

Estimation of Axle Loads of Heavy Vehicles for Pavement Studies

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A statistical approach was used to characterize axle loads of heavy vehicles for use in highway pavement design and performance analysis. On the basis of actual axle loads of 12,638 vehicles measured on Singapore roads, the characteristics of variations of vehicle gross weights and axle loads were investigated. Vehicles were grouped into various classes according to their axle configurations. Weibull functions were used to model distributions of vehicle weights by vehicle class. Various models of axle load distributions were examined, and it was found that a second-order polynomial regression model offered the best estimates of axle loads. On the basis of the analysis of the axle load data, there is a need to conduct axle load studies to provide reliable estimates of traffic loading for effective management of the existing road network and the economical design of new pavements.

It is generally accepted that structural damage of road pavements caused by traffic is mainly a result of the axle loads imposed by trucks. This observation is clearly reflected in the equivalent traffic load computations used by pavement researchers and highway agencies in pavement design and pavement performance analysis (1-4). For example, in terms of the AASHTO equivalent single-axle load (ESAL) (5), one tractor-semitrailer combination is equivalent to about 2.0 ESALs, one bus to about 0.39 ESAL, and one passenger car to only 0.0004 ESAL.

In view of the importance of heavy vehicles in traffic load computation for pavement design and analysis, studies have been conducted by many highway agencies to quantify the axle load distributions of these vehicles (6-8). This paper is a report of a recent study in Singapore to characterize the axle loads of heavy vehicles for use in pavement design and performance analysis. Currently local highway agencies apply conversion factors obtained from design practice in the United Kingdom (9) and the United States (2) to compute equivalent standard axle loads. This study was undertaken with the aim of providing an improved analytical tool to quantify traffic loadings for pavement studies.

METHODOLOGY

A common practice in characterizing heavy vehicle loadings is to determine the ESAL (sometimes also known as the truck factor) for each vehicle type (2,9,10). Another method of characterization is by calculating axle load distributions. The first method provides a speedy means of computing the total design ESAL from traffic volume data. However, by not pre-

senting the axle load distributions used to derive the ESAL, the first method is not usable for more elaborate analysis of traffic loading effects on pavements. For example, the load equivalency factors used for computing the ESAL vary with the type and design of the pavement. In addition, there exist pavement distresses that cannot be explained by ESAL alone (4,11). Axle load data are also required for the design of concrete pavements and for the selection of appropriate design loads for highway bridges (12,13). Knowing axle load distributions also allows engineers to have a better understanding of the loading patterns produced by heavy vehicles and the relative damaging effect of various axles. This study therefore characterizes vehicle loading of various vehicle types by axle load distributions.

The main steps involved in the traffic loading characterization procedure adopted in this study are shown in Figure 1. Vehicle weight modeling and axle load modeling were the two key elements in the procedure. A vehicle weight distribution model was developed for each vehicle class, and an axle load distribution model was proposed for each axle of a vehicle class. Statistical techniques were employed to formulate both the vehicle weight and the axle load distribution models.

Weigh-in-motion equipment was used to measure axle weights as vehicles passed instrumented sites at normal traveling speeds. The equipment had piezoelectric weight sensors and a loop vehicle detector, enabling it to record axle weights as well as axle spacings for vehicle classification purposes. The accuracy of the weigh-in-motion measurements was checked against axle weight measured by static weighbridges at selected sites: these values were found to be within 15 percent of the static weights 95 percent of the time.

CLASSIFICATION OF VEHICLE TYPES

The data recorded by the weigh-in-motion equipment were classified into nine classes according to the number of axles, as shown in Table 1. This system was similar to the classification scheme adopted by the vehicle registration authority of Singapore. Because the loading impact of the first three classes is small compared with that of the heavier vehicles in the other classes, the present study focused on vehicles classified under Classes 4 through 9. The total number of these heavy vehicles recorded at 45 sites was 12,638. An initial attempt to formulate axle load models based on the above classification, however, did not produce satisfactory results for some of the classes. Further, subclassifications were found necessary.

