Effect of Heavy Multiple Axle Trucks on Flexible Pavement Damage Using In-Service Pavement Performance Data

Hassan K. Salama[1]; Karim Chatti[2]; and Richard W. Lyles, P.E.[3]

Abstract: Truck axle configurations and weights have changed significantly since the AASHO road study was conducted in the late 1950s and early 1960s. Emerging concerns about the effects of new axle configurations on pavement damage, which is unaccounted for in the AASHTO procedure, have prompted several researchers to investigate the impacts of different axle and truck configurations on pavement performance. However, there is still a need to strengthen the mechanistic findings using field data. In this paper, actual in-service traffic and pavement performance data for flexible pavements in the state of Michigan are considered. Monitored truck traffic data for different truck configurations are used to identify their relative damaging effects on flexible pavements in terms of cracking, rutting, and roughness. The analysis included simple, multiple, and stepwise regression. The results indicated that trucks with multiple axles (tridem or more) appear to produce more rutting damage than those with only single and tandem axles. On the other hand, trucks with single and tandem axles tend to cause more cracking. Pavement roughness results did not show enough evidence to draw a firm conclusion.

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CE Database subject headings: Trucks; Flexible pavements; Damage; Data analysis.

Background

Factors such as traffic, environment, materials, and design considerations affect pavement damage over time, with traffic loads playing a key role in deterioration. Trucks are the major consumers of the pavement network, applying the heaviest loads to the pavement. Truck loads are transferred to the pavements through various combinations of axle configurations depending on the truck type. The AASHTO pavement design guide has been used to convert different axle load configurations to a standard axle load (18 kips) using load equivalency factors (LEFs). These LEFs are based on loss of present serviceability index (PSI) and were developed for a limited number of pavement types, load magnitudes, load applications, ages, and environments. The PSI is based on the functional performance of the road surface (serviceability), but only marginally accounts for other key performance measures such as fatigue cracking and rutting for flexible pavements. Increased demand due to economic growth has led to changes in truck dimensions and weights, and a need to examine damage caused by new axle and truck configurations using field data from in-service pavements. In addition, investigating the relationship between truck traffic and pavement performance from in-service pavements can be used to verify previous mechanistic and laboratory findings.

Mechanistic Analysis

Hajek and Agarwal (1990) highlighted the factors to be considered in calculating the load equivalency factors for various axle configurations and developed those factors using strain criteria. It was concluded that pavement response parameters such as deflections and strains have considerable influence on LEFs, and that axle weight and spacing significantly contribute to pavement damage. Chatti and Lee (2003) studied the effects of various truck and axle configurations on flexible pavement fatigue using different summation methods to calculate damage. Gillespie et al. (1993) analyzed the effect of various axle and truck configurations on pavement damage using different performance measures (fatigue, rutting, and roughness). One of the conclusions of the study by Gillespie and co-workers was that pavement rutting is influenced by the total vehicle gross weight (i.e., the heavier the vehicle, the more pavement rutting impact). All these studies were based on mechanistic (static or dynamic) analyses.

Laboratory Investigations

Chatti and El Mohtar (2004) and El Mohtar (2003) studied the fatigue life of an asphalt mixture in the laboratory under different truck axle configurations using the indirect tensile cyclic load test by applying load pulses that are equivalent to the passage of an entire axle group or truck. The dissipated energy-based analysis determined the number of repetitions to failure for each case, and a unique fatigue curve for multi-axle configurations was developed. Their laboratory results showed that multiple-axle groups were less damaging in fatigue per tonnage as compared to single

[1]Research Associate, Dept. of Civil and Environmental Engineering, Michigan State Univ., 3546 Engineering Building, East Lansing, MI 48824. E-mail: salamaha@egr.msu.edu

[2]Associate Professor, Dept. of Civil and Environmental Engineering, Michigan State Univ., 3546 Engineering Building, East Lansing, MI 48824 (corresponding author). E-mail: chatti@egr.msu.edu

[3]Professor, Dept. of Civil and Environmental Engineering, Michigan State Univ., 3546 Engineering Building, East Lansing, MI 48824. E-mail: lyles@egr.msu.edu

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axles. Increasing the number of axles carrying the same load resulted in less damage. This decrease in damage was found to be more significant between single, tandem, and tridem axles, whereas it starts to level off at higher axle numbers. Similar results were obtained for trucks with larger axle groups, which had lower truck factors per tonnage than those with single and tandem axles. A similar laboratory study focused on rutting of asphalt mix under various axle and truck configurations concluded that rutting is proportional to the axle/vehicle weight (Salama 2005).

