

Correlation between Properties of Axle Load Distribution and Rigid Pavement Performance Measures

Syed Waqar Haider, Ph.D., P.E.¹
Ronald S. Harichandran, Ph.D., P.E.²

Abstract

The new Mechanistic-Empirical Pavement Design Guide (M-E PDG) utilizes axle load spectra to characterize the unique traffic loadings for a site. These loading characteristics are employed to calculate pavement response and for subsequent damage computations. Generally, these axle load distributions exhibit a bimodal shape and a mixture of two continuous distributions can be used to model them. In this paper, closed-form solutions are developed to estimate the characteristics of a mixture bimodal axle load distribution. The observed axle load spectra from eleven sites in different states were used to relate load distribution characteristics with predicted rigid pavement performance. Cracking performance was related to the 85th percentile load, faulting was found to be strongly related to the overall mean, and roughness (IRI) was strongly associated with the root of the 4th moment of the axle load spectra, respectively. These findings imply that cracking in rigid pavements is mainly caused by the highest 15 percent of loads while faulting is mostly caused by the overall average loads in an axle load distribution. The overall loads, along with higher contributions from the heavier loads, seem to cause higher roughness in rigid pavements. In addition, the relationships developed for different performance measures can directly indicate the relative pavement damage caused by axle distributions.

Introduction

Axle load spectra were used to develop the mechanistic-empirical pavement design guide (M-E PDG). Use of these load distributions provides a more direct and rational approach for the analysis and design of pavement structures to estimate the effects of actual traffic on seasonal pavement response and distress. In the AASHTO Guide for Design of Pavement Structures, a mixed traffic stream of different axle loads and configurations is converted into a design traffic number by transforming each axle load into an equivalent number of 18-kip single-axle loads, known as equivalent single-axle loads (ESALs). Load equivalency factors (LEFs) are used to determine the number of ESALs for each axle load and configuration. These factors are based on the Present Serviceability Index (PSI) concept and depend on the pavement type, structure, and axle configuration. The AASHTO load equivalency factors were empirically derived using statistical analysis of the observed data. In addition, no endeavor was made to distinguish between different modes of distress; the equivalency factors were related only to performance as

¹ Research Associate, Department of Civil and Environmental Engineering, Michigan State University, 3546 Engineering Building, East Lansing, MI-48824, Tel: (517) 353-9782; Fax: (517) 432-1827, e-mail: syedwaga@egr.msu.edu.

² Professor and Chairperson, Department of Civil and Environmental Engineering, Michigan State University, e-mail: harichan@egr.msu.edu

measured by the PSI (Carey Jr. and Irick 1960). Studies indicate that these factors also are influenced by pavement condition, distress type, failure mode, and other parameters. Therefore, the ESAL concept has inherent limitations. The most important concerns are regarding its empirical nature and lack of consideration for other performance measures typically considered in current mechanistic-empirical approaches (e.g., cracking and faulting). Therefore, there is a need to establish precise relationships between axle load and a particular distress types (cracking, faulting and roughness) to bridge the gap between ESALs and axle load spectra.

The main objective of this paper is to link axle load distribution properties to rigid pavement performance. This is accomplished by characterizing axle load spectra as a bimodal mixture distribution and then relating its properties to typical rigid pavement distresses (cracking, faulting, and IRI). Two specific aspects of this paper are to: (a) develop closed-form solutions to estimate the properties of a bimodal mixed normal distribution; and (b) relate the axle load spectra properties to various distresses as predicted by M-E PDG. The closed form solutions are developed and their applicability is demonstrated by utilizing axle load spectra observed in the field from eleven sites in the SPS-2 experiment in the Long Term Pavement Performance (LTPP).

Background

Several researchers have modeled axle load spectra (Haider and Harichandran 2007a; Hong et al. 2006; Prozzi et al. 2006; Timm et al. 2005). Recent works by Haider and Harichandran (2007a) considered a mixture of two normal distributions to characterize axle load spectra. The general formulation of a mixture model is

$$f^* = \sum_i^n p_i f_i \quad (1)$$

where

$$\begin{aligned} f^* &= \text{Probability density function (PDF) of mixture distribution} \\ p_i &= \text{proportions (weights) for each theoretical PDF} \\ f_i &= \text{PDFs for each theoretical distribution} \end{aligned}$$

Figure 1 shows the schematic of a mixture distribution. Since the combination of truck payload and truck weight contribute to gross vehicle and axle loads, and also since these weights are the sum of the weights of several smaller components, the central limit theorem will apply, and the load distributions for loaded and unloaded truck weights should each be nearly normal. Haider and Harichandran (2007a) determined that the bimodal shape of axle spectra could be effectively captured by using a mixture of two normal distributions:

$$f^*(x) = \left(p_1 \frac{1}{\sigma_1 \sqrt{2\pi}} e^{-(x-\mu_1)^2 / 2\sigma_1^2} + (1-p_1) \frac{1}{\sigma_2 \sqrt{2\pi}} e^{-(x-\mu_2)^2 / 2\sigma_2^2} \right) \quad (2)$$

For a bimodal mixture distribution containing two PDFs, the two weights are complimentary (i.e., $p_2 = 1 - p_1$).

