highway (SH) 7, westbound direction (WB) in the Bryan District (Robertson County, Texas), as a case study:

- Measure and collect ME-compatible traffic data (load spectra) using a portable WIM system on SH 7 (WB).

FIG. 1 Example of Texas permanent WIM station locations.



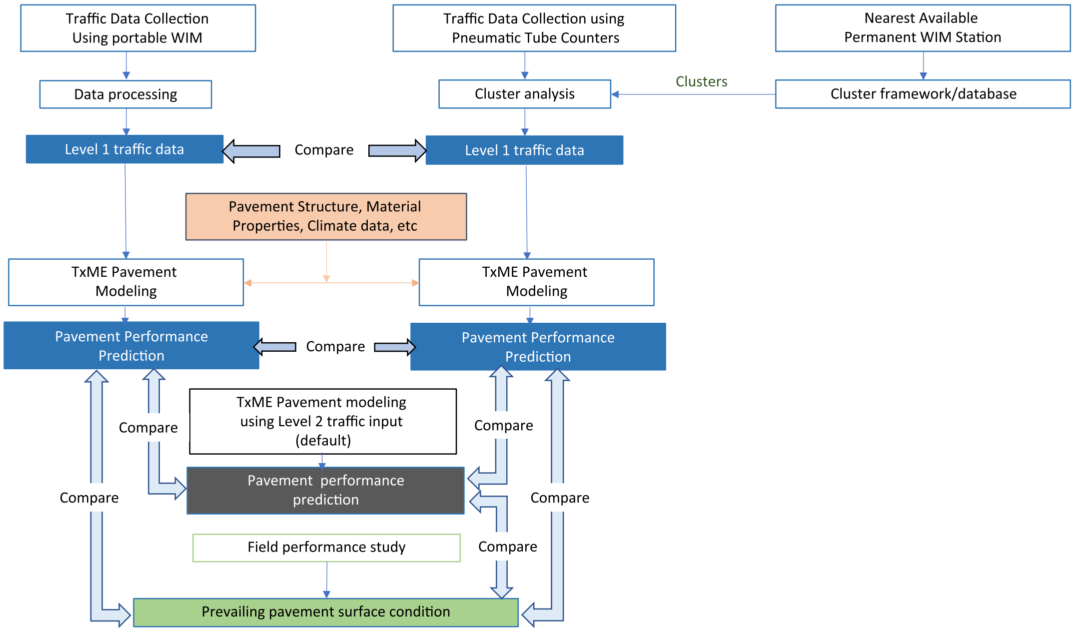
- Develop a cluster analysis framework (namely, clusters or a cluster database) based on the nearest available permanent WIM station data and, with the aid of pneumatic traffic tube (PTT) counter–measured traffic volume counts, utilize it to generate ME-compatible traffic data (axle load spectra) for SH 7 (WB).
- Compare the traffic load spectra generated with cluster analysis versus that measured with the portable WIM.
- Conduct pavement performance modeling of SH 7 (WB) with the TxME pavement design system using Level 1 generated traffic data.
- Conduct pavement performance modeling of SH 7 (WB) with the TxME pavement design system using default (Level 2) traffic inputs and compare with the Level 1 results obtained from both site-specific portable WIM traffic data measurements and cluster analysis.
- Compare the predicted pavement performance with in situ pavement conditions and field performance.

Figure 2 illustrates the flow chart of the work plan and research methodology employed to achieve the study objective, namely, traffic data collection, data analysis, ME modeling, pavement performance prediction, and comparison with the in-service pavement field conditions. These aspects are discussed in the subsequent sections. Note in **figure 2** that the ME traffic data generation based on "data processing" from actual portable WIM measurements and traffic data collection was considered more reliable and representative of in situ field conditions and was thus used as the reference datum. For the Clustering analysis method, the more the traffic data (i.e., stations) and the more current they are, the better the reliability and prediction accuracy.

ME Traffic Data Rendering Methods

As previously stated, the ME-compatible traffic data for SH 7 were generated via two methods: (1) direct measurements using a portable WIM system and (2) estimation of the axle load spectra data using the cluster analysis technique applied to vehicle classification data obtained from PTT counters. As illustrated in **figure 2**, traffic data gathered from nearest available permanent WIM stations were merely used to develop the clustering framework and cluster database. The data collection procedures are described in the subsequent sections.

FIG. 2 Flow chart of the research methodology.