Analysis of In-Service Pavements

Chatti et al. (2004) used field data from a general pavement study in a long term pavement performance program to investigate the relative damage (fatigue and rutting) to asphalt pavements by various axle and truck configurations. There were no conclusive results from the analysis about the effect of axle/truck configurations on fatigue and rutting damage.

In examining their special overload permits, the Ohio Department of Transportation recognized that trucks traveling from Michigan to northern Ohio cities were substantially heavier than those in Ohio (Ilves and Majidzadeh 1991; Saraf et al. 1995). Therefore, a field study was conducted to investigate the effect of Michigan heavy vehicles on pavement performance. The following field data were collected for this study: Traffic, rutting, faulting, cracking, roughness, and deflection measurements. Regression analysis of rutting data produced the following equation:

$$\mathrm{RUTF} = 0.035 + 0.984(C_{13}) + 0.03(B + C) + 0.0007(\mathrm{months}) \tag{1}$$

where RUTF=rutting (in inches) in flexible pavement; C_{13}=number of FHwA Class 13 vehicles in the lane per day in thousands; B=total number of trucks in FHwA Classes 8–12 in thousands; C=total number of trucks in FHwA Classes 4–7 in thousands; and months is the number of months of testing with January 1986 as month=1.

They concluded that heavy axle loads influenced rutting for flexible and composite pavements; however, the field traffic and performance data used in this study were from only four roads linking Ohio and Michigan. In addition, the analysis did not compare the relative damage resulting from various axle/truck configurations on pavement cracking and roughness.

In the present study, actual field data from the state of Michigan were analyzed to study the effects of various axle and truck configurations on critical pavement distresses. The Michigan Department of Transportation (MDOT) has very comprehensive pavement surface distress data files. MDOT also collects rutting and roughness data, as well as traffic count and weight data throughout its network. Collection of traffic and weight data has been recently upgraded by using new weigh in motion technology. This allows for a more accurate representation of the distribution of truck axle weights and configurations along MDOT's trunklines. The details of the truck traffic and pavement performance data, as well as the analyses conducted, are explained in the following sections.

Research Objective

The objective of this research is to investigate the effect of different axle/truck configurations on flexible pavement damage in terms of cracking, as measured by the distress index (DI), rutting, and roughness, as measured by ride quality index (RQI) using weigh station truck traffic and in-service pavement performance data.

Performance Data

Great effort has gone into selecting sections with the same pavement type, age, cross-sectional design, and traffic loading. The same control section was divided into several sections that have similar average daily truck traffic (ADTT) so that if pavement age varies, the cumulative control section traffic will reflect each subsection's age. MDOT surveys the pavement distress for half of their network every year. The survey includes three main performance measures: (1) DI, (2) rutting, and (3) RQI. The distress survey includes only outside (slow) lane where most trucks travel.

Distress Index

MDOT uses the DI as one measure of pavement performance within its pavement management system. Through observation and assessment of pavement surface conditions, DI is determined as a measure of distresses (primarily load related) and is currently used to determine the need for preventive maintenance and rehabilitation/reconstruction. Although it is a visually determined quantity (e.g., severity and extent of cracks), DI is based on specific metrics. The DI scale starts at zero for a new pavement and increases (without limit) as the pavement condition worsens. MDOT categorizes DI into three levels: Low ($\mathrm{DI} < 20$), medium ($20 < \mathrm{DI} < 40$), and high ($\mathrm{DI} > 40$). A pavement with a DI of 50 is considered to be exhausted and is a candidate for major rehabilitation or reconstruction. DI is a cumulative value, which includes all surface distresses since the original construction of the pavement, but can be affected (reduced) by preventive maintenance or major rehabilitation.

Rutting

Rutting is a main load-related distress in flexible pavements. It is the permanent deformation in the transverse profile in the wheel path, starting at 0 rut depth and increasing with the number of heavy load repetitions. MDOT considers a rutting threshold of 0.5 in. (12 mm) to be the boundary between good and poor pavement conditions. Rutting is cumulative over time unless major rehabilitation is applied to the pavement.

Ride Quality Index

As its name suggests, the RQI describes the ride quality of the road. The RQI was developed by MDOT in the early 1970s, as a weighted wavelength based index that is correlated with subjective opinions of highway users. A RQI value between 0 and 30 indicates excellent ride quality, 31–54 good ride quality, 55–70 fair ride quality, and pavements with more than 70 are considered to have poor ride quality (Darlington 1995).

Pavement Prior Condition

Some of the pavement control sections in the study recently received major rehabilitation or preventive maintenance that altered the pavement surface distresses to zero even though these pavements were not reconstructed. The prior condition of the pavement can affect the future growth rate of the distresses such that

Table 1. Effect of Prior Condition on Distress Index

(a) ANOVA

	Sum of squares	*df*	Mean square	*F*	*p*-value
Regression	69.270	2	34.635	14.351	0.00001[a]
Residual	137.564	57	2.413		
Total	206.834	59			

(b) Regression coefficient and *p*-value

Independent variables	Unstandardized coefficients *B*	Std. Error	Standardized coefficients β	*p*-value
Constant	0.622	0.408		0.13308
PC	0.003	0.008	0.047	0.70390
Age	0.141	0.029	0.600	0.00001

[a]Predictors: (Constant), age, PC.

these pavements may behave differently compared to newly constructed pavements. All available prior DI data were taken into account to investigate the effect of the prior condition on pavement deterioration. This was done using a weighted (with respect to pavement age) average of DI values, which is calculated as follows:

$$\widetilde{DI} = \frac{\sum DI \times Age}{\sum Age} \qquad (2)$$

The $\widetilde{DI}$ takes into account the variability of DI over time due to distress survey errors and unrecorded routine maintenance. The prior condition was treated as a covariate in the multiple linear regression analysis. Table 1 shows the regression coefficients and *p*-values from the ANOVA analysis. The results show that the prior condition is not statistically significant for the DI when age is taken into account. Therefore, having the latest distress survey and the corresponding pavement's age for calculating the cumulative traffic is sufficient for determining the relative effect of axles/trucks on pavement damage.

Traffic Data

The Federal Highway Administration (FHwA website: http://apps.fhwa.dot.gov/vtris/vtris.aspx) assembles highway traffic information all over the United States and provides it in its Vehicle Travel Information System (*VTRIS*), which is available as a public domain software. The FHwA classifies truck traffic into nine categories according to number of axles and number/type of truck units. Most of the truck categories include different truck configurations. The program provides the count of each FHwA truck class without differentiating between different configurations or providing the proportion of each configuration under a given category. Not all needed traffic counts/proportions and the average weights of each truck configuration are available in the *VTRIS* program. It was therefore necessary to analyze raw traffic data provided by MDOT in order to extract all essential truck information.

Vehicle Travel Information System, VTRIS

The FHwA traffic data are classified into 13 classes. Classes 5–13 are for truck traffic, reported as the ADTT count per class type. Table 2 shows the class definition, the axle groups (number of axles within an axle group), and examples of truck configurations for Classes 5–13. Axle spectra are also available from FHwA data but only for single, tandem, tridem, and quad axles. The program does not have the count for large (⩾5) axle groups, which are the point of interest in this research. Using the FHwA data (from "W-2" tables at the website), the ADTT for Classes 5–13 were extracted for the control sections corresponding to the outside lane. The improvement year of the control section was also obtained from MDOT's sufficiency-rating books. The improvement year represents the most recent year the segment received significant work that improved the pavement condition or extended the life of the pavement. The cumulative truck traffic, (CTT) for Classes 5–13 was calculated as follows:

$$\text{CTT of class} = \text{ADTT of class} \times \text{pavement age} \times 365 \qquad (3)$$

where ADTT=average daily truck traffic of a given class and pavement age=year of improvement−distress survey year.