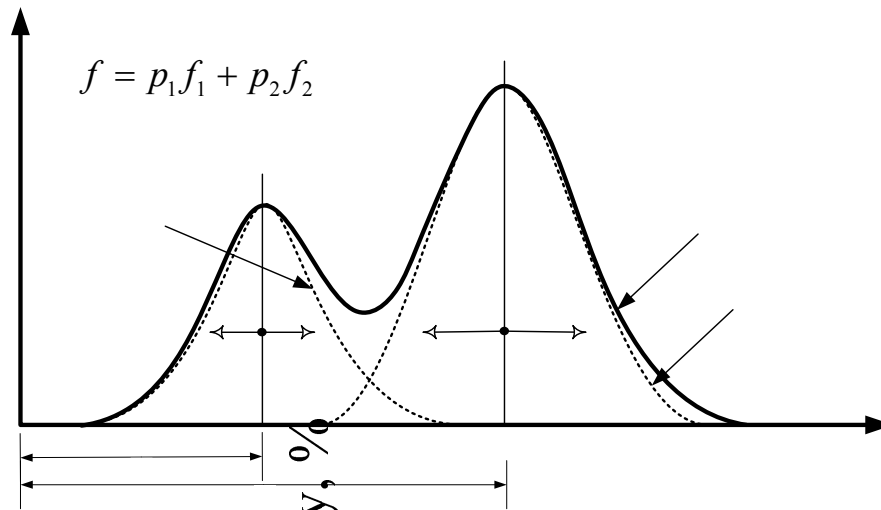


Figure 1 Modeling axle load spectra using bimodal mixture distributions

Furthermore, by using LTPP axle load data the authors showed that a mixture of two normal distributions can reasonably fit observed single and tandem axle load distributions. This model has five parameters which need to be estimated from data (Haider and Harichandran 2007c).

In this study the M-E PDG (Version 1.0) was utilized to analyze a typical rigid pavement in unique environmental conditions. The only variable considered in the M-E PDG analyses was the axle load spectra. The pavement performance measures—cracking, faulting and IRI, at 30 year service life were considered in subsequent analyses to seek relationships with properties of the load distribution characteristics.

Characterization of Axle Load Spectra

Axle load spectra for a tandem axle configuration from eleven sites located in different states were obtained from the SPS-2 experiment in the LTPP database. The SPS-2 experiment was designed to investigate the effects of design and site factors on rigid pavement performance. All axle load spectra demonstrated a bimodal shape as shown in Figure 2. These axle spectra are based on weight data collected by weigh-in-motion technology at all eleven sites over a one-year period. A bimodal mixture model was fitted to these axle load spectra.

Estimating Bimodal Distribution Parameters. Figure 1 presents the schematic of a bimodal mixture distribution. Five parameters are required to characterize the mixture distribution as shown in Equation (2). Each of these parameters has a practical meaning. It is hypothesized that the first peak corresponds to the average axle weight of empty or partially loaded trucks, while the second peak corresponds to the average axle weight of fully loaded trucks. The standard deviations associated with both peaks explain the variations of weights for empty or partially and fully loaded trucks (Haider and Harichandran 2007b). Furthermore, the weight factors for each distribution type control the frequency of the trucks in each category.

The parameters of each bimodal mixture distribution can be estimated from data (i.e., a sample) of the corresponding axle load spectra. Several methods can be used to obtain unbiased estimates of these unknown parameters. Generally, least square estimation is used due to its computational efficiency (Haider and Harichandran 2007a; Timm et al. 2005).

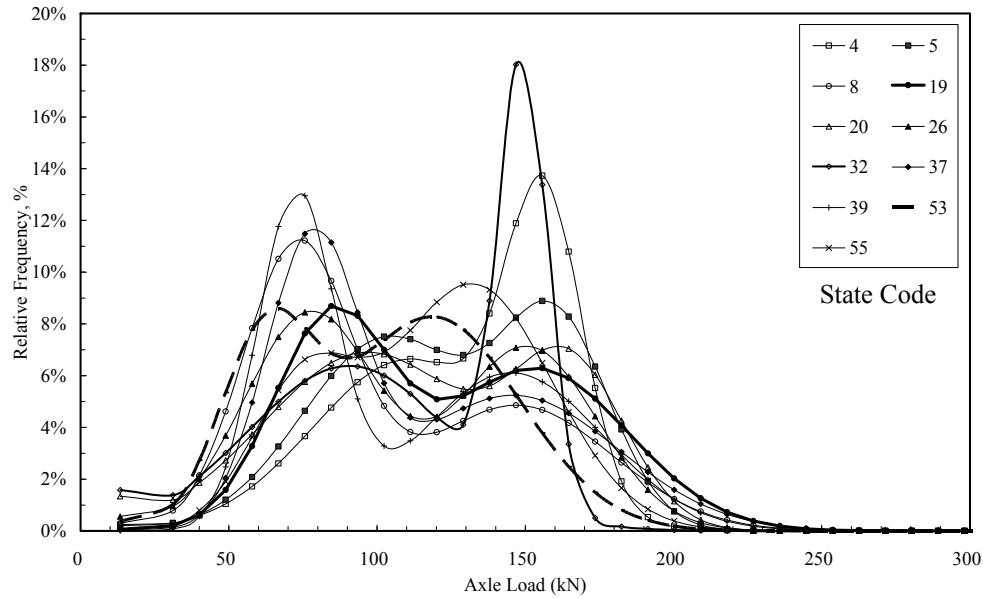


Figure 2 Axle load spectra for tandem axles used in the study

In this method the distribution parameters are estimated by minimizing the sum of squared errors between fitted and observed axle load spectra. It should be noted that numerical least squares algorithms are very sensitive to the constraints imposed on the parameters which can significantly affect the uniqueness and stability of the solution. A practical and simple method of estimating the parameters of the bimodal spectra based on closed-form solutions for its moments was developed by Haider et al. (2008). The parameters of the bimodal spectra were estimated based on these solutions and are shown in Table 1. It can be seen from the results that a mixture of two normal distributions reasonably fit the observed axle load spectra with $R^2 > 0.90$.