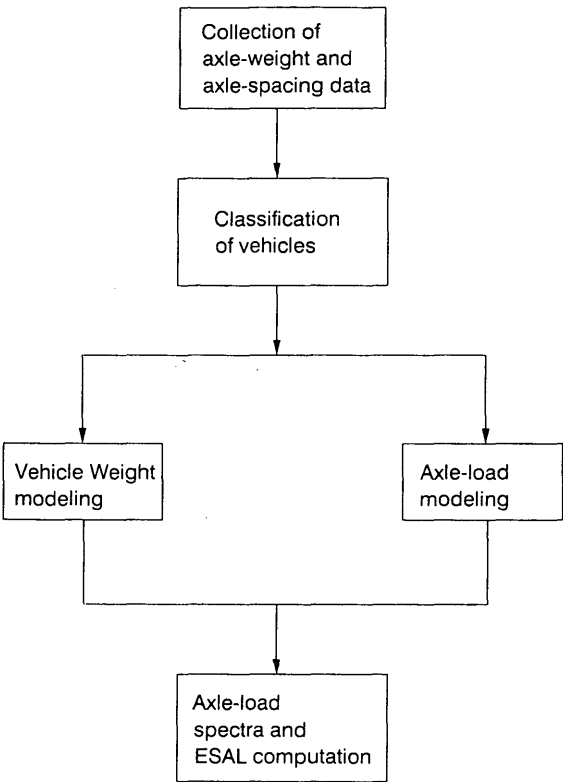


FIGURE 1 Traffic loading characterization procedure.

The classification system in Table 1 was made on the basis of the number of axles alone. On the basis of the reasoning that the spacings between axles and the relative positions of axles would also affect the distribution of loads among axles, a refinement to the classification system in Table 1 was made by considering the detailed pattern of axle arrangement. In addition, a distinction between single, tandem, and tridem axles was also made. Following the definition by AASHTO (5), a tandem axle consists of two axles that are positioned within a distance of 101.6 cm (40 in.) and 243.8 cm (96 in.), and a tridem axle consists of a group of three axles

that are positioned within the same distance. The revised classification system is presented in Table 2 in which the ranges of axle spacing between all adjacent axles are indicated. Classes 4, 8, and 9 were each broken into two subclasses.

The two subclasses of buses in Class 4 were the short wheelbase type, for which the spacing between the front and rear axles is less than 610 cm (20 ft), and the long wheelbase type for which the axle spacing is greater than 610 cm (20 ft). The two subclasses of Class 8 vehicles were also differentiated on the basis of wheelbase length. Class 8A vehicles were used for carrying 20-ft (6.1-m) containers, and Class 8B vehicles were used for carrying 40-ft (12.2-m) containers. The two subclasses of Class 9 represented vehicles with different axle configurations. Subclass 9A had two single front axles and a rear tridem axle, whereas Subclass 9B had a single front axle followed by two rear tandem axles.

DEVELOPMENT OF VEHICLE WEIGHT DISTRIBUTION MODELS

The gross operating weight of a heavy vehicle, whether it is a bus or a truck, is a function of the number of passengers and the amount and type of goods it carries. The loads carried, which may be considered to be randomly distributed, may vary from a minimum value equal to or close to zero to the full capacity of the vehicle. However, because of the constantly present dead weight of the vehicle, the vehicle weight distribution tends to be skewed to the higher load range (i.e., having a longer tail on the heavy load end) as illustrated in Figure 2a. Another form of vehicle weight distribution with two peaks, as shown in Figure 2b, was also found in the recorded data. The Weibull distribution function (14) has the ability to describe the trends of vehicle weight variation shown in Figure 2, and was thus used in the present study to model the weight distribution in each vehicle class. The density distribution of the Weibull function is given by










f(W) = ab(W - c)^{b-1}e^{-a(W-c)} (1)