The consistency of weigh station traffic data from year to year was examined for total ADTT and individual truck classes. Fig. 1 shows a comparison of ADTT in 2001 and 2002 traffic data for all weigh stations in the state of Michigan. No significant change can be seen in the traffic data. Therefore, the 2001 traffic data were used for truck classes' analysis.

Raw Traffic Data

As VTRIS does not provide some essential data needed for this research, raw truck traffic data for 2000 were analyzed to determine the distribution of axle and truck configurations for all axle groups including those with a large number of axles for each

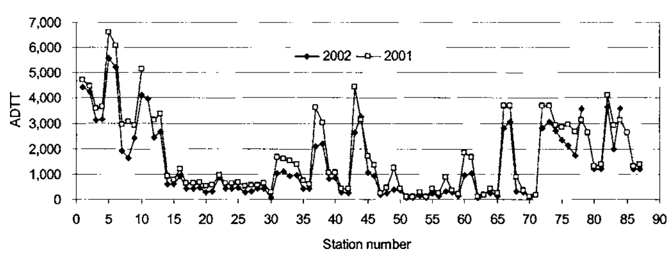
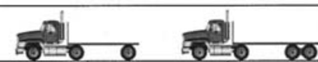
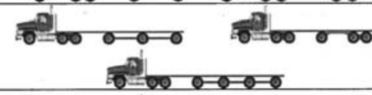
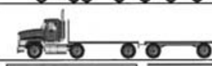
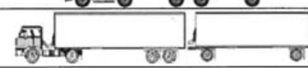
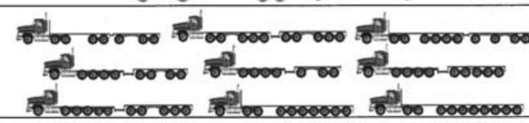


Fig. 1. One-to-one comparison between 2001 and 2002 total average daily truck traffic

Table 2. FHwA Vehicle Class Definition, Axle Groups, and Example of Truck Configurations

FHWA Class Type	Class Definition	Axle Group	Example truck configurations
5	Two-axle, six-tire, single-unit trucks	1	
6	Three-axle single-unit trucks	1 and 2	
7	Four or more axle single-unit trucks	1, 3 and 4	
8	Four or fewer axle single-trailer trucks	1and 2	
9	Five-axle single-trailer trucks	1and 2	
10	Six or more axle single-trailer trucks	1, 2, 7 and 8	
11	Five or fewer axle multi-trailer trucks	1	
12	Six-axle multi-trailer trucks	1 and 2	
13	Seven or more axle multi-trailer trucks	1, 2, 3, 4, 5, 7and 8	

weigh station. Trucks were categorized according to their largest axle group. For example, a quad axle is an axle group that has four axles that share the same weight, so that trucks with a quad-axle are all trucks that have quad axle as the largest axle group. Table 3 shows the axle and truck categories used in the analysis. The analysis of raw traffic data also allowed for determining the proportions of each truck type within each FHwA Truck Class. Table 4 shows the proportions, average truck weight, and the percentage of truck configurations within each class. FHwA Truck Class 13, which is the heaviest truck class, includes many different configurations with most having very small numbers. The table shows that Truck Classes 7–12 have very small percentages ($<0.4\%$) and Truck Class 5 has the lowest overall average weight (6.0 t). These trucks will not significantly contribute in explaining the pavement damage; therefore they were excluded from the analysis.

Analysis

The analysis was conducted using three different independent variables: (1) axle configuration (29 subsections); (2) truck configuration (29 subsections); and (3) FHwA truck class (53 subsections). The effects of these on DI, rutting, and RQI were investigated using simple, multiple, and stepwise linear regression.

Regression Analysis

A series of simple univariate linear regressions was used to investigate the effect of each axle/truck configuration on each different pavement distress type. The simple linear regression provides the value of the slope and the correlation coefficient of the relationship between the independent variables (axle/truck configurations) and dependent variables (DI, rutting, and RQI). Univariate

Table 3. Axle/Truck Configurations Extracted from Raw Data

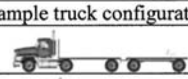
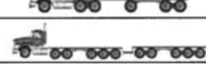
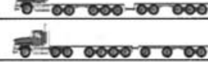
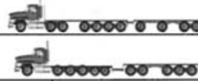
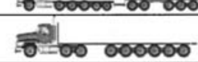
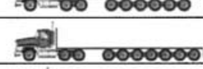
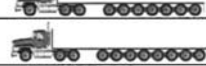
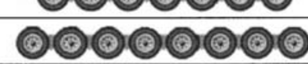
Axle/truck	Example truck configurations	Axle configurations
Single		
Tandem		
Tridem		
Quad		
Five		
Six		
Seven		
Eight		

Table 4. Proportions and Average Weights for FHwA Truck Classes

FHwA class	Truck configuration	Truck count	Total count	Proportions (%)	Average truck weight (t)	Weighted average truck weight (t)	Percentage of each truck class
5	5F1[a]	892,451	905,700	98.5	6.0	6.0	40.7
	5F12	10,635		1.2	7.0		
	5F11	1,405		0.2	6.8		
	5F111	1,209		0.1	7.7		
6	6F2	91,657	91,657	100.0	13.3	13.3	4.1
7	7F3	6,096	6,975	87.4	19.8	20.5	0.3
	7F21	879		12.6	25.6		
8	8F11	149,141	229,718	64.9	30.7	25.3	10.3
	8F12	65,798		28.6	15.3		
	8F21	7,880		3.4	16.1		
	8F111	6,899		3.0	14.6		
9	9F22	631,743	738,310	85.6	21.4	21.6	33.2
	9F211	106,567		14.4	23.0		
10	10F23	35,972	51,930	69.3	24.4	27.8	2.3
	10F2111	10,657		20.5	37.1		
	10F212[b]	5,234		10.1	32.6		
	10F221	67		0.1	29.2		
11	11F1111	37,790	37,790	100.0	21.8	21.8	1.7
12	12F2111	1,323	1,323	100.0	31.2	31.2	0.1
13	Trucks with 8-axle[c]	6,987	158,305	4.4	58.3	57.42	7.2
	Trucks with 7-axle	5,753		3.6	68.7		
	Trucks with 6-axle	4,284		2.7	66.5		
	Trucks with 5-axle	31,383		19.7	61.7		
	Trucks with 4-axle	52,190		32.8	58.5		
	Trucks with 3-axle	33,914		21.3	51.1		
	Trucks with 2-axle	23,794		14.9	53.8		

[a]FHwA Class 5 front and single axle.

[b]FHwA Class 10 front, tandem, single, and tandem.

[c]Trucks with 8-axle group as the largest group.

analysis can only partially explain the distresses on pavement as it does not account for other variables. It was primarily used to gain insight into the data.

Multiple linear regression takes into account all specified variables at the same time. The multiple linear equations produced herein are not intended to be a universal model to predict pavement damage. The regression parameter (β), coefficient of determination (R^2), and test statistic (p-values) were utilized to compare the effect of different axle and truck configurations on pavement damage. Throughout the multiple linear regression analysis, checking the normality assumption and constant variance of the residual, as well as deleting the influential points based on Cook's distance, were considered.

Stepwise regression was also used to confirm the results from simple and multiple linear regressions. Stepwise regression is a technique for choosing the variables to include in a multivariate regression model. Forward stepwise regression starts with no model terms. At each step, it adds the most statistically significant term (the one with the highest F statistic or lowest p-value) until the addition of the next variable makes no significant difference. An important assumption behind the method is that some input variables in a multiple regression do not have an important explanatory effect on the response. Stepwise regression keeps only the statistically significant terms in the model.

Standardized Regression Coefficients

The value of the slopes (β's) in simple, multiple, and stepwise linear regression depends on the unit of measurement (number of truck repetitions). This slope represents the change in distress (dependent variable) due to a unit increase in the number of axle or truck repetitions (independent variables). Axle/truck configurations with fewer repetitions will have a larger slope value, whereas those axle/truck configurations with more repetitions will have a very small slope value, which does not represent the actual effect regardless of the number of repetitions. Moreover, the intercept for each independent variable will be different from each other, which may not help in comparing the relative effects. The standardized slope has been documented as a measure to compare the relative importance of different independent variables (Dillon and Goldstein 1984; Allen 2001). Standardized slope values are determined by converting all variables (dependent and independent) into Z scores. Having the variables in Z-score form will convert the distribution mean to zero and standard deviation to one, such that all variables will have a common measurement scale and one can determine which independent variable is relatively more important. The following equation represents the nonstandardized simple linear regression:

Table 5. Component Matrix

Class	Component 1	Component 2
6	0.886	0.350
7	0.528	0.806
8	0.897	0.284
9	0.953	−0.211
10	0.870	−0.293
11	0.694	−0.503
13	0.721	−0.257

$$Y = \alpha + \beta X \quad (4)$$

where Y=dependent variable (DI, rutting, or RQI); α=intercept; β=nonstandardized slope; and X=independent variable (e.g., single-tandem or multiple axle repetitions).

The following equations represent the standardized simple linear regression:

$$Y^* = \beta^* X^* \quad (5)$$

$$X^* = Z_x = \frac{\bar{X} - X}{\sigma_x} \quad (6)$$

$$Y^* = Z_y = \frac{\bar{Y} - Y}{\sigma_y} \quad (7)$$

where Y^*=standardized dependent variable; β^*=standardized slope; $\bar{Y}$=average value of dependent variable; X^*=standardized independent variable; and $\bar{X}$=average value of independent variable.

The same procedures were used to standardize the regression coefficient parameters in multiple and stepwise regression. The standardized slope was used to compare the relative effect of the axle/truck configurations in all regression analyses presented in the following sections.

Multicollinearity

In multiple linear regression analysis, having several independent correlated variables in the model will affect the values of the regression coefficients and in some cases cause the signs to switch to counterintuitive values. There are several outcomes that result from multicollinearity in the data (Neter and Wasserman 1996):

1. Disagreement between the F-test in the overall ANOVA table and the marginal t-tests;

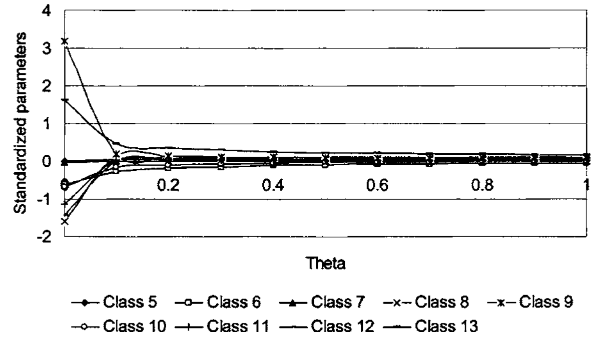


Fig. 2. Ridge traces for different truck classes

2. Inaccurate estimation of the regression parameters (β's), where some of the β values are negative in multiple linear regression whereas they are positive in simple linear regression;
3. Large standard errors for the regression parameters;
4. A large variance inflation factor (VIF), which measures how much the variance of a coefficient is increased because of multicollinearity. A VIF$\geq$10 indicates a serious multicollinearity problem;
5. Correlation matrix of the independent variables—an examination of the correlation matrix showed that the weigh station traffic data for different truck types were highly correlated with each other ($\rho > 0.7$).

Remedies for the Multicollinearity Problem

There are several methods suggested in the literature (Belsley et al. 1980) to remedy the multicollinearity problem. Some of these methods are outlined here:

1. Remove one or several predictor variables from the model in order to reduce the multicollinearity and standard error of the regression parameters.
2. Principle component analysis can be used to form one or several composite indices based on the highly correlated predictor variables. The principle components method provides combined indices that are uncorrelated.
3. Ridge regression is one of the remedies for such a problem. Ridge regression introduces bias to the diagonal of $X'X$ (where X=$n \times k$ matrix of independent variables, and X' is the inverse of the X matrix) for calculating the regression coefficients, shrinks the coefficient values toward zero, and decreases the standard error of the coefficients.
4. Based on judgment, combine similar truck configurations.

The results from multiple linear regression analysis showed

Table 6. Effect of Different Truck/Axle Configurations of Pavement DI

Axle/truck configurations	Independent variables	Simple linear regression β	Simple linear regression p-value	Simple linear regression R^2	Multiple linear regression β	Multiple linear regression p-value	Multiple linear regression R^2	Stepwise regression β	Stepwise regression p-value	Stepwise regression R^2
Axle types	1 and 2	0.430	0.02	0.185	0.617	0.032	0.343	0.585	0.001	0.342
	3, 4, 5, 6, 7, and 8	0.265	0.164	0.070	−0.040	0.883		N/S	NA	
Truck types	1 and 2	0.466	0.011	0.218	0.580	0.007	0.437	0.654	0.003	0.427
	3, 4, 5, 6, 7, and 8	0.272	0.154	0.074	0.122	0.540		N/S	NA	
Truck classes	6, 8, 9, 10, and 11	0.272	0.048	0.074	0.340	0.090	0.092	0.301	0.028	0.091
	13	0.095	0.497	0.009	−0.053	0.790		N/S	NA	

Note: N/S=not selected by model and NA=not applicable.

Table 7. Effect of Different Truck/Axle Configurations on Pavement Rutting

Axle/truck configurations	Independent variables	Simple linear regression			Multiple linear regression			Stepwise regression		
		β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
Axle types	1 and 2	0.399	0.032	0.159	0.059	0.773	0.58	N/S	NA	0.578
	3, 4, 5, 6, 7, and 8	0.441	0.017	0.194	0.715	0.002		0.790	0.0000	
Truck types	1 and 2	0.283	0.137	0.079	−0.009	0.957	0.584	N/S	NA	0.584
	3, 4, 5, 6, 7, and 8	0.440	0.017	0.193	0.769	0.0006		0.695	0.0000	
Truck classes	6, 8, 9, 10, and 11	0.395	0.004	0.156	0.073	0.6316	0.412	N/S	NA	0.409
	13	0.537	0.0004	0.288	0.590	0.0003		0.639	0.0000	

Note: N/S=not selected by model; NA=not applicable.

that Truck Class 9 has a very high VIF (119), with Classes 8, 11, and 13 also having large values (>10). Removing Class 9 from the model in order to reduce the multicollinearity and standard error of the regression parameters leads to a VIF of 12.58 for Class 13. This means that the first remedy calls for removing truck Classes 9 and 13 from the analysis. This is not acceptable as Truck Class 13 includes the heaviest trucks and Truck Class 9 represents 33% of the total truck population. Therefore, this method was not selected.

The results from principle component analysis indicate that more than 83% of the variance can be explained by the first two components. However, each component is composed of all truck classes (see Table 5). Therefore, this method was not selected since it lumps totally dissimilar truck configurations together, which is not desirable for meeting the objective of this research.

The analysis using ridge regression showed that the appropriate theta value as determined from ridge trace graph (see Fig. 2) is 0.1. At this value, the majority of coefficient estimators (β's) are positive except for Classes 6, 10, and 12. To make these β coefficients positive, a much higher value of theta is required. However, a much higher value will introduce significant bias, and therefore, is not acceptable.

Based on the previous analyses, none of the remedies for the multicollinearity problem meet the objective of this research; therefore, the analysis was done using the last method (combining similar truck configurations). Single and tandem axles/trucks were lumped together as one group and multiple axles/trucks (tridem, quad, 5-axle, 6-axle, 7-axle, and 8-axle) were lumped together as another group.

Results and Discussion

As mentioned earlier, the most logical way to compare the effect of different correlated axle/truck configurations and truck classes was to group similar configurations together. Therefore, axles/trucks were categorized into two groups: single-tandem and multiple axles/trucks. FHwA truck classes have nine different truck types (Classes 5–13). Classes 7 and 12 were excluded based on their low percentage and Class 5 was excluded due to the insignificant effect caused by its light weight. Trucks with single and tandem axles can be found in Classes 6, 8, 9, 10, and 11, whereas trucks with multiple axles are only in Class 13. A given weigh station can be the source of traffic data for several subsections based on their age; whereas the level of traffic is the same for these subsections, their different ages will make their cumulative traffic different.

The results from the analyses are summarized in Tables 6–8 for DI, rutting and RQI, respectively. Table 6 shows the standardized regression coefficients (β values), p-values, and R^2 for DI. The β values for single-tandem axles/trucks from all three regression methods are higher than those of multiple axles/trucks. More importantly, the p-values for multiple axles/trucks show that they are not significant ($p > 0.05$), suggesting that multiple axles cause less cracking damage per load carried. This conclusion agrees with the laboratory investigations conducted recently (Chatti and El Mohtar 2004; El Mohtar 2003).

In Table 7, models and statistics for rutting are reported. The results show that multiple axles/trucks are significant and show higher β values than single-tandem axles/trucks, which are not significant. This indicates that rutting is more influenced by heavier loads (axle/truck gross weight), which agrees with the results from other studies (Gillespie et al. 1993; Salama 2005).

It should be noted that the R^2 values for simple linear regression analyses are low; however this is expected since the individual axle/truck groups will not solely explain the distresses. A significant improvement of R^2 values occurs when using multiple linear regression except for the analysis of FHwA truck classes. This refers to the fact that Truck Class 13 has some single and tandem axle trucks. More importantly, the main goal of using these regression models is to have a relative comparison; they are not suggested for any future prediction.

Table 8. Effect of Different Truck/Axle Configurations on Pavement RQI

Axle/truck configurations	Independent variables	Simple linear regression			Multiple linear regression			Stepwise regression		
		β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
Axle types	1 and 2	0.129	0.502	0.017	1.019	0.0006	0.424	N/S	NA	NA
	3, 4, 5, 6, 7, and 8	−0.264	0.166	0.069	−1.092	0.0003		N/S	NA	
Truck types	1 and 2	0.318	0.093	0.101	0.796	0.00020	0.473	N/S	NA	NA
	3, 4, 5, 6, 7, and 8	−0.268	0.159	0.072	−0.751	0.00037		N/S	NA	
Truck classes	6, 8, 9, 10, and 11	−0.111	0.435	0.012	0.608	0.00356	0.314	0.608	0.00356	0.314
	13	−0.423	0.002	0.179	−0.909	0.00003		−0.909	0.00003	

Note: N/S=not selected by model; NA=not applicable.

The statistical results for RQI are found in Table 8. Single-tandem axles/trucks show higher β values than multiple axle/trucks. However, even though *p*-values for both axle/truck configurations are significant ($p < 0.05$), β values for multiple axles are negative. This can be interpreted to mean that pavement sections with higher proportion of multiple axles/trucks configurations tend to have lower RQI values (lower roughness), while those with higher proportion of single and tandem axle/truck configurations tend to have higher RQI values (higher roughness). To date, no known analytical or laboratory-based investigations have been conducted to look at the effect of different axle/truck configurations on pavement roughness, therefore the results reported herein could not be independently verified. Therefore, for the RQI results, there was not enough evidence to draw a firm conclusion.

Conclusion

Based on the analyses of performance data from in-service pavements in the state of Michigan, the effect of heavy multiple axle trucks on flexible pavement damage can be summarized as follows:

1. Trucks with single and tandem axles appear to affect pavement cracking (DI) more than those with multiple axles (tridem and higher).
2. Conversely, heavier trucks with multiple axles tend to have more effect on rutting than those with single and tandem axles.
3. There was not enough evidence to draw a firm conclusion on whether trucks with different axle configurations affected pavement roughness differently.

These findings are more valuable for truck weight and size policy purposes than pavement design protocols, since trucks with multiple axles represent a small percentage of the total truck traffic compared to trucks with single and tandem axles only.

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Disclaimer

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