Table 1 Estimated parameters for bimodal axle load distributions

State	Code	μ_1	μ_2	σ_1	σ_2	p_1	p_2	R^2
Arizona	4	110.66	156.57	32.04	12.33	0.60	0.40	0.996
Arkansas	5	103.48	160.40	28.43	18.18	0.60	0.40	0.997
Colorado	8	72.98	146.95	18.03	32.07	0.56	0.44	0.956
Iowa	19	84.53	153.54	19.41	30.92	0.45	0.55	0.996
Kansas	20	96.65	164.99	34.90	18.76	0.68	0.32	0.960
Michigan	26	77.66	150.71	22.15	23.35	0.53	0.47	0.980
Nevada	32	90.52	149.22	33.85	7.65	0.61	0.39	0.923
North Carolina	37	78.06	145.85	15.43	35.11	0.48	0.52	0.983
Ohio	39	72.72	145.22	12.78	30.67	0.47	0.53	0.905
Washington	53	62.53	118.69	15.34	29.50	0.31	0.69	0.994
Wisconsin	55	75.50	132.25	17.59	26.72	0.28	0.72	0.990

Closed-form Solution for Bimodal Distribution Properties. If the axle load spectrum is bimodal (i.e., has two distinct peaks) then the two means can be directly estimated from the frequency distribution. The remaining three parameters (p_1 , σ_1 and σ_2) can be estimated by either the non-linear least square method or the closed-form solutions developed elsewhere (Haider et al. 2008). Once all five parameters that characterize a bimodal axle load spectra are estimated, these can be used to estimate other properties of the distribution. The closed-form solutions for moments of the bimodal distribution based on the mixture of two normal distributions were developed and are elaborated below. The first moment about the origin is the mean of a distribution. For the mixture distribution, the mean is:

$$\mu^* = \int_{-\infty}^{\infty} xf^*(x) = p_1\mu_1 + p_2\mu_2 \quad (3)$$

where

μ^* = Mean of bimodal axle load distribution

p_1 = Weight factor for the first distribution— loads for empty or partially loaded axle, and $p_2 = 1-p_1$, which represent weight factors for the second distribution— loaded axle

μ_1 and μ_2 = Means of unloaded and loaded distributions, respectively

The second central moment is the variance. For the mixture distribution, the variance is:

$$\sigma^{*2} = \int_{-\infty}^{\infty} (x - \mu)^2 f^*(x) = [p_1\sigma_1^2 + p_1(\mu_1 - \mu)^2 + p_2\sigma_2^2 + p_2(\mu_2 - \mu)^2] \quad (4)$$

where

σ^{*2} = Variance of the bimodal axle load distribution

σ_1 and σ_2 = Standard deviations of unloaded and loaded distributions, respectively

The n^{th} moment of the distribution about the origin is

$$m^{(n)} = \int_{-\infty}^{\infty} x^n f^*(x) dx \quad (5)$$

Substituting Equation (2) into Equation (5), the n^{th} moment of a bimodal mixture involving two normal distributions is given by

$$m^{(n)} = p_1 \int_{-\infty}^{\infty} x^n \left(\frac{1}{\sigma_1 \sqrt{2\pi}} e^{-(x-\mu_1)^2/2\sigma_1^2} \right) dx + (1-p_1) \int_{-\infty}^{\infty} x^n \left(\frac{1}{\sigma_2 \sqrt{2\pi}} e^{-(x-\mu_2)^2/2\sigma_2^2} \right) dx \quad (6)$$

In order to evaluate the integral in Equation (6), assume $y_1 = x - \mu_1$ and $y_2 = x - \mu_2$. Hence $x = y_1 + \mu_1 = y_2 + \mu_2$ and $dx = dy_1 = dy_2$. Substituting for x in Equation (6) yields

$$m^{(n)} = p_1 \int_{-\infty}^{\infty} (y_1 + \mu_1)^n \left(\frac{1}{\sigma_1 \sqrt{2\pi}} e^{-(y_1)^2/2\sigma_1^2} \right) dy_1 \\ + (1-p_1) \int_{-\infty}^{\infty} (y_2 + \mu_2)^n \left(\frac{1}{\sigma_2 \sqrt{2\pi}} e^{-(y_2)^2/2\sigma_2^2} \right) dy_2 \quad (7)$$

To further simplify Equation (7), the series expansion can be used for the $(y_j + \mu_j)^n$ term:

$$(y_j + \mu_j)^n = \sum_{i=0}^n \binom{n}{i} y_j^i \mu_j^{n-i}, j=1,2 \quad (8)$$

Thus the first term in Equation (7) can be written as

$$\text{First term} = p_1 \sum_{i=0}^n \binom{n}{i} \mu_1^{n-i} \int_{-\infty}^{\infty} y_1^i \left(\frac{1}{\sigma_1 \sqrt{2\pi}} e^{-(y_1)^2/2\sigma_1^2} \right) dy_1 \quad (9)$$

and the solution to the integral is (Papoulis and Pillai 2002):

$$\int_{-\infty}^{\infty} x^n \frac{1}{\sigma \sqrt{2\pi}} e^{-x^2/2\sigma^2} dx = \begin{cases} 0, \text{ when } n \text{ is odd} \\ 1 \times 3 \times \dots (n-1) \sigma^n, \text{ when } n \text{ is even} \end{cases} \quad (10)$$