where a, b, and c are constants that define the shape of the

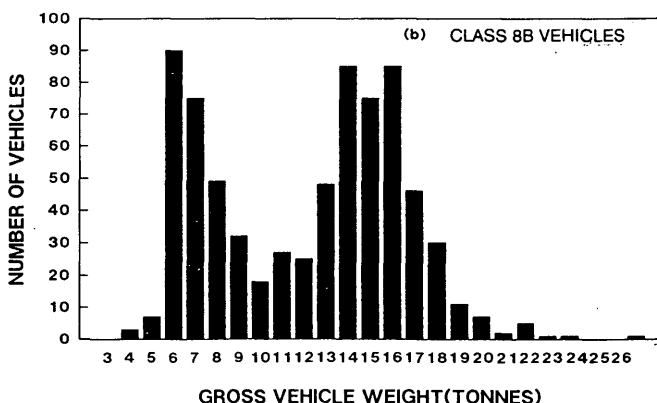
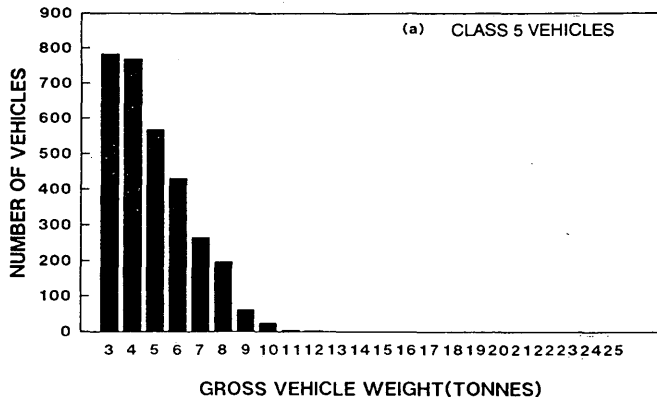
TABLE 1 Vehicle Classification by Number of Axles

VEHICLE CLASS	VEHICLE TYPE	NUMBER OF AXLES
1	motorcycles	-
2	passenger cars	2
3	pickups, vans	2
4	buses	2
5	single unit trucks	2
6	single unit trucks	3
7	tractor-trailer combination trucks	3
8	tractor-trailer combination trucks	4
9	tractor-trailer combination trucks	5 or more

TABLE 2 Vehicle Classification for Present Study

VEHICLE CLASS	VEHICLE TYPE	AXLE SPACING(m)	VEHICLE CONFIGURATION
4A	2 AXLE BUSES (long wheelbase)	5.5-6.1	
4B	2 AXLE BUSES (short wheelbase)	6.1-7.0	
5	2 AXLE TRUCKS SINGLE UNIT	4.0-6.0	
6	3 AXLE TRUCKS SINGLE UNIT	3.0-5.0 ⁽¹⁾	
7	3 AXLE TRUCKS TRACTOR-TRAILER COMBINATION	6.0-7.0 ⁽²⁾	
8A	4 AXLE TRUCKS TRACTOR-TRAILER COMBINATION	3.0-6.0 ⁽³⁾	
8B	4 AXLE TRUCKS TRACTOR-TRAILER COMBINATION	8.5-10.0 ⁽³⁾	
9A	5 AXLE TRUCKS TRACTOR-TRAILER COMBINATION	7.5-11.0 ⁽⁴⁾	
9B	5 AXLE TRUCKS TRACTOR-TRAILER COMBINATION	7.5-9.0 ⁽⁴⁾	

Note: (1) Spacing between front single axle and rear tandem axle
 (2) Spacing between middle single axle and rear single axle
 (3) Spacing between middle single axle and rear tandem axle
 (4) Spacing between middle single (or tandem) axle and rear tridem (or tandem) axle

**FIGURE 2 Examples of vehicle weight distribution.**

distribution and W is the gross vehicle weight of individual vehicles. The corresponding Weibull cumulative function is

$$F(W) = 1 - \exp[-a(W - c)^b] \quad (2)$$

Vehicle Weight Distribution Models

A vehicle weight distribution model for each vehicle class was developed for this study. Together with axle load distribution models, the ESAL contribution from various vehicle classes could be calculated. For each vehicle class, the Weibull cumulative function of Equation 2 was used for the purpose of model calibration. The Weibull constants a , b , and c were obtained by the following steps: (a) extract vehicle weight data for all vehicles in the vehicle class of interest from field survey records; (b) arrange vehicle weight data in increasing order; (c) construct cumulative vehicle weight distribution from Item b; and (d) determine constants a , b , and c by fitting Equation 2 to the cumulative distribution of Item c using the method of least squares.

Table 3 gives all the vehicle weight distribution models derived for the various vehicle classes. For distributions with two peaks, it was necessary to fit the data using two Weibull functions. This happened for vehicle Classes 6, 7, 8A, and 8B. The goodness of fit of the models was examined by the Kolmogorov-Smirnov test (14). As shown in the last column of Table 3, all tests accepted the Weibull distribution at the 99 percent confidence level. Figure 3 shows examples of the cumulative distribution plots of actual vehicle weight data and predicted weight values.

DEVELOPMENT OF AXLE LOAD MODELS

Two methods for specifying the axle load distribution of a vehicle were examined in the study. One expresses axle load distribution in terms of percentages of gross vehicle weight; the other estimates the individual axle loads directly. Both methods of representing axle load distribution are examined in this section.

Variables in Axle Load Models

Statistical regression techniques were adopted for developing the axle load prediction models. The analyses involved identification of parameters that affect the load transmitted to each axle and the determination of statistically significant mathematical forms that could predict axle load distribution satisfactorily.

Assuming the body of a vehicle to be rigid, the parameters that affect the magnitude of load carried by each axle of the vehicle include the following: (a) axle configuration of the vehicle, including the number of axles, type of axle, and arrangement of the axles; (b) dead weight of the vehicle and its center of gravity; and (c) the weight of goods and passengers carried by the vehicle and their distributions along the length of the vehicle. Theoretically it might be possible to develop an overall axle load model having the three forms of parameters identified above as the independent variables. This

TABLE 3 Vehicle Weight Distribution Models

VEHICLE CLASS	WEIBULL CUMULATIVE DISTRIBUTION MODEL	WEIBULL DENSITY DISTRIBUTION MODEL
4A	$1 - \text{EXP}(-0.2481 \cdot (W-4)^{2.4819})$	$0.6158 \cdot (W-4)^{1.4819} \cdot \text{EXP}(-0.2481 \cdot (W-4)^{2.4819})$
4B	$1 - \text{EXP}(-0.0610 \cdot (W-3.3)^{3.0962})$	$0.1889 \cdot (W-3.3)^{2.0962} \cdot \text{EXP}(-0.0610 \cdot (W-3.3)^{3.0962})$
5	$1 - \text{EXP}(-0.1574 \cdot (W-1.5)^{1.5971})$	$0.2514 \cdot (W-1.5)^{0.5971} \cdot \text{EXP}(-0.1574 \cdot (W-1.5)^{1.5971})$
6	$0.1413(1 - \text{EXP}(-0.0774 \cdot (W-3)^{3.8214})) + 0.8587(1 - \text{EXP}(-4.6E-5 \cdot (W-3)^{5.0824}))$	$0.1413(0.2958 \cdot (W-3)^{2.8214} \cdot \text{EXP}(-0.0774 \cdot (W-3)^{3.8214})) + 0.8587(2.338E-4 \cdot (W-3)^{4.0824} \cdot \text{EXP}(-4.6E-5 \cdot (W-3)^{5.0824}))$
7	$0.3891(1 - \text{EXP}(-0.1132 \cdot (W-3)^{2.8656})) + 0.6181(1 - \text{EXP}(-6.3E-5 \cdot (W-3)^{4.5790}))$	$0.3819(0.6244 \cdot (W-3)^{1.8656} \cdot \text{EXP}(-0.1132 \cdot (W-3)^{2.8656})) + 0.6181(5.436E-6 \cdot (W-3)^{3.5790} \cdot \text{EXP}(-6.3E-5 \cdot (W-3)^{4.5790}))$
8A	$0.5227(1 - \text{EXP}(-0.0363 \cdot (W-3)^{2.3399})) + 0.4773(1 - \text{EXP}(-9.8E-8 \cdot (W-3)^{6.7198}))$	$0.5227(0.0849 \cdot (W-3)^{1.3399} \cdot \text{EXP}(-0.0363 \cdot (W-3)^{2.3399})) + 0.4773(6.585E-7 \cdot (W-3)^{5.7198} \cdot \text{EXP}(-9.8E-8 \cdot (W-3)^{6.7198}))$
8B	$0.3379(1 - \text{EXP}(-0.0103 \cdot (W-3)^{3.4652})) + 0.6621(1 - \text{EXP}(-9.8E-7 \cdot (W-3)^{5.5470}))$	$0.3379(0.0357 \cdot (W-3)^{2.4652} \cdot \text{EXP}(-0.0103 \cdot (W-3)^{3.4652})) + 0.6621(5.436E-6 \cdot (W-3)^{4.5470} \cdot \text{EXP}(-9.8E-7 \cdot (W-3)^{5.5470}))$
9A	$1 - \text{EXP}(-0.0487 \cdot (W-4.5)^{1.4268})$	$0.0695 \cdot (W-4.5)^{0.4268} \cdot \text{EXP}(-0.0487 \cdot (W-4.5)^{1.4268})$
9B	$1 - \text{EXP}(-0.0099 \cdot (W-4.5)^{2.4489})$	$0.0242 \cdot (W-4.5)^{1.4489} \cdot \text{EXP}(-0.0099 \cdot (W-4.5)^{2.4489})$

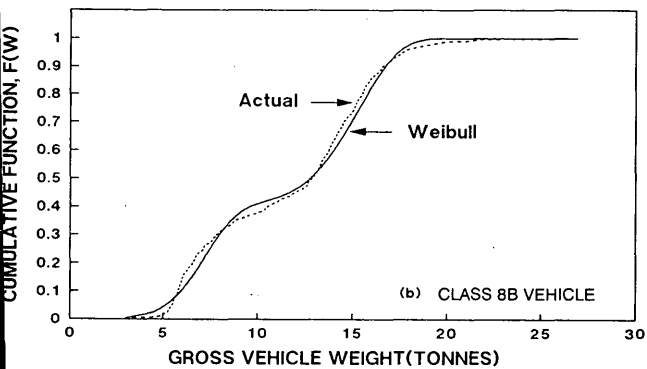
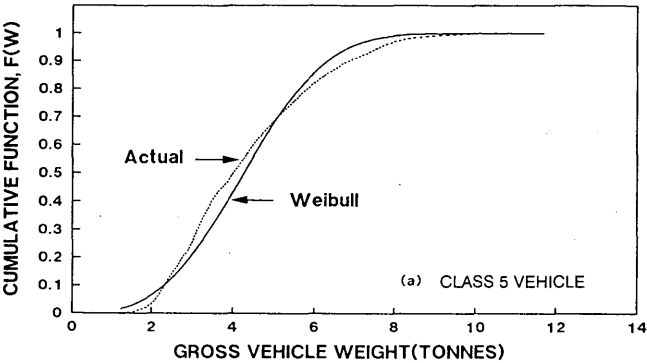


FIGURE 3 Examples of cumulative distribution of vehicle weights.

is, however, impractical for pavement studies because it would not be easy to obtain all the information required to use the model. This problem can be overcome by choosing to develop separate models for individual vehicle classes, such as those in Table 2, and using the total vehicle weight as the independent variable.

After a preliminary analysis that examined various forms of mathematical models, two forms of models were found to produce satisfactory results. One was the polynomial regression model; the other was a nonlinear model that expressed the magnitude of an axle load as a function of a power term of gross vehicle weight.

Polynomial Regression Models

The polynomial regression models take the following form:

L-model:

$$L = a_0 + a_1W + a_2W^2 + \dots + a_nW^n + \epsilon_a \tag{3}$$

P-model:

$$P = b_0 + b_1W + b_2W^2 + \dots + b_nW^n + \epsilon_b \tag{4}$$

where *L* is the magnitude of an axle load, *P* is the percentage share of the axle load expressed as a percentage of gross vehicle weight *W*, subscripted coefficients *a* and *b* are regression constants, and ϵ_a and ϵ_b are error terms. Statistical analyses showed that all the *L*-models, but not all the *P*-models, were statistically significant at the 99 percent confidence level. Figure 4a shows that the coefficients of multiple determination

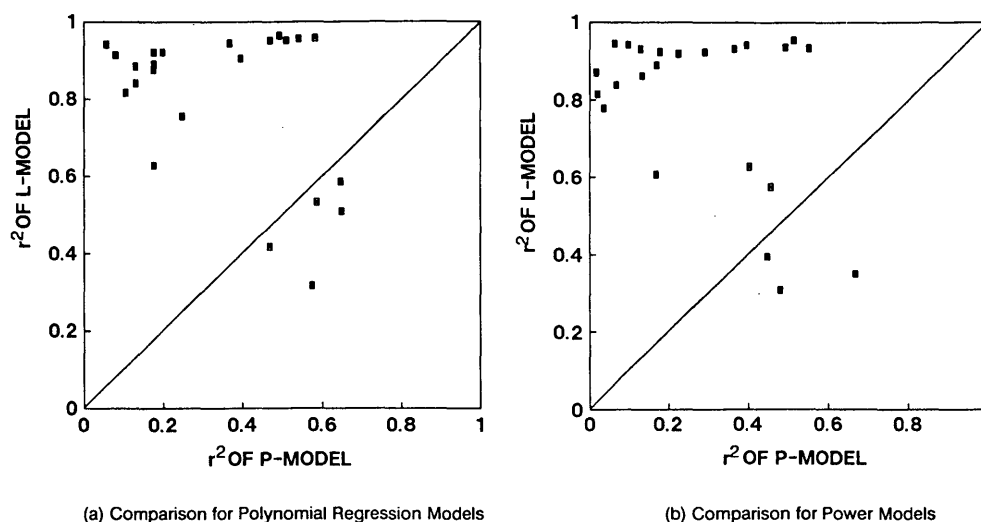


FIGURE 4 Comparison of *L*- and *P*-models for axle loads.

(r^2) of the *L*-models were much higher than the r^2 of the corresponding *P*-models. It is apparent that the *L*-models were superior to the *P*-models in their ability to estimate axle loads.

Table 4 presents the *L*-models with those terms that are statistically significant at the 99 percent confidence level. In

the case of Classes 4A and 4B, instead of identifying their two axles as front and rear axles, it was found that better axle load models could be developed by differentiating the two axles as heavy (HMAX) and light (HMIN) axles. This procedure was effective in accounting for the two different bus designs commonly found in Singapore—some with engines

TABLE 4 Polynomial Regression Models for Axle Loads

VEHICLE CLASS	POLYNOMIAL FUNCTION	r^2	PROB. > F
4A	HMAX = $0.3851 + 0.6284*W - 0.0049*W^2$	0.9216	0.0001
	HMIN = $-0.3851 + 0.3716*W + 0.0049*W^2$	0.8904	0.0001
4B	HMAX = $0.9208 + 0.2037*W + 0.0295*W^2$	0.8850	0.0001
	HMIN = $-0.9208 + 0.7963*W - 0.0294*W^2$	0.8410	0.0001
5	X1 = $0.7262 + 0.1707*W + 0.0159*W^2$	0.6293	0.0001
	X2 = $-0.7264 + 0.8292*W - 0.0159*W^2$	0.8759	0.0001
6	X1 = $1.9279 - 0.0053*W + 0.0090*W^2$	0.4177	0.0001
	X23 = $-1.9280 + 1.0053*W - 0.0090*W^2$	0.9514	0.0001
7	X1 = $2.1481 - 0.1918*W + 0.0157*W^2$	0.5852	0.0001
	X2 = $-0.9945 + 0.6510*W - 0.0135*W^2$	0.9419	0.0001
	X3 = $-1.1536 + 0.5408*W - 0.0021*W^2$	0.9572	0.0001
8A	X1 = $0.6488 + 0.2783*W - 0.0084*W^2$	0.5092	0.0001
	X2 = $-0.0496 + 0.2845*W + 0.0015*W^2$	0.9271	0.0001
	X34 = $-0.5991 + 0.4373*W + 0.0069*W^2$	0.9635	0.0001
8B	X1 = $1.2051 + 0.1375*W - 0.0013*W^2$	0.5326	0.0001
	X2 = $-0.3525 + 0.3623*W - 0.0023*W^2$	0.9139	0.0001
	X34 = $-0.8526 + 0.5002*W + 0.0036*W^2$	0.9513	0.0001
9A	X1 = $0.9816 + 0.1870*W - 0.0048*W^2$	0.3166	0.0001
	X2 = $0.0450 + 0.2852*W - 0.0028*W^2$	0.8169	0.0001
	X345 = $-1.0267 + 0.5277*W + 0.0076*W^2$	0.9556	0.0001
9B	X1 = $-0.3808 + 0.3715*W - 0.0081*W^2$	0.7555	0.0001
	X23 = $-0.3176 + 0.3246*W + 0.0054*W^2$	0.9444	0.0001
	X45 = $0.6984 + 0.3040*W + 0.0027*W^2$	0.9047	0.0001

Note:

(1) *W* is gross vehicle weight in tonnes.

(2) HMAX refers to the load of heavy axle, and HMIN the lighter axle in tonnes.

(3) X_i = load on the *i*th axle from the front in tonnes.

(4) X_{ij} = load on the tandem axle comprising the *i*th and *j*th axles from the front in tonnes.

(5) X_{ijk} = load on the tridem axle comprising the *i*th, *j*th and *k*th axles from the front in tonnes.

located in the front and others with engines located in the rear of the vehicle.

Table 4 also shows that the r^2 of the models for front axles was significantly lower than the r^2 of the models for other axles, that is, while the load on most front axles was not highly correlated to the gross vehicle weight. To determine the axle load distribution of a vehicle, it is therefore reasonable to compute first the estimated loads of other axles using the A -models (see the following section) and then subtract these loads from the gross vehicle weight to obtain an estimate of the front axle load.

Power Models

Power models express axle load A or percentage axle load P in terms of gross vehicle weight raised to a power as follows:

A -model:

$$A = c(W^d) \quad (5)$$

P -model:

$$P = e(W^f) \quad (6)$$

where c , d , e , and f are model coefficients. The model coefficients were determined using the linear regression technique

by taking the logarithmic transformation of Equations 5 and 6.

As in the case of polynomial regression models, Figure 4b shows that L -models were superior to P -models. Table 5 presents the L -models obtained. The results also confirmed the earlier finding concerning the relationship between gross vehicle weight and the load on the front axle.

Comparison of Axle Load Models

The relative accuracy of the two forms of axle load models derived above, namely, the polynomial L -models and the power L -models, was compared using the actual field survey data collected in this study. The comparison was carried out for each vehicle class as follows: (a) from the gross weight of a vehicle, the load on each axle of the vehicle was computed using the two models respectively; (b) Step a was repeated for all the vehicles in the survey records; (c) for the results obtained from each model, the coefficient of multiple determination and the root-mean-square difference between the actual and predicted axle loads were computed.

The results of the comparison, as shown in Table 6, indicate that both models gave predicted axle loads that were highly correlated with the actual loads. Judging from the relative values of r^2 and root-mean-square differences, the polynomial L -models appeared to be marginally better than the power L -models.

TABLE 5 Power Models for Axle Loads

VEHICLE CLASS	POWER MODELS	r^2	PROB. > F-STATISTIC
4A	HMIN = $0.2416 \cdot W^{1.1787}$ HMAX = $0.7883 \cdot W^{0.9050}$	0.8671 0.9310	0.0001 0.0001
4B	HMIN = $0.4097 \cdot W^{1.0706}$ HMAX = $0.5809 \cdot W^{0.9526}$	0.8142 0.8700	0.0001 0.0001
5	X1 = $0.6098 \cdot W^{0.7330}$ X2 = $0.4264 \cdot W^{1.1912}$	0.6066 0.8890	0.0001 0.0001
6	X1 = $0.9361 \cdot W^{0.4726}$ X23 = $0.3655 \cdot W^{1.2913}$	0.3945 0.9539	0.0001 0.0001
7	X1 = $0.8752 \cdot W^{0.3411}$ X2 = $0.3458 \cdot W^{1.0666}$ X3 = $0.1505 \cdot W^{1.4160}$	0.3494 0.9457 0.9338	0.0001 0.0001 0.0001
8A	X1 = $0.6842 \cdot W^{0.5600}$ X2 = $0.2386 \cdot W^{1.0901}$ X34 = $0.2417 \cdot W^{1.2574}$	0.5746 0.9411 0.9320	0.0001 0.0001 0.0001
8B	X1 = $0.5856 \cdot W^{0.6125}$ X2 = $0.2033 \cdot W^{1.1555}$ X34 = $0.2826 \cdot W^{1.1926}$	0.6272 0.9237 0.9181	0.0001 0.0001 0.0001
9A	X1 = $0.8745 \cdot W^{0.4103}$ X2 = $0.3260 \cdot W^{0.8936}$ X345 = $0.2196 \cdot W^{1.3487}$	0.3079 0.8385 0.9354	0.0001 0.0001 0.0001
9B	X1 = $0.1887 \cdot W^{1.1119}$ X23 = $0.1926 \cdot W^{1.2539}$ X45 = $0.5784 \cdot W^{0.8434}$	0.7785 0.9410 0.9228	0.0001 0.0001 0.0001

Note: See Table 4 for definitions of symbols.

TABLE 6 Comparison of Axle Load Models

CLASS	AXLE * LOAD (Tonnes)	POLYNOMIAL L-MODEL		POWER L-MODEL	
		r ²	root-mean-square of difference (tonnes)	r ²	root-mean-square of difference (tonnes)
4A	HMIN	0.9436	0.1707	0.9442	0.1761
	HMAX	0.9600	0.1707	0.9602	0.1761
4B	HMIN	0.9171	0.1752	0.9088	0.1866
	HMAX	0.9407	0.1752	0.9348	0.1866
5	X1	0.7933	0.4400	0.7802	0.4533
	X2	0.9359	0.4401	0.9324	0.4533
6	X1	0.6216	0.4770	0.4621	0.5421
	X23	0.9740	0.4770	0.9679	0.5421
7	X1	0.7650	0.3191	0.5564	0.5350
	X2	0.9705	0.3345	0.9579	0.4041
	X3	0.9784	0.3486	0.9723	0.4048
8A	X1	0.7136	0.4429	0.7218	0.4592
	X2	0.9629	0.3481	0.9629	0.3486
	X34	0.9816	0.4409	0.9820	0.4592
8B	X1	0.7284	0.4686	0.7369	0.5025
	X2	0.9553	0.4459	0.9536	0.4698
	X34	0.9749	0.6110	0.9760	0.6568
9A	X1	0.5329	0.4993	0.5635	0.5009
	X2	0.9021	0.4780	0.9033	0.4776
	X345	0.9763	0.7272	0.9778	0.7082
9B	X1	0.8575	0.3288	0.8636	0.3283
	X23	0.9705	0.2914	0.9721	0.2841
	X45	0.9507	0.3154	0.9493	0.3236

* See Table 4 for definitions of symbols

ESAL COMPUTATION USING PROPOSED MODELS

A verification test of the applicability of the approach developed in this study was carried out by comparing the ESAL values computed using the derived models with the ESAL values calculated on the basis of actual axle data, and with ESAL values calculated using the following three other methods:

1. *U.K. Road Note 29 conversion factor method (9)*: In this method the total ESAL is obtained by multiplying the volume of commercial vehicles (U.K. term for heavy vehicles) by a constant ESAL conversion factor. For public roads, the conversion factor given is 0.45.

2. *Asphalt Institute truck factor method (2)*: This method is similar to the U.K. Road Note 29 method in that truck factors are multiplied by truck volumes to arrive at the design ESAL. The main difference is that this method provides truck factors for various vehicle classes as shown in Table 7.

3. *The constant-percentage axle load method (15)*: This method assumes constant-percentage shares among the various axles for a given vehicle type. In the present comparative study, the constant-percentage shares were taken as the mean percentage values computed from axle load data collected. Table 8 gives the mean axle load percentage shares for various vehicle classes.

Comparisons of all the above computational methods were made for the overall ESAL, including contributions from all heavy vehicle classes, as well as for ESALs of individual vehicle classes. The values of computed ESAL are given in Table 9 and plotted in Figure 5. The following observations can be made:

1. The Asphalt Institute method and the U.K. Road Note 29 method both are volume-based methods that compute ESAL directly by multiplying heavy vehicle volume by certain factors, producing highly conservative ESAL values for Singa-

TABLE 7 ESAL Computation: