

Mechanistic-Empirical Compatible Traffic Data Generation: Portable WIM versus Cluster Analysis

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ABSTRACT

Axle load distribution factors (ALDFs) are used as one of the primary traffic data input for Mechanistic-Empirical (ME) pavement design methods for predicting the impacts 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, due to 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) constitute an effective means for rapidly collecting reliable site-specific ME-compatible traffic data.

KEY WORDS

Traffic load spectra, Axle load distribution factors (ALDFs), Weigh-in-motion (WIM), Portable WIM, Cluster analysis, Mechanistic-Empirical (ME), 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 (MEPDG) under the National Cooperative Highway Research Program (NCHRP) 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. More 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. The 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, where 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 paper (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).
- 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 it is, the better the reliability and prediction accuracy.**

ME TRAFFIC DATA RENDERING METHODS

As previously stated, the ME compatible traffic data for SH 7 was 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.

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 piezo-electric (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. [~2.438

m] long by 6-inch [~0.150 m] width and 0.04 inches [~0.001 m] thick) 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 Figure 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 since the weight measurements are done in a single wheel path, the selection of the Hp-WIM installation location/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 0.58% 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 inch/mile, well below the FHWA's condition rating criterion of 170 inch/mile [12-16]. Therefore,

the dynamic effects that could have negatively impacted the traffic measurements were considered minimal [13, 17].

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 Federal Highway Administration (FHWA)'s vehicle classification system as illustrated in Figure 4, Class 9 is the most common truck found on the USA roads (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.

Due to 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 onsite calibration procedure described in Faruk et al. [12], a representative calibration factor (CF), within $\pm 5\%$ 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 $\pm 20\%$ [12].

Once the unit was properly installed and calibrated, real-time traffic data was 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]:

- 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 pound), and GVW (in pound).

The obtained raw data was 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, daily and hourly volume count distribution.
- b) Axles 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/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:

- 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 (stdev), and coefficient of variation (COV) [13]. The centroid of each K cluster then becomes the new mean, and the above 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 six clusters, herein referred to as the cluster database. The number of clusters was determined based on the mean square error (MSE) considerations for the vehicle class distribution (VCD) and axle load distribution (ALD) data. A detailed description of the clustering techniques adapted in this study can be found in Oh et al. [22] 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 whilst 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 Figure 7) were deployed for also three weeks. Typical practice for PTT traffic measurements and data collection is 48 hrs versus the 504 hrs conducted in this study [13]. This system collects traffic volume, speed, and vehicle classification information. However, no weight data is 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 was analyzed to obtain the following traffic parameters [12, 13]:

- ADT
- ADTT
- Truck percentage

- Vehicle speed information (average, maximum, and minimum speed for cars and trucks)
- FHWA VCD (Class 1 thru to 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 thru to Class 13) was used as an input 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 to 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 axle load distribution data/factors corresponding to the selected cluster (i.e., Cluster 1 in Figure 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 two methods are reasonably close; as can be seen in Table 1, with arithmetic differences significantly less than $\pm 20\%$. As compared to 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 $\pm 5\%$ difference) is statistically acceptable and bears a little negative impact on the ME pavement performance prediction results.

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%

Figures 9 (a) and (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 that 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% over-weight tandem axles), whereas, the cluster analysis does not predict too many overloaded tandem axles (a total of 3.8% over-weight 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 cluster analysis based ALDF estimation scheme where 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/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 were the comparisons are unacceptable with significant differences, the ALDF data generated based on actual portable WIM measurements should take precedence, while the Cluster analysis would be revisited including reviewing the clusters and population with more current traffic data.**

Figures 10 shows bar-chart 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 three 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/type. Based on the magnitude of the average arithmetic differences,

it is also 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 $\pm 20\%$ [12-16].

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%	

Of distinctive observation 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 Federal Highway Administration (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 axles per truck class/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 two 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 sub-sections.

Pavement Structure and Material Properties for Highway SH 7 (WB)

The pavement structure details of State Highway 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].

Table 3. SH 7 Pavement Structure Details

#	Layer Description	Thickness (inch)	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 \cong 25 mm

Table 4. HMA Material Properties (Lab-Measured) Used for ME Modeling

Dynamic Modulus (ksi)						
Temp ($^{\circ}$ F)	0.1 Hz	0.5 Hz	1 Hz	5 Hz	10 Hz	25 Hz
14 (-10 $^{\circ}$ C)	1319.7	1879.2	2157.2	2635.6	2932.1	3226.8
40 (4.44 $^{\circ}$ C)	667.9	1003.2	1163.1	1532.5	1740.5	2007.6
70 (21.11 $^{\circ}$ C)	289.1	431.6	550.4	809.5	944.5	1181.4
100 (37.78 $^{\circ}$ C)	54.7	93.8	123.9	226.7	291.7	411.0
130(54.44 $^{\circ}$ C)	20.2	30.9	40.8	74.1	99.2	154.0

Rutting Properties			Fracture Properties		Thermal Coefficient
Temp ($^{\circ}$ F)	α	μ	A	n	α (in/in/ $^{\circ}$ F)
104	0.62	1.47	4.65×10^{-6}	4.13	7.76×10^{-5}

122	0.52	0.24		
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Note: 1 ksi \cong 6895 kN/m² \cong 6.895 MPa; 1 inch \cong 25 mm.

Table 5. Back-Calculated Layer Moduli (Field-Measured) from FWD Testing

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

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 Table 1, 3 and 4, respectively [30]. 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 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 highway 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 was used. Rutting performance predictions for both Cluster analysis generated axle load spectra (Level-1) and default (Level-2) traffic data under-predicted 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 difference 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, since, 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 under-prediction 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) provides the most reliable predictions of the pavement performance.

Note that while in this study, the Clustering analysis under-predicted rutting performance, the opposite has been reported by Qiang et al. [33]. These differences in the results and findings could partially be attributed to the accuracy/currency of the Cluster database and 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 it is, 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, while Clustering analysis offers a rapid and cost-effective estimate of traffic loading, actual traffic measurements provide the most accurate/reliable data and, where practically/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 Figure 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 State Highway 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 a hybrid portable WIM system (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 axle load distribution factors) 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, %trucks, ApT, etc., were satisfactorily comparable (i.e., with less than 20% arithmetic difference) between the Hp-WIM measurements and the Clustering analysis method. By 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 axle load distribution factors.
- 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 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, since no visible cracking distresses were observed on the pavement and the fact that performance modeling/evaluation was 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 paper), 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 it is, 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.

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