Based on the above solution, Equation (7) may be expressed as

$$m^{(n)} = p_1 \sum_{\substack{i=0 \\ i=\text{even}}}^n \binom{n}{i} \mu_1^{n-i} [1 \times 3 \times \dots (i-1)] \sigma_1^i + (1-p_1) \sum_{\substack{i=0 \\ i=\text{even}}}^n \binom{n}{i} \mu_2^{n-i} [1 \times 3 \times \dots (i-1)] \sigma_2^i \quad (11)$$

The general solution given by Equations (11) can be used to find the closed-form solution for any moment of the bimodal mixture model. For example, the closed-form solution for $n=2$ is

$$p_1 \left[\binom{2}{0} \mu_1^{2-0} + \binom{2}{2} \mu_1^{2-2} \sigma_1^2 \right] + p_2 \left[\binom{2}{0} \mu_2^{2-0} + \binom{2}{2} \mu_2^{2-2} \sigma_2^2 \right] = p_1 [\mu_1^2 + \sigma_1^2] + p_2 [\mu_2^2 + \sigma_2^2] \quad (12)$$

Following the same steps as demonstrated above, the closed-form solution for the 3rd and 4th moments are given by

$$m^{(3)} = p_1 [\mu_1^3 + 3\mu_1\sigma_1^2] + p_2 [\mu_2^3 + 3\mu_2\sigma_2^2] \quad (13)$$

and

$$m^{(4)} = p_1 [\mu_1^4 + 6\mu_1^2\sigma_1^2 + 3\sigma_1^4] + p_2 [\mu_2^4 + 6\mu_2^2\sigma_2^2 + 3\sigma_2^4] \quad (14)$$

The α -percentile corresponding to the value x_α for the normal bimodal mixture distribution can be determined by

$$\alpha = \Phi\left(\frac{x_\alpha - \mu_1}{\sigma_1}\right)p_1 + \Phi\left(\frac{x_\alpha - \mu_2}{\sigma_2}\right)p_2 \quad (15)$$

where; Φ is the cumulative standard normal distribution

Conversely, for a given percentile value of α , the value of x_α can be determined iteratively. It should be noted that $\alpha = P[X < x_\alpha]$.

The purpose of developing closed-form solutions for the properties (μ^* , σ^{*2} , $m^{(2)}$, $m^{(3)}$, $m^{(4)}$ and the 85th percentile) of the bimodal mixture distribution is to determine if they are correlated to predicted rigid pavement performance. Table 2 presents the summary of calculated properties of axle load distributions. It should be noted that the 2nd, 3rd and 4th moments were calculated by using Equations (12) through (14) and the table shows the 2nd, 3rd and 4th roots of these moments, respectively. The respective roots of the moments are used since these have units of load (kN) and are located on the x-axis of the axle load spectra.

The respective percentiles represented by each root of the moments were computed using Equation (15) and are also shown in Table 2. The results are discussed subsequently in the paper.

Table 2 Characteristics for bimodal axle load distributions

State	Code	Axle Load Distribution Characteristics								
		m^* (kN)	s^* (kN)	85th Percentile (kN)	$\sqrt{m^{(2)}}$ (kN)	Percentile of 2 nd Root	$\sqrt[3]{m^{(3)}}$ (kN)	Percentile of 3 rd Root	$\sqrt[4]{m^{(4)}}$ (kN)	Percentile of 4 th Root
Arizona	4	128.8	34.4	163.1	133.3	47.2%	137.0	50.3%	140.0	53.2%
Arkansas	5	126.2	37.3	167.0	131.6	52.6%	136.2	56.2%	140.2	59.5%
Colorado	8	105.8	44.6	160.4	114.8	62.1%	123.1	65.6%	130.4	69.0%
Iowa	19	122.2	43.3	172.0	129.6	57.0%	136.3	61.0%	142.2	64.9%
Kansas	20	118.4	44.2	168.3	126.4	55.4%	132.8	59.3%	138.1	62.5%
Michigan	26	112.3	43.0	161.8	120.2	55.7%	126.9	59.2%	132.6	62.6%
Nevada	32	113.6	39.3	152.6	120.2	49.1%	125.0	51.4%	128.8	53.0%
North Carolina	37	113.6	43.6	165.6	121.7	60.4%	129.3	64.3%	136.2	68.1%
Ohio	39	111.5	43.4	163.0	119.6	57.3%	127.1	61.3%	133.6	65.4%
Washington	53	101.5	36.7	142.0	107.9	55.4%	113.5	60.5%	118.4	65.1%
Wisconsin	55	116.1	35.4	153.7	121.4	52.8%	126.0	57.5%	130.0	61.8%

Rigid Pavement Performance Prediction from Axle Load Spectra

Traffic is one of the key factors influencing the performance of Jointed Plain Concrete Pavements (JPCP). The new M-E PDG uses each axle load distribution to describe traffic loads while classification and count data are also required to represent load repetitions. The latter data

are used to calculate hourly and monthly traffic volumes, vehicle class distributions, and growth factors.