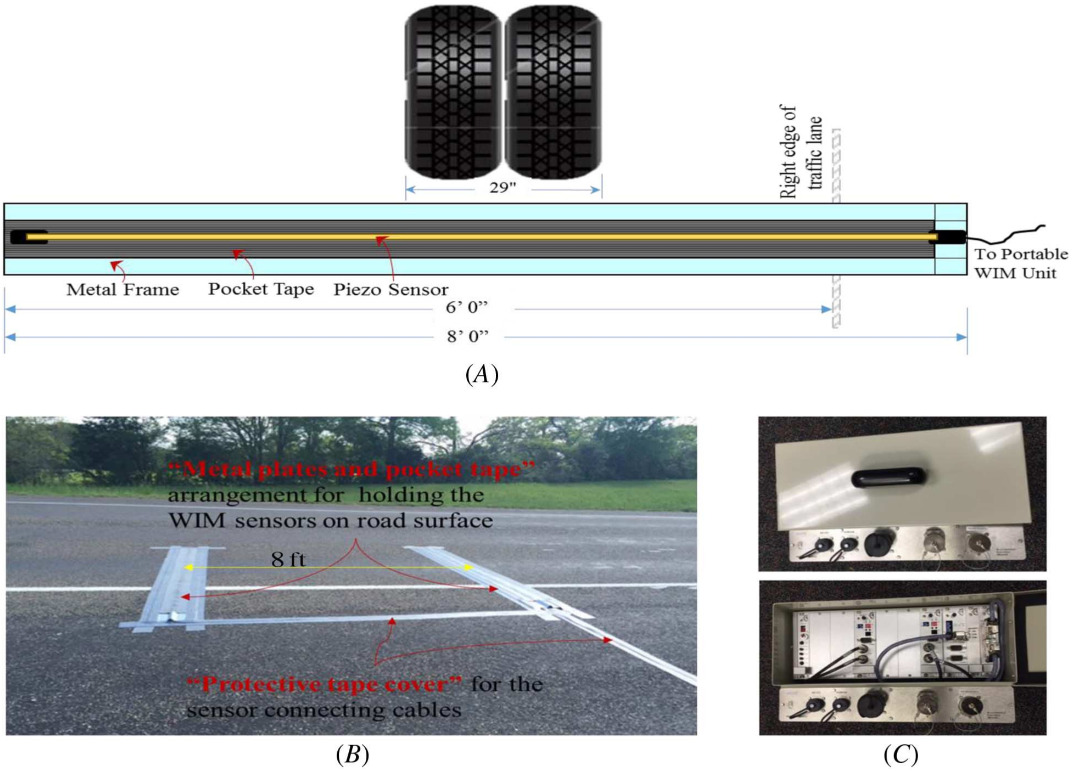
DIRECT TRAFFIC MEASUREMENTS USING A PORTABLE WIM SYSTEM

A hybrid, portable WIM (Hp-WIM) system deployed in this study was set up using off-the-shelf components and commercially available WIM controllers/data acquisition systems (namely, the Hastia units from EMC Inc.). **Figure 3** illustrates the schematic arrangement of the Hp-WIM setup and the sensor placement configuration on the pavement surface. A custom-devised metal plate was used to install the piezoelectric (PZT) sensors on to the pavement surface as well as to provide protection (durability) to the sensors, as can be seen in **figure 3**. The metal plates (8 ft. by 6 in. by 0.04 in. [~2.438 by ~0.150 by ~0.001 m], length by width by depth) also aided to provide a stable flat surface for improved accuracy in the traffic data measurements, sensitivity, stability, and longevity of the sensors.[11–13] An end-cap crown provided protection at the sensor-cable joint connection. The metal plates and end-cap crown were affixed to the pavement surface using silicon adhesives, road tapes, and concrete nails.[13] The piezo sensors were, in turn, affixed to the metal plates using pocket tape (see **fig. 3**).

A set of two piezo sensors (affixed on metal plates using pocket tape), placed 8 ft. (~2.438 m) apart, were installed in the one-wheel path only (typically, the right wheel path). The portable WIM unit automatically converts the data collected from the single wheel path (or half lane width) to the total axle weight and gross vehicle weight (GVW) data by applying a built-in multiplication factor of two, i.e., the measured wheel load is multiplied by two to obtain the axle load. It should, however, be emphasized that because the weight measurements are done in a single wheel path, the selection of the Hp-WIM installation location or site is critical in order to minimize measurement errors. As noted in **figure 3**, the length of the PZT sensor is sufficient to cover the dual-tire width, including the wandering effects.

Generally, the preferred location for Hp-WIM installation should have less than 1 % and 2 % longitudinal slope and transverse slope (cross fall), respectively.[11] The measured longitudinal and transverse slopes at the site location were 0.5 8 % and 1.06 %, respectively. Furthermore, a high-speed profile survey conducted prior to the portable WIM setup indicated that the pavement surface was smooth enough and appropriate for the installation of the portable WIM system. The measured international roughness index (IRI) for the site location was 85.15 in./mile (1.34 mm/m), well below the Federal Highway Administration (FHWA)'s condition rating criterion of 170 in./mile (2.68 mm/m).[12–16] Therefore, the dynamic effects that could have negatively impacted the traffic measurements were considered minimal.[13,17]

FIG. 3 Hp-WIM system setup on SH 7 in Bryan District: (*A*) sensor configuration, (*B*) pavement surface setup, (*C*) WIM controller (1 ft ≈ 0.304 m).

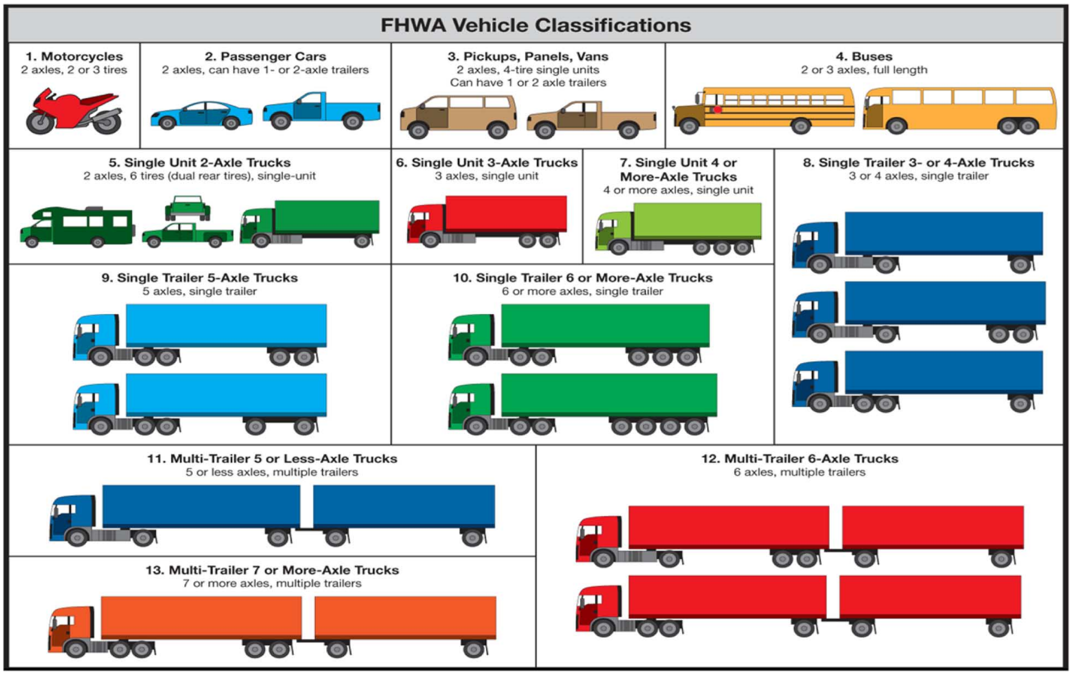


Prior to any real-time traffic data measurements, the Hp-WIM system must be calibrated on-site, preferably using a Class 9 (or Class 6 dump) truck.[12–14] Based on the FHWA's vehicle classification system (as illustrated in fig. 4), Class 9 is the most common truck found on the roads in the United States (i.e., over 50 % of trucks are Class 9), and hence, it is the preferred reference datum for calibration purposes.[15,16] In the state of Texas, Class 6 dumps trucks are also very common, and virtually almost all the state transportation/road agency at district level has a Class 6 dump truck, and hence, this is often used in lieu of a Class 9 truck.

Because of the absence of a standard Class 9 (or Class 6) truck, a Class 3 pickup truck was used for on-site Hp-WIM calibrations in this study. In accordance with the portable WIM on-site calibration procedure described in Faruk et al.,[12] a representative calibration factor, within ±5 % error margin of the steering axle weight and GVW, was obtained by making several calibration runs of the pickup truck (with known weight) at different wheel speeds. In addition to the manual in situ calibration, the portable WIM also employs an auto-calibration function to recalibrate the system continuously.[12] This accounts for any loss of sensor functionality and sensitivity with time throughout the data collection process. Note that the WIM controller unit used in this study, as shown in figure 3*C*, had an accuracy/error rating of ±20 %.[12]

Once the unit was properly installed and calibrated, real-time traffic data were measured and collected intermittently for one year. A one-year's traffic measurement period allowed for the determination of the monthly adjustment factors that are required as inputs for ME pavement design. Routine service maintenance (including sensor replacement as needed) and calibrations were conducted every three-months' period to maintain data quality and accuracy. The Hp-WIM system used for this study had the capability to measure and record traffic data for vehicle speeds of at least 20 mph (~32.180 km/h), including[12,13]]:

FIG. 4 FHWA vehicle classification system.[15,16]



- Vehicle volume counts,
- Axle spacing (in feet),
- Vehicle classification (FHWA class),
- Speed (in mph),
- Total number of axles,
- Axle configuration (combination and arrangement of single, tandem, tridem, or quad axles),
- Weight of each axle (in pounds) and GVW (in pounds).

The obtained raw data were processed using some customized in-house developed data analysis software and Microsoft (MS) excel macros to obtain the following traffic volume and weight parameters[12,13]:

a) Traffic volume parameters: Average daily traffic (ADT), average daily truck traffic (ADTT), percentage of trucks, vehicle speed distribution, FHWA vehicle class distribution, and daily and hourly volume count distribution.
b) Axle counts: number of axles per truck (ApT).
c) Traffic adjustment factors: hourly (HAF) and monthly (MAF).
d) Traffic weight parameters and axle load spectra: GVW distribution and axle weight distribution (axle load spectra) for each axle group (single, tandem, tridem, and quad), equivalent axle load factors, axle load distribution factors (ALDFs), and 18-kip (~80 kN) ESALs.

ESTIMATION OF THE AXLE LOAD SPECTRA USING CLUSTER ANALYSIS

An alternative to using directly measured traffic data from WIM systems (permanent or portable) is to employ cluster analysis techniques to estimate the axle load distribution based on available easy-to-obtain traffic data such as volume counts and vehicle classification. As defined in various literature, cluster analysis is a process that enables the generation of indirect traffic information for a specific site by synthesizing available ME-compatible traffic information of sites that exhibit traffic characteristics similar to the specific site being analyzed.[18–22]

A detailed description of the clustering concepts can be found elsewhere.[23–29] Obtaining axle load distribution data for a specific highway through cluster analysis is basically a three-step process, namely, as follows:

- Step 1: Collecting traffic data from existing permanent WIM stations and grouping these data into clusters of similar attributes to create a cluster database;
- Step 2: Collecting some easy-to-obtain traffic data, e.g., vehicle classification distribution (VCD), or using empirical estimates for the specific highway location for which ME-compatible traffic data is being sought; and
- Step 3: Assigning the specific site to one of the clusters with closely matching attributes such as VCD and using the representative traffic data (e.g., axle load distribution factors) of that cluster.

A variety of clustering analysis methodologies are available in the literature.[18–22] Among these, the *K*-means clustering[18,19,22] and the hierarchical clustering[20] have been successfully used to establish regional and statewide axle load spectra data. In this study, the *K*-means clustering technique was used, following the graphical concepts illustrated in **figure 5**.[13]

The *K*-means clustering predefines the number of clusters.[13,18,19] Given a predefined cluster, *K* clusters are created by associating every observation with the nearest mean and the least mean square error (MSE), standard deviation, and coefficient of variation.[13] The centroid of each *K* cluster then becomes the new mean, and the previous steps are repeated until convergence has been reached.[13,18,19] In this study, three years' (2010 to 2012) worth of traffic data from 29 (out of 35) selected Texas permanent WIM stations were grouped into 6 clusters, herein referred to as the cluster database. The number of clusters was determined based on the MSE considerations for the VCD and axle load distribution (ALD) data. A detailed description of the clustering techniques adapted in this study can be found in Oh, Walubita, and Leidy[21] and Walubita et al.[13,30] **Figure 6** exemplifies a graphical representation of six Texas clusters based on the Class 9 tandem axle weight distribution data.[22] As previously stated, Class 9 are the most common trucks on the Texas roads, and the tandem constitutes the most commonly loaded axle configuration and hence is exemplified in **figure 6**.[13,22,30]

To generate the ME-compatible traffic data for SH 7, PTT counters (as can be seen in **fig. 7**) were deployed for also three weeks. Typical practice for PTT traffic measurements and data collection is 48 h versus the 504 h conducted in this study.[13] This system collects traffic volume, speed, and vehicle classification information. However, no weight data are measured nor collected with the PTT counters and hence, the need to use clustering analysis to estimate the axle load spectra and weight data. The collected data from the PTT counters were analyzed to obtain the following traffic parameters[12,13]:

- ADT,
- ADTT,
- Truck percentage,

FIG. 5 *K*-means clustering concept. (*A*) One Cluster, (*B*) Two Clusters, (*C*) Four Clusters, (*D*) Six Clusters.

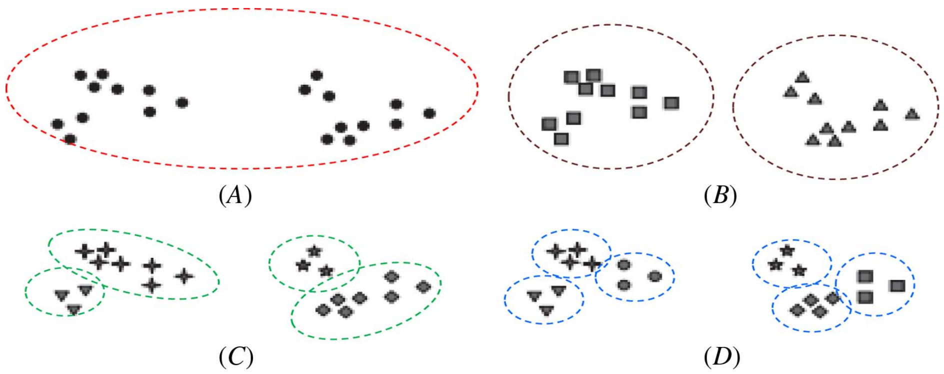


FIG. 6

Clusters based on Class 9 tandem axle weights.

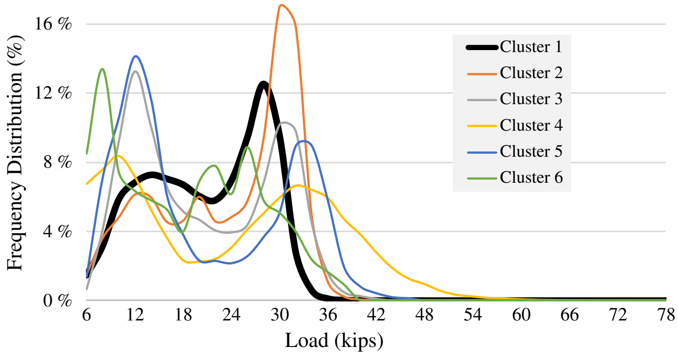
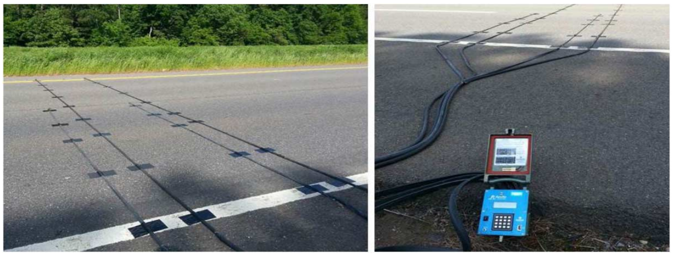


FIG. 7

PTT counters deployed on SH 7 WB, Bryan District.



- Vehicle speed information (average, maximum, and minimum speed for cars and trucks),
- FHWA VCD (Class 1 through 13).