In this study, the effects of loading characteristics and traffic levels in terms of repetition on pavement performance were evaluated using Version 1.0 of the M-E PDG software. A typical JPCP pavement cross-section with a 225-mm slab thickness over an 200-mm thick crushed gravel base on A-6 subgrade type was assumed for the analyses. A fixed joint spacing of 4.5-m with doweled joints was assumed. It should be noted that all structural, environmental and materials related inputs were fixed in this analysis and only the effects of traffic loadings (axle load spectra) and traffic levels (repetitions) on JPCP performance was studied. The eleven tandem axle load distributions and three traffic levels (5000, 10000 and 15000 axle repetitions per year) were used to investigate pavement performance after 30 years of service life. Three performance measures, cracking, faulting, and roughness (IRI), as predicted by M-E PDG were evaluated to investigate their correlations with load distribution properties. Table 3 shows the summary results of the performance measures predicted by M-E PDG after 30-years. The results show that axle load spectra and traffic levels affect all predicted distresses at different levels.

Table 3 Performance predictions for three traffic levels

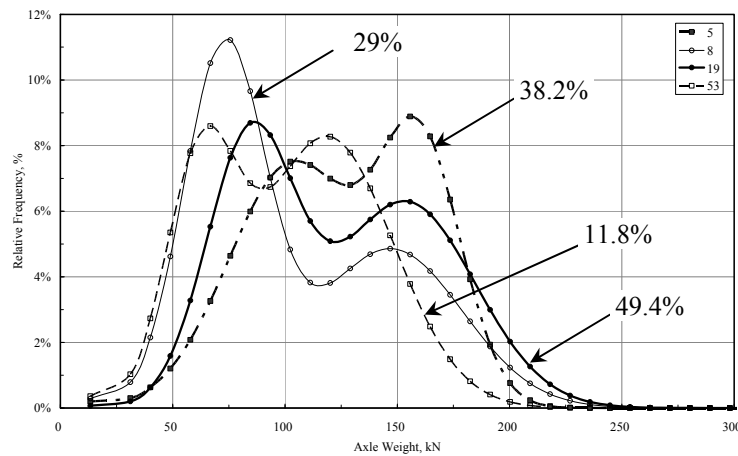
State	Code	Performance Measures								
		5000 Repetitions			10000 Repetitions			15000 Repetitions		
		Faulting (mm)	Cracking (%)	IRI (m/km)	Faulting (mm)	Cracking (%)	IRI (m/km)	Faulting (inches)	Cracking (%)	IRI (m/km)
Arizona	4	3.15	5.4	2.51	3.99	19.1	2.96	4.50	35.8	3.34
Arkansas	5	3.12	5.9	2.51	3.96	20.6	2.97	4.45	38.2	3.36
Colorado	8	2.79	4.1	2.37	3.66	15.0	2.79	4.14	29	3.14
Iowa	19	3.07	8.7	2.53	3.91	28.4	3.06	4.42	49.4	3.49
Kansas	20	3.02	5.6	2.47	3.86	19.7	2.93	4.37	37	3.31
Michigan	26	2.90	3.9	2.41	3.76	14.1	2.82	4.24	27.7	3.15
Nevada	32	2.92	2.6	2.40	3.76	9.8	2.77	4.27	19.9	3.06
North Carolina	37	2.92	6.3	2.44	3.78	21.6	2.92	4.27	39.8	3.32
Ohio	39	2.87	4.6	2.41	3.73	16.6	2.85	4.22	31.9	3.20
Washington	53	2.67	1.5	2.30	3.56	5.6	2.64	4.04	11.8	2.88
Wisconsin	55	2.95	3.2	2.42	3.81	11.6	2.80	4.29	23.3	3.11

Note: Cracking is quantified in terms of percent slab cracked.

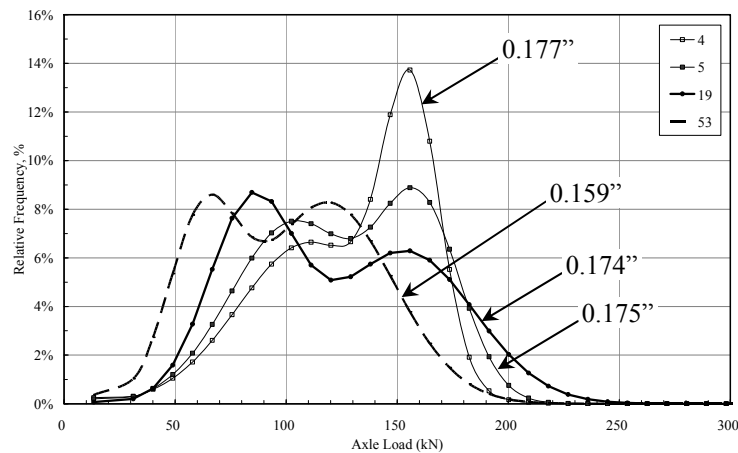
Correlation between Properties of Axle Load Spectra and Pavement Performance Measures

Tables 2 and 3 present axle load distribution properties for the eleven unique axle load spectra considered in this study and predicted pavement performance in terms of cracking, faulting and IRI for the same load distributions. It is interesting to first explore the uniqueness of each axle load distribution in causing different levels of distresses. For example, Figure 3 presents several axle load distributions. Figure 3(a) shows four of the axle load distributions in Table 3 and the amount of cracking they are expected to cause after 15000 repetitions. The maximum and minimum cracking are expected to occur in State 19 and 53, respectively. It appears that more cracking will be caused by load distributions having greater proportions of extreme axle loads.