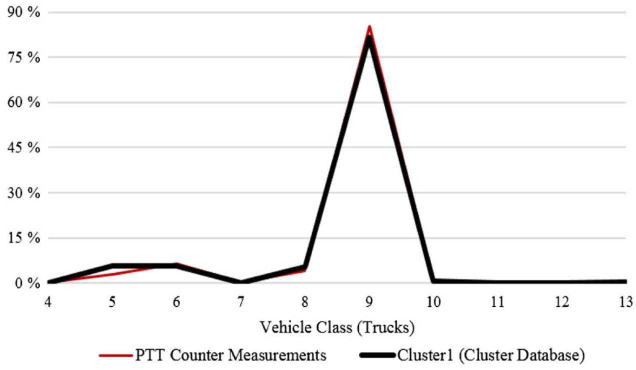
The ADT, ADTT, truck percentage, and speed are among the traffic parameters that can be used as direct inputs for ME modeling.[13,22,30] The measured VCD data for trucks (namely, FHWA designation Class 4 through Class 13) were used as inputs for cluster analysis to identify the appropriate cluster from the cluster database as follows: the measured VCD from SH 7 was mathematically and iteratively compared with the VCD of each of the six established clusters and was assigned to a specific cluster (Cluster 1) by taking the least absolute difference error between the measured and established VCD.[13,22] That is, as shown in **figure 8**, the VCD (trucks) measured from the PTT counters on SH 7 closely matched the VCD (trucks) for Cluster 1 in the cluster database with an absolute MSE less than 0.05 %. Thereafter, the representative ALD data and factors corresponding to the selected cluster (i.e., Cluster 1 in **fig. 6** for this study) from the cluster database were then used as the traffic input for the Level 1 ME pavement modeling and analysis. In theory, the clustering analysis is essentially enabling a statistical-based selection of a cluster using the VCD data for the PTT counters and then using the corresponding axle load spectra data for that cluster for ME pavement design, modeling, and analysis.

ME Traffic Data Comparisons

The traffic data generated for the ME pavement modeling and analysis using the two aforementioned methods are presented in **Table 1** and **figure 9**. It was observed that the volumetric traffic parameters obtained from the 2 methods are reasonably close, as can be seen in **Table 1**, with arithmetic differences significantly less than ±20 %. As compared

FIG. 8 Comparison of truck VCD data (PTT counters versus cluster database).

Vehicle Class	PTT Counter Measurements	Cluster1 (Cluster Database)	Error Squared
Class 4	0.12 %	0.02 %	0.0001 %
Class 5	2.88 %	5.78 %	0.0841 %
Class 6	6.35 %	5.73 %	0.0039 %
Class 7	0.12 %	0.09 %	0.0000 %
Class 8	3.96 %	5.48 %	0.0231 %
Class 9	85.37 %	81.70 %	0.1351 %
Class 10	0.48 %	0.53 %	0.0000 %
Class 11	0.12 %	0.08 %	0.0000 %
Class 12	0.12 %	0.15 %	0.0000 %
Class 13	0.48 %	0.45 %	0.0000 %
Sum	100.00 %	100.00 %	0.2464 %
		MSE	0.0246 %



with the Hp-WIM, the PTT counters recorded slightly higher ADT. However, the recorded ADTT was lower with a lower truck percentage. Assuming 95 % reliability level, this small difference in the traffic volume measurements (i.e., less than ±5 % difference) is statistically acceptable and bears a little negative impact on the ME pavement performance prediction results.

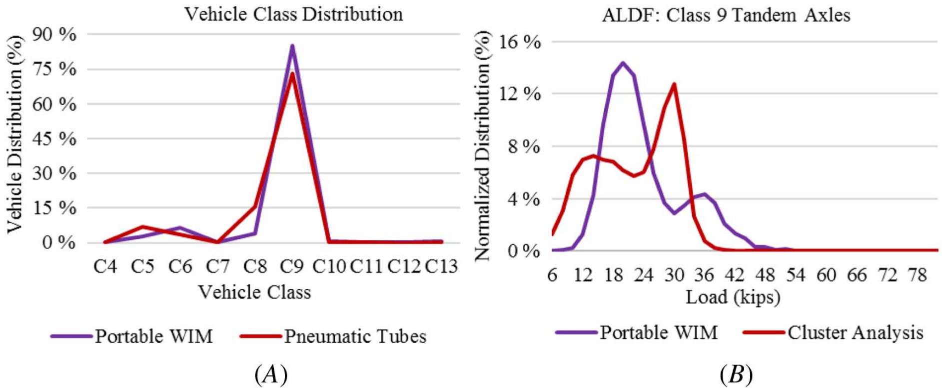
Figure 9*A* and 9*B* present the VCD for the truck classes and the ALDFs for the Class 9 tandem axle. It needs to be noted that the ALDFs were generated for all axle groups (single, tandem, tridem, and quad) and for all truck classes (Class 4 through 13) to be used as ME modeling inputs. However, in figure 9*B*, the Class 9 truck tandem axles were used as an example because it was the most commonly encountered truck axle configuration on highway SH 7 as well as most US roads.

It is noted that figure 9*A* shows similar truck class distribution patterns for both methods with a high percentage of Class 9 trucks. However, the ALDFs obtained from the Hp-WIM varied significantly from those estimated from the cluster analysis (Cluster 1), as shown in figure 9*B*. The Hp-WIM identifies a number of overloaded Class 9 tandem axles with axle loads of 34 kips (~151.240 kN) or higher (a total of 17.5 % overweight tandem axles), whereas the cluster analysis does not predict too many overloaded tandem axles (a total of 3.8 % overweight tandem axles). It needs to be noted that the ALDFs from the portable WIM are direct field measurement results, whereas those from the cluster analysis are estimated based on the measured VCDs, and this could be one potential source of the disparity. Nonetheless, this shows the limitations of a cluster analysis–based ALDF estimation scheme in which a limited number of clusters or groups are established to represent a large number of highways. Considering that two highways with similar VCDs can have vastly different traffic loading patterns and distributions, cluster analysis can produce ALDFs that considerably diverge from the actual loading patterns for a particular highway, as is the case observed in figure 9*B*. Thus, continuous update of the cluster database with more current traffic data (and more stations) is inevitable to optimize the prediction accuracy and reliability of the clustering analysis. Otherwise, in such scenarios in which the comparisons are unacceptable with

TABLE 1
Basic traffic input parameters for ME pavement analysis (SH 7, WB)

Parameter	Hp-WIM	PTT Counter	Arithmetic Difference
ADT	940	955	+1.57 %
Truck percentage	38.2 %	37.0 %	−3.24 %
ADTT	359	354	−1.41 %
Number of lanes in design direction	1	1	…
% truck in design lane	100	100	…
Operation speed	68.0	66.8	−1.80 %

FIG. 9 Example traffic inputs for ME modeling: (*A*) VCD and (*B*) ALDF.



significant differences, the ALDF data generated based on actual portable WIM measurements should take precedence, whereas the cluster analysis would be revisited, including reviewing the clusters and population with more current traffic data.

Figure 10 shows bar-chat plots of the ApT based on the Hp-WIM measurements and the values corresponding to the Cluster 1 (PTT-cluster analysis). Like the volumetric traffic parameters in **Table 1**, the ApT are fairly comparable, with only 3 data points registering an arithmetic difference exceeding 5 % for the Class 4 (9.24 % for the single axles), Class 10 (6.80 % for tandem axles), and Class 10 (15.38 % for the tandem axles) trucks (see **Table 2**). Thus, the two methods could be considered indifferent with respect to the axle counts and configuration characterization per truck class or type. Based on the magnitude of the average arithmetic differences, it is also

FIG. 10 Number of ApT. (*A*) Hp-WIM, and (*B*) Cluster 1.

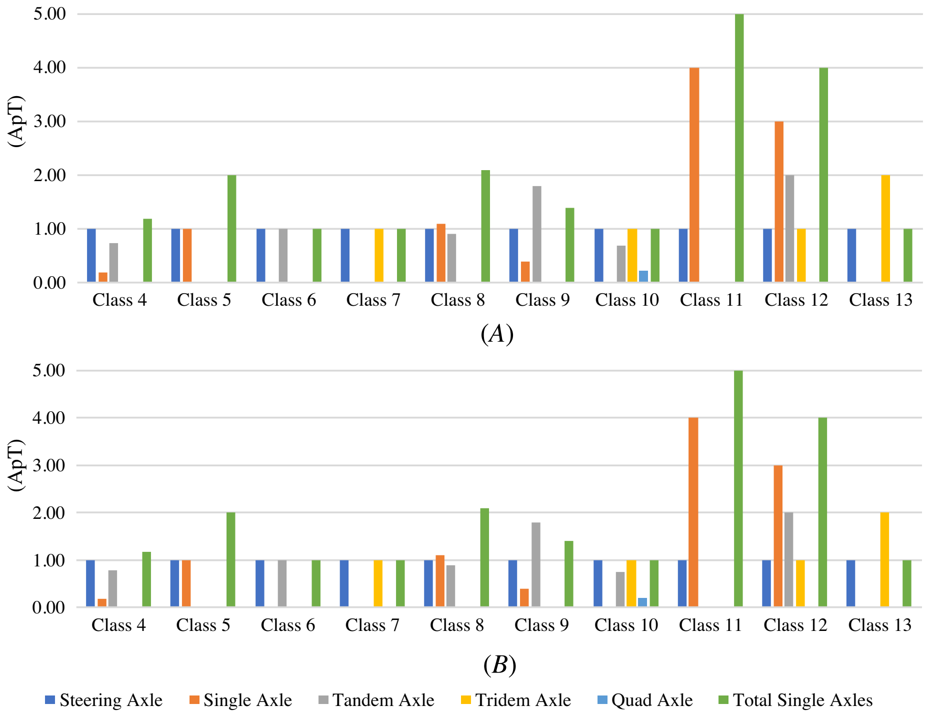


TABLE 2
Arithmetic differences in the ApT data between the Hp-WIM measurements and Cluster 1

Truck Class	Absolute Differences in the Axle Configuration/Type Quantification per Truck						Overall Average
	Steering	Single	Tandem	Tridem	Quad	Total Singles	
Class 4	0.00 %	9.24 %	4.43 %	…	…	2.27 %	3.99 %
Class 5	0.00 %	0.00 %	…	…	…	0.00 %	0.00 %
Class 6	0.00 %	…	0.00 %	…	…	0.00 %	0.00 %
Class 7	0.00 %		…	0.00 %	…	0.00 %	0.00 %
Class 8	0.00 %	0.65 %	0.80 %	…	…	0.34 %	0.45 %
Class 9	0.00 %	0.44 %	0.05 %	…	…	0.13 %	0.15 %
Class 10	0.00 %	…	6.80 %	0.00 %	15.38 %	0.00 %	4.44 %
Class 11	0.00 %	0.00 %	…	…	…	0.00 %	0.00 %
Class 12	0.00 %	0.00 %	0.00 %	0.00 %	…	0.00 %	0.00 %
Class 13	0.00 %	…	…	0.00 %	…	0.00 %	0.00 %
Overall average	0.00 %	1.72 %	2.01 %	0.00 %	15.38 %	0.27 %	…

evident that truck Class 10 (at 4.44 % difference) and the quad axle (at 15.38 %) are associated with the highest data variability but, nonetheless, less than ±20 %.[12–16]

Distinctly observed in figure 10 are the truck Classes 5, 6, 7, 10, 11, and 12 that consistently exhibit 2, 1, 1, 1, 5, and 4 total single axles, respectively, which is in concurrence with the FHWA axle configuration shown in figure 4.[15,16] Evidently, this further substantiates the accuracy/credibility of both methods (Hp-WIM and clustering analysis) when it comes to volumetric counts in terms of the number and configuration of ApT class or type. Similarly, the HAF and MAF analyses, which are also computed from the volume counts of vehicles, were comparable, with both the arithmetic mean difference and MSE being less than 20 %. As exemplified in figure 9*B*, it is therefore apparent that the major difference (>20 %) between the 2 methods (i.e., Hp-WIM versus clustering [PTT-cluster analysis]) is predominantly related to the axle load spectra and weight data, namely, the ALDFs—which, as presented, subsequently could have a significant impact on ME pavement modeling and performance prediction.

ME Modeling for Pavement Performance Prediction

The ME pavement modeling and performance prediction for SH 7 (WB) were conducted using the TxME software and the traffic data generated using the two aforementioned methods, namely, the Hp-WIM direct measurements and PTT-cluster analysis (i.e., using Cluster 1 traffic data). The pavement structure and the material properties used for ME modeling are described in the subsequent subsections.

PAVEMENT STRUCTURE AND MATERIAL PROPERTIES FOR HIGHWAY SH 7 (WB)

The pavement structure details of SH 7 (WB) in Robertson County (Bryan District) is presented in Table 3, along with a picture of the pavement surface. As documented in the Texas Flexible Pavements and Overlays Database (namely, the DSS), the SH 7 pavement was rehabilitated with a 2.5-inch-thick hot-mix asphalt (HMA) overlay (Type C) and surface treatment (seal coat) in March of 2014.[30] The HMA material properties presented in Table 4 were obtained from laboratory tests conducted on the overlay materials collected during the rehabilitation process. Moduli of the existing underlying layers, as presented in Table 5, were back-calculated from falling-weight-deflectometer (FWD) deflection measurements.[30,31]

COMPARISON BETWEEN ME-PREDICTED AND FIELD PERFORMANCE DATA

The TxME software was used for ME pavement performance modeling to predict the SH 7 performance based on the traffic parameters, pavement structure, and material properties, listed in Tables 1, 3, and 4, respectively.[30]

TABLE 3
SH 7 pavement structure details

#	Layer Description	Thickness, in.	Year Constructed	Pavement Surface Condition after 28-Months Service Life
1	Surface treatment (seal coat)	<1.0	March, 2014	
2	Overlay (Type C, PG 64-22)	2.5	March, 2014	
3	Existing HMA	3.5	…	
4	Cement-treated base	10.5	…	
5	Flex base	8.0	…	
6	Subgrade	∞	…	

Note: 1 inch ≅ 25 mm.

TABLE 4
HMA material properties (lab measured) used for ME modeling

Dynamic Modulus (ksi)						
Temp (°F)	0.1 Hz	0.5 Hz	1 Hz	5 Hz	10 Hz	25 Hz
14 (−10°C)	1,319.7	1,879.2	2,157.2	2,635.6	2,932.1	3,226.8
40 (4.44°C)	667.9	1,003.2	1,163.1	1,532.5	1,740.5	2,007.6
70 (21.11°C)	289.1	431.6	550.4	809.5	944.5	1,181.4
100 (37.78°C)	54.7	93.8	123.9	226.7	291.7	411.0
130 (54.44°C)	20.2	30.9	40.8	74.1	99.2	154.0

Rutting Properties			Fracture Properties		Thermal Coefficient
Temp (°F)	α	μ	A	n	A, in/in/°F
104	0.62	1.47	4.65×10^{-6}	4.13	7.76×10^{-5}
122	0.52	0.24			

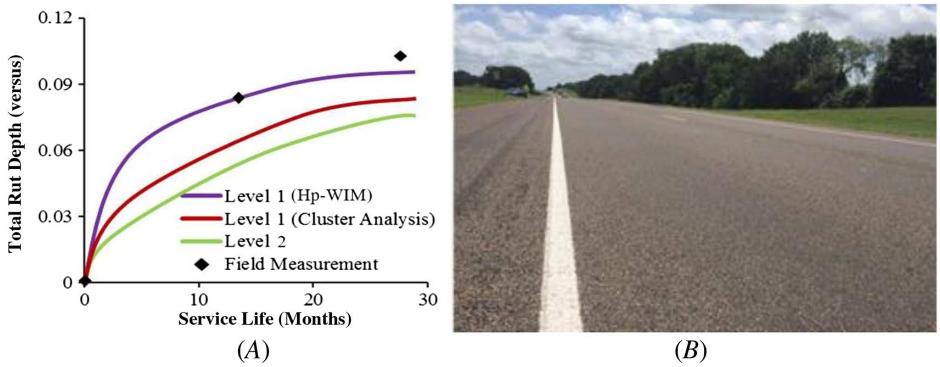
Note: 1 ksi ≅ 6,895 kN/m^2 ≅ 6.895 MPa; 1 in. ≅ 25 mm.

TABLE 5
Back-calculated layer moduli (field measured) from FWD testing

Pavement Temperature, °F			
At Surface	At 1-in. (~25-mm) Depth	Layer	Average Layer Modulus, ksi
105.95(41.08°C)	107.00(41.67°C)	Overlay	344 (~2,372 MPa)
		Existing HMA	629 (~4,337 MPa)
		Cement-treated base	187 (~1,289 MPa)
		Flexible base	70 (~483 MPa)
		Subgrade	15 (~103 MPa)

Three sets of analysis were conducted, namely (a) Level 1 traffic data generated from the Hp-WIM system, denoted as "Hp-WIM" in figure 11; (b) Level 1 traffic data generated from PTT-cluster analysis (i.e., Cluster 1 traffic data), denoted as "Cluster Analysis" in figure 11; and (c) Level 2 default traffic data. For all the three case scenarios, the pavement structural conditions and material properties were kept the same, thus ensuring an objective and similar baseline comparison of the effects of the traffic input parameters on the pavement performance prediction. The TxME software predicted pavement performances in terms of total pavement rutting, thermal cracking, and fatigue cracking as a function of time in months, which is presented in figure 11*A* for rutting

FIG. 11 SH 7 (WB) (*A*) rutting performance and (*B*) visual surface conditions after 28-months service life.



performance. Figure 11*A* also includes the actual field-measured surface rutting (i.e., pavement total rutting) after 28 months of service life.[30] On the other hand, figure 11*B* pictorially presents the field pavement surface conditions on the WB direction of SH 7 after 28 months of service life.

Rutting Performance—ME Prediction versus Actual Field Measurements

Figure 11*A* illustrates that the field rutting measurements closely matched with the TxME-predicted results for this highway section when Level 1 traffic data generated from the Hp-WIM were used. Rutting performance predictions for both cluster analysis–generated axle load spectra (Level 1) and default (Level 2) traffic data underpredicted the pavement rutting performance for SH 7 (WB section), with the former performing slightly better than the latter. Considering that the pavement structure and material property inputs for the TxME models were identical, the differences in TxME model–predicted rutting performances are clearly derived from the differences in the traffic inputs, specifically, the ALDF data. Indeed, from the Class 9 tandem ALDFs presented in figure 9*B*, it was seen that the Hp-WIM identifies a number of overloaded Class 9 tandem axles with axle loads of 34 kips or higher (17.5 %), whereas the cluster analysis does not predict too many overloaded axles (3.8 %).

The observed difference in the axle load spectra and overweight trucks in figure 9*B* is very critical, given that pavement damage increases exponentially with axle loading.[32,33] That is, the limitation of cluster analysis to accurately predict the presence of overweight axles on the SH 7 WB is probably why the ME performance prediction using the Level 1 cluster analysis traffic inputs is underestimating the actual pavement rutting damage. Similarly, the default traffic input (Level 2) underestimates the rutting damage even more, because no ALDF is considered in this case, i.e., the ME modeling is conducted based only on basic traffic input parameters such as ADTT, truck percentage, etc. (Table 1). The underpredictions by the Level 1 cluster analysis and Level 2 were computed to be about 24.11 % and 40.15 % lower than the actual field rut measurements, respectively, whereas the average arithmetical difference between the Hp-WIM–based TxME predictions and actual field rut measurements was only 5.30 %.

Cracking Performance—ME Prediction versus Actual Field Measurements

In terms of thermal and fatigue cracking, all three traffic-based inputs predicted zero damage. Indeed, the prevailing pavement condition after 28 months of service life, as presented in Table 3 and figure 11*B*, also showed no visible cracking damage. Overall, the results in figure 11 shows that even though the traffic parameters generated using the cluster analysis method can perform better than the default (Level 2) traffic input values when it comes to ME pavement performance prediction, the actual field-measured traffic weight data (site specific) provide the most reliable predictions of the pavement performance.

Note that although in this study, the clustering analysis underpredicted rutting performance, the opposite has been reported by Li et al.[33] These differences in the results and findings could partially be attributed to the accuracy and currency of the cluster database and the calibration status of the ME performance prediction models used. Thus, as previously stated, it is imperative to always populate the cluster database with more up-to-date current traffic data and, if possible, use locally calibrated ME performance prediction models that are more representative of the local field conditions so as to optimize accuracy and reliability.[13] That is, the more the traffic data and the more current they are, the better the prediction accuracy of the clustering analysis. Additionally, the clustering analysis technique used, such as the *K*-means in this study, can also be a contributing factor to the differences in the generated traffic data and performance predictions. Therefore, for given available traffic data sets, an exhaustive exploration of various clustering techniques is recommended to select the best clustering technique that will optimize accuracy and reliability.

Overall, although clustering analysis offers a rapid and cost-effective estimate of traffic loading, actual traffic measurements provide the most accurate and reliable data, and when practically and financially feasible, it is strongly recommended to always use actual traffic data measurements for ME modeling, pavement design, and performance predictions.[13,34] Therefore, in the event of different ME performance predictions (as exemplified in **fig. 11*A***), the predictions based on actual portable WIM traffic measurements, which are more representative of in situ field conditions, should take precedence over the performance predictions based on cluster analysis.

Summary of Findings

In this study, two traffic data collection methods for generating site-specific ME-compatible traffic data were adopted for a Texas SH section, namely SH 7 in Bryan District. In the first of the two methods, volume, speed, and axle load spectra data were directly measured using an Hp-WIM. For the second method, volume and speed data were directly collected using a pneumatic tube–based traffic counters and the axle load information (the ALDFs) were then estimated using a cluster analysis technique. The traffic input parameters thus generated were used to predict pavement performances using the TxME software. State default traffic input parameters were also used to conduct ME pavement performance prediction modeling. The ME-predicted pavement performances were then comparatively studied against the actual field pavement performance, in terms of three pavement distresses, namely, total pavement rutting, thermal cracking, and fatigue cracking. The overall findings and recommendations from the study are summarized as follows:

- Traffic volumetric counts and speed data, including the ADT, ATT, percent of trucks, ApT, etc., were satisfactorily comparable (i.e., with less than 20 % arithmetic difference) between the Hp-WIM measurements and the clustering analysis method. In contrast, differences were noted with the axle load spectra data (in particular, the ADFs), as was exemplified for the Class 9 tandem axles in this study.
- Site-specific traffic input parameters (Level 1 traffic inputs) are vital for accurate estimation of pavement performance. With the increasing trend of truck loading on Texas highways, the default (Level 2) traffic input parameters are not always able to accurately predict the actual traffic loading conditions because they lack the level of detailed traffic loading information that Level 1 traffic data can convey through parameters such as the ALDFs.
- Even though the cluster analysis method can provide axle load spectra data suited for Level 1 traffic input, it is not always 100 % representative of the actual site-specific traffic loading patterns (as was observed in case of the SH 7 in this study), with the need for caution when interpreting the ME modeling results. This can be due to the fact that the cluster analysis method is typically based on existing traffic databases that may not contain the most recent traffic data nor adequately reflect the current trends of increased axle loads. Thus, continuously updating the cluster analysis framework and cluster database with more recent traffic data is critical to maximize the prediction accuracy of the clustering analysis.
- For the SH 7 (WB) section, the portable WIM system (Hp-WIM) was able to generate Level 1 traffic data with reasonably reliable quality. The ME model–predicted pavement rutting, when using portable WIM-generated traffic data, closely matched the actual pavement rutting performance, thus providing validity to the traffic data measured using this rather novel approach.

- The ME model–predicted pavement performance indicators, such as fatigue cracking and thermal cracking, did not yield any conclusive result, because no visible cracking distresses were observed on the pavement and the fact that performance modeling and evaluation were conducted for a relatively shorter service life.

In general, the study findings showed that the Hp-WIM (with proper setup, installation, and calibration) can be used as an effective and practical means for collecting reliable site-specific ME-compatible traffic data as well as to supplement traditional methods such as permanent WIM stations.[13,34] Therefore, the portable WIM (such as the Hp-WIM discussed in this article), where feasible and practically applicable, would be the technically preferred method over cluster analysis for generating ME traffic data.[13,34,35] With respect to clustering analysis, continuously updating the clusters (i.e., the cluster database) with more up-to-date traffic data is imperative to optimize its prediction accuracy and reliability.[13] The more the traffic data and the more current they are, the better the reliability and prediction accuracy of the clustering analysis. For given available traffic data sets, an exhaustive exploration of various (and perhaps more advanced) clustering techniques (in addition to the *K*-means used in this study) is also strongly recommended to select the best clustering technique that will optimize accuracy and reliability. Overall, interpretive caution should be exercised with the clustering analysis, particularly with respect to the axle load spectra data, namely, the ALDFs.

ACKNOWLEDGMENTS

The authors thank the TxDOT and the FHWA for their support (Project 0-6940) and all those who helped during the course of this research work. Special thanks also go to all those who assisted with the field performance survey, traffic data collection, and laboratory testing of the HMA materials during the course of this study.

The contents of this article reflect the views of the authors, who are solely responsible for the facts and accuracy of the data presented herein and do not necessarily reflect the official views or policies of any agency or institute. This article does not constitute a standard, specification, nor is it intended for design, construction, bidding, contracting, tendering, or permit purposes. Trade names were used solely for information purposes and not for product endorsement, advertisement, or certification.

References

1. ARA, Inc., *ERES Consultants Division, Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, Final Report, NCHRP Project 1-37A* (Washington, DC: Transportation Research Board, 2004).
2. S. Hu, F. Zhou, and T. Scullion, *Development of Texas Mechanistic-Empirical Flexible Pavement Design System (TxME), FHWA/TX-14/0-6622-2* (Austin, TX: Texas Department of Transportation, 2014).
3. S. Cooper Jr., M. A. Elseifi, and L. N. Mohammad, "Parametric Evaluation of Design Input Parameters on the Mechanistic-Empirical Pavement Design Guide Predicted Performance," *International Journal of Pavement Research and Technology* 5, no. 4 (2012): 218–224.
4. S. W. Haider, N. Buch, K. Chatti, and J. Brown, "Development of Traffic Inputs for Mechanistic-Empirical Pavement Design Guide in Michigan," *Transportation Research Record* 2256, no. 1 (January 2011): 179–190. https://doi.org/10.3141/2256-21
5. S. Ishak, H. Shin, B. K. Sridhar, and Z. Zhang, "Characterization and Development of Truck Axle Load Spectra for Implementation of New Pavement Design Practices in Louisiana," *Transportation Research Record* 2153, no. 1 (January 2010): 121–129. https://doi.org/10.3141/2153-14
6. J. Li, L. M. Pierce, M. E. Hallenbeck, and J. Uhlmeyer, "Sensitivity of Axle Load Spectra in the Mechanistic-Empirical Pavement Design Guide for Washington State," *Transportation Research Record* 2093, no. 1 (January 2009): 50–56. https://doi.org/10.3141/2093-06
7. S. A. Romanoschi, S. Momin, S. Bethu, and L. Bendana, "Development of Traffic Inputs for New Mechanistic-Empirical Pavement Design Guide: Case Study," *Transportation Research Record* 2256 (January 2011): 142–150. https://doi.org/10.3141/2256-17
8. B. C. Smith and B. K. Diefenderfer, "Analysis of Virginia-Specific Traffic Data for Use with Mechanistic-Empirical Pavement Design Guide," *Transportation Research Record* 2154, no. 1 (January 2010): 100–107. https://doi.org/10.3141/2154-09
9. S. W. Haider, G. Musunuru, N. Buch, O. Selezneva, and J. P. Schenkel, "Updating Traffic Inputs for Use in the Pavement Mechanistic-Empirical Design in Michigan," *Transportation Research Record* 2673, no. 11 (June 2019): 13–28. https://doi.org/10.1177/0361198119849913

10. R. W. Sauber, N. P. Vitillo, S. Zaghloul, A. Ayed, and A. Abd El Halim, "Sensitivity Analysis of Input Traffic Levels on Mechanistic-Empirical Design Guide Predictions," in *Transportation Research Board 85th Annual Meeting* (Washington, DC: Transportation Research Board, 2006).
11. *Specifications for the Provision of Traffic and Weigh-in-Motion Monitoring Service*, Technical Methods for Highways TMH 3 (Pretoria, South Africa: Committee of Transport Officials, 2015).
12. A. N. M. Faruk, W. Liu, S. I. Lee, B. Naik, D. H. Chen, and L. F. Walubita, "Traffic Volume and Load Data Measurement Using a Portable Weigh in Motion System: A Case Study," *International Journal of Pavement Research and Technology* 9, no. 3 (May 2016): 202–213. https://doi.org/10.1016/j.ijprt.2016.05.004
13. L. F. Walubita, A. Prakoso, A. Aldo, S. I. Lee, and C. Djebou, *Using WIM Systems and Tube Counters to Collect and Generate ME Traffic Data for Pavement Design and Analysis, Technical Report FHWA/TX-18/0-6940-R1* (Austin, TX: Texas Department of Transportation, 2019).
14. *Standard Specification for Highway Weigh-In-Motion (WIM) Systems with User Requirements and Test Methods*, ASTM E1318–09 (2017) (West Conshohocken, PA: ASTM International, approved January 1, 2017). https://doi.org/10.1520/E1318-09R17
15. United States Department of Transportation, *Traffic Monitoring Guide, Publication Number FHWA-PL-01-021* (Washington, DC: United States Department of Transportation, 2001).
16. Texas Department of Transportation, *Traffic Data and Analysis Manual* (Austin, TX: Texas Department of Transportation, 2001).
17. W. Härdle and L. Simar, *Applied Multivariate Statistical Analysis*, 4th ed. (New York: Springer, 2003).
18. Q. Lu, Y. Zhang, and J. T. Harvey, "Estimation of Truck Traffic Inputs for Mechanistic-Empirical Pavement Design in California," *Transportation Research Record* 2095, no. 1 (January 2009): 62–72. https://doi.org/10.3141/2095-07
19. F. Sayyady, J. R. Stone, K. L. Taylor, F. M. Jadoun, and Y. R. Kim, "Clustering Analysis to Characterize Mechanistic-Empirical Pavement Design Guide Traffic Data in North Carolina," *Transportation Research Record* 2160, no. 1 (January 2010): 118–127. https://doi.org/10.3141/2160-13
20. A. T. Papagiannakis, M. Bracher, and N. C. Jackson, "Utilizing Clustering Techniques in Estimating Traffic Data Input for Pavement Design," *Journal of Transportation Engineering* 132, no. 11 (November 2006): 872–879. https://doi.org/10.1061/(ASCE)0733-947X(2006)132:11(872)
21. J. Oh, L. F. Walubita, and J. Leidy, "Establishment of Statewide Axle Load Spectra Data Using Cluster Analysis," *KSCE Journal of Civil Engineering* 19, no. 7 (November 2015): 2083–2090. https://doi.org/10.1007/s12205-014-0374-9
22. E. Mooi and M. Sarstedt, "Cluster Analysis," in *A Concise Guide to Market Research* (Berlin: Springer, 2011), 237–284.
23. G. W. Milligan and M. C. Cooper, "An Examination of Procedures for Determining the Number of Clusters in a Data Set," *Psychometrika* 50, no. 2 (June 1985): 159–179. https://doi.org/10.1007/BF02294245
24. M. R. Anderberg, *Cluster Analysis for Applications*, 1st ed. (Amsterdam, the Netherlands: Elsevier, 1973). https://doi.org/10.1016/C2013-0-06161-0
25. R. Mojena, "Hierarchical Grouping Methods and Stopping Rules: An Evaluation," *The Computer Journal* 20, no. 4 (January 1977): 359–363. https://doi.org/10.1093/comjnl/20.4.359
26. National Academies of Sciences, Engineering, and Medicine, *Traffic Data Collection, Analysis, and Forecasting for Mechanistic Pavement Design, NCHRP Report 538* (Washington, DC: The National Academies Press, 2004). https://doi.org/10.17226/13781
27. J. N. R. Jeffers, "Two Case Studies in the Application of Principal Component Analysis," *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 16, no. 3 (1967): 225–236.
28. S. M. S. Nagendra and M. Khare, "Principal Component Analysis of Urban Traffic Characteristics and Meteorological Data," *Transportation Research Part D: Transport and Environment* 8, no. 4 (July 2003): 285–297. https://doi.org/10.1016/S1361-9209(03)00006-3
29. L. F. Walubita, S. I. Lee, A. N. M. Faruk, T. Scullion, S. Nazarian, and I. Abdallah, *Texas Flexible Pavements and Overlays: Year 5 Report—Complete Data Documentation, Report No. FHWA/TX-15/0-6658-3* (Austin, TX: Texas Department of Transportation, 2017).
30. L. Walubita, A. Faruk, and S. Lee, *Traffic Data Collection and Analysis for the Texas Flexible Pavement Data Storage System, Research Report FHWA/TX-15/0-6658-P8* (College Station, TX: Texas A&M Transportation Institute, 2015).
31. K. Dey, "Minimizing Bridge and Pavement Deterioration from Large Trucks: A Policy Analysis for Damage Recovery" (PhD diss., Clemson University, 2014).
32. P. Sebaaly, "Pavement Damage as Related to Tires, Pressures, Axle Loads, and Configurations," in *Vehicle, Tire, Pavement Interface*, ed. J. Henry and J. Wambold (West Conshohocken, PA: ASTM International, 1992), 54–68. https://doi.org/10.1520/STP15909S
33. Q. J. Li, K. C. P. Wang, S. Qiu, Z. Zhang, and M. Moravec, "Development of Simplified Traffic Loading for Secondary Road Pavement Design," *International Journal of Pavement Engineering* 16, no. 2 (2015): 97–104. https://doi.org/10.1080/10298436.2014.926446
34. L. Walubita, E. Mahmoud, L. Fuentes, J. Komba, E. Teshale, and A. Faruk, "Portable WIM Systems: Comparison of Sensor Installation Methods for Site-Specific Traffic Data Measurements," *Journal of Testing and Evaluation*. Published ahead of print, July 15, 2019. https://doi.org/10.1520/JTE20190040
35. L. F. Walubita, A. N. M. Faruk, and L. Ntaimo, *Intelligent Freight Monitoring: A Review of Potential Technologies, Policy Brief* (College Station, TX: Texas A&M Transportation Institute Policy Research Center, 2015).