Figure 3(b) illustrates four axle load distributions and their effects on rigid pavement faulting. It should be noted that the axle load distribution in State 19 that is expected to cause maximum cracking is not the one expected to have the worst effects on faulting. The axle load distribution in State 4 is expected to cause the maximum faulting, while that in State 53 is expected to cause the minimum faulting damage. For roughness, the load distribution rankings are similar to cracking.



(a) Four bimodal distributions—cracking



(b) The most and the least damaging axle load spectra—faulting

Figure 3 Axle load spectra characteristics (1 inch = 25.4 mm)

The above preliminary assessment reveals that different pavement performance measures in rigid pavement are affected by different load distribution properties. It is therefore of interest to determine which property of axle load spectra correlate best with each distress. Only relative effects due to varying axle distribution (loadings) and traffic levels (repetitions) on pavement performance were considered in this analysis. Consequently, structural, environmental, and material related effects were not included. Also, only tandem axle load spectra were used. Similar analyses can be conducted for other axle configurations, if desired.

Cracking Performance. Several correlations were explored between axle load distribution properties and cracking. The best correlation was found between the 85th percentile of the load and percent slab cracked. Figure 4 shows these correlations for different traffic levels and illustrates the interactive effect between load magnitude and traffic levels on JPCP cracking. Cracking is affected by both load magnitudes and traffic levels. More cracking is expected on rigid pavements having higher loads and repetitions of those loads. Further, the effect of load repetitions is more significant at higher loads. In other words, the effect of load magnitude on cracking is non-linear. The load magnitude characterized by the 85th percentile of the axle load distribution correlated very well with cracking performance. It should be noted that both bottom-up and top-down cracking types were considered in this study. The load combination for top-down cracking assumes a steering axle and a tandem axle. The steering axle is assumed to have a fixed load of 54 kN while the tandem axle has a load spectra distribution (NCHRP Project 1-37A 2003). In this study, the default axle spacing of 131-cm was used for tandem axle while typical axle spacing of 3.65, 4.6, and 5.5-m were used to represent short, medium, and long wheelbases, respectively.

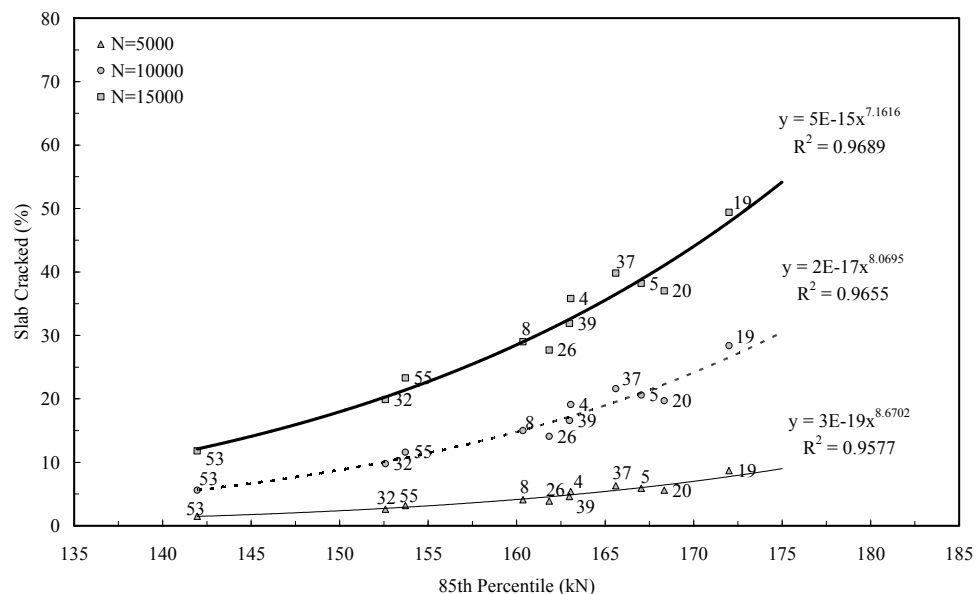


Figure 4 Correlation between cracking and the 85th percentile of axle load spectra

Faulting Performance. Faulting in rigid pavements correlated best to the overall average load (mean of bimodal distribution). Figure 5 shows these correlations for different traffic levels and illustrates that faulting is affected more by traffic levels than by the magnitude of loads. Higher faulting is expected on rigid pavements having more repetitions of loads and the increase in faulting with load magnitude is relatively independent of load repetitions. The correlation between the overall mean of the axle load distribution and the predicted faulting performance is very strong as indicated by the high R^2 values.

A power model is used to relate the overall mean load to faulting because such models have often been used in the past to relate load to damage. However, it is clear that for the range of mean load in Figure 5, the relationship is almost perfectly linear and a linear model also would provide an excellent fit. At high load levels, the power model is quasi-linear.

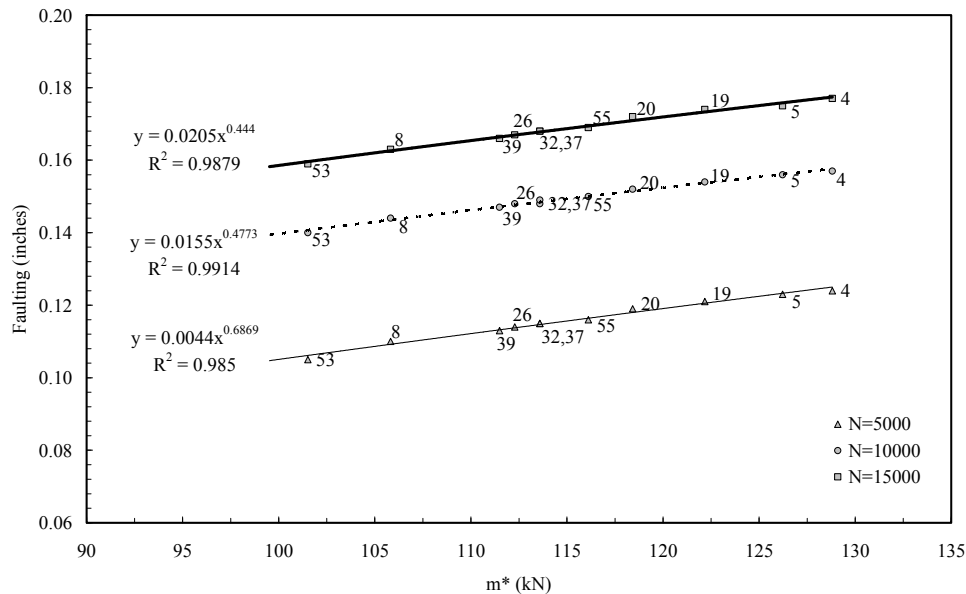


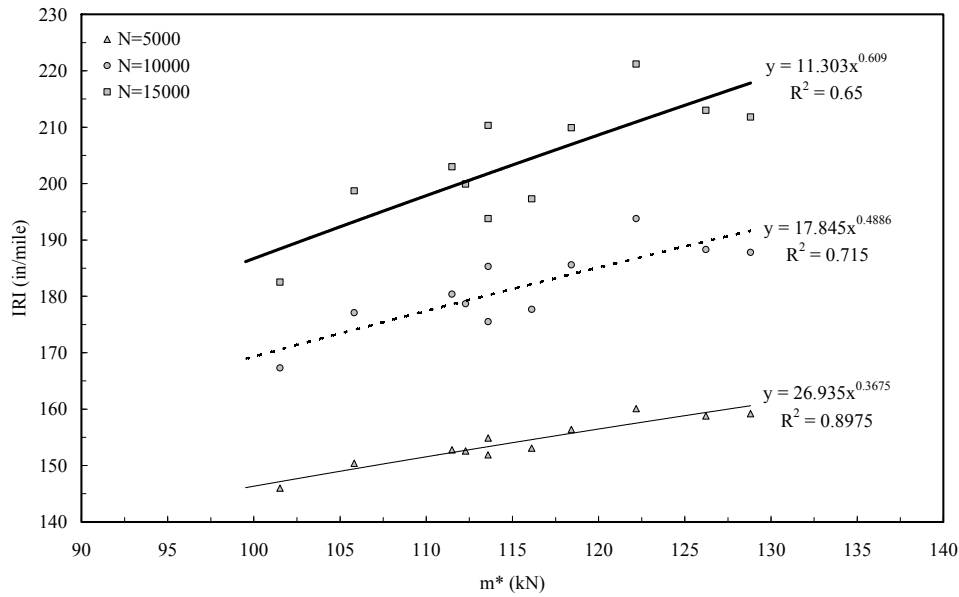
Figure 5 Correlation between faulting and overall mean of axle load spectra (1 inch = 25.4 mm)

Roughness (IRI). Road roughness is predicted in terms of the International Roughness Index (IRI) in M-E PDG. Different axle load distribution properties were correlated to IRI. However, no strong correlations were found with the overall mean of the distributions or the 85th percentile. For example, Figure 6(a) shows the correlation between the predicted IRI and the overall mean of the distributions. Two features are apparent: (a) the correlation is not strong; and (b) the correlation becomes poorer at higher traffic levels. Therefore, roots of different moments were explored to identify correlations between IRI and load magnitude. It was found that the fourth root of the 4th moment of axle load distributions correlated well with different levels of IRI as shown in Figure 6(b). These correlations also illustrate an interactive effect between load magnitude and traffic level on IRI in JPCP; i.e., IRI is affected by both load magnitudes and traffic levels. More roughness is expected on rigid pavements having higher loads and repetitions of those loads.

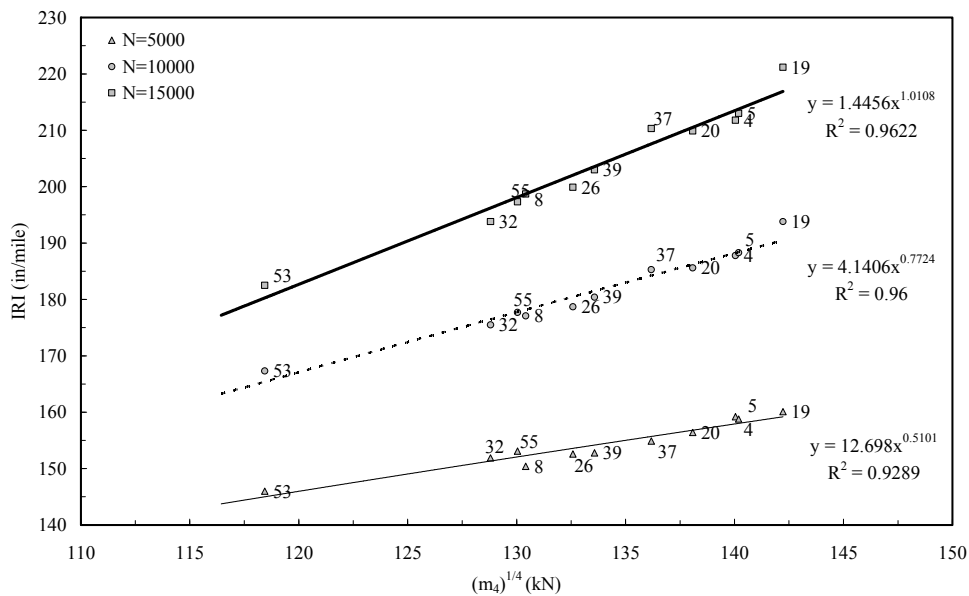
Discussion of Results

Considering only axle load magnitudes and their repetitions, the results presented herein show that cracking in rigid pavement is mainly caused by higher loads, and is strongly correlated to the 85th percentile of the axle load distribution. Several other studies have also highlighted similar findings considering the effects of dynamic loads caused by pavement roughness on cracking performance (Cebon 1988; Gillespie et al. 1993).

Faulting in rigid pavements is correlated strongly to the overall average loads in an axle load distribution. This means that each axle load magnitude and repetition will contribute toward faulting damage over time. Higher traffic levels will cause considerably more faulting in jointed concrete pavements.



(a) Overall mean of bimodal distribution



(b) Fourth root of fourth moment of bimodal distribution

Figure 6 Correlation between IRI and properties of axle load spectra (1 in./mile = 0.015783 m/km)

Pavement roughness does not correlate well with the simpler properties of axle load distributions. The strongest correlation was found between the fourth root of the 4th moment of axle load distribution and IRI. For the eleven axle load spectra considered in this study, the fourth root of the 4th moment varied from the 53rd to the 68th percentile load magnitudes. This moment is not a fixed percentile value and varies from one axle load distribution to another.

Conclusions

This paper develops correlations between properties of axle load spectra and rigid pavement performance measures predicted by the M-E PDG. Closed-form solutions are developed for

common properties of axle load distributions that can be represented by a bimodal mixture model. It is found that cracking performance is strongly correlated with the 85th percentile load, faulting is strongly correlated to the overall mean, and roughness (IRI) is strongly correlated to the fourth root of the 4th moment of axle load spectra, respectively. These findings imply that cracking in rigid pavements is mainly caused by the highest 15 percent of loads, while faulting is mostly caused by the overall average loads in an axle load distribution. The overall average loads along with higher contributions from the heavier loads seem to cause higher roughness in rigid pavements. The correlations developed for different performance measures can directly indicate the relative pavement damage caused by axle load distributions.

Acknowledgement

The authors are grateful to Mr. Monther Dwaikat, a Ph.D. candidate in the Department of Civil and Environmental Engineering at Michigan State University, for his assistance in obtaining the closed-form solutions presented in this paper.

References

- Carey Jr., W. N., and Irick, P. E. (1960). "The pavement Serviceability-Performance Concept." *Highway Research Board*, Bulletin 250, 40-58.
- Cebon, D. (1988). "Theoretical Road Damage Due to Dynamic Tyre Forces of Heavy Vehicles. Part 2: Simulated Damage Caused by a Tandem-Axle Vehicle." *Proc. I. Mech.E.*, 202, No. C2 (1988), 109-117.
- Gillespie, T. D., Karamihas, S. M., Sayers, M. W., Nasim, M. A., Hansen, W., Ehsan, N., and Cebon, D. (1993). "Effect of Heavy-Vehicle Characteristics on Pavement Response and Performance." *NCHRP Report 353*, National Cooperative Highway Research Program, Washington, D.C.
- Haider, S. W., and Harichandran, R. S. (2007a). "Characterizing Axle Load Spectra by Using Gross Vehicle Weights and Truck Traffic Volumes." *CD ROM, 86th Annual Meeting of Transportation Research Record*.
- Haider, S. W., and Harichandran, R. S. "Quantifying the Effects of Truck Weights on Axle Load Spectra of Single and Tandem Axles Configurations." *the Fifth International Conference on Maintenance and Rehabilitation of Pavements and Technological Control*, Park City, Utah, USA.
- Haider, S. W., and Harichandran, R. S. (2007c). "Relating Axle Load Spectra to Truck Gross Vehicle Weights and Volumes." *ASCE Journal of Transportation Engineering*, 133(12), 696-705.
- Haider, S. W., Harichandran, R. S., and Dwaikat, M. B. (2008). "Estimating Bimodal Distribution Parameters and Traffic Levels from Axle Load Spectra." *CD ROM, 87th Annual Meeting of Transportation Research Record*.
- Hong, F., Pereira, F. M., and Prozzi, J. A. (2006). "Comparison of Equivalent Single Axle Loads from Empirical and Mechanistic-Empirical Approaches." *CD ROM 85th Annual Meeting Transportation Research Record*.
- NCHRP Project 1-37A. (2003). "Appendix KK: Transverse Cracking of JPCP." *Final Report: Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures*, ARA, inc., ERES division, 505 west University Avenue, Champaign, Illinois 61820, 2004.

- Papoulis, A., and Pillai, S. U. (2002). *Probability, Random Variables, and Stochastic Processes*, McGraw-Hill, Inc., New York.
- Prozzi, J. A., Hong, F., and Leidy, J. (2006). "Optimum Statistical Characterization of WIM Data Based on Pavement Impact." *CD ROM 85th Annual Meeting Transportation Research Record*.
- Timm, D. H., Tisdale, S. M., and Turochy, R. E. (2005). "Axle Load Spectra Characterization by Mixed Distribution Modeling." *ASCE Journal of Transportation Engineering* 131(2), 83-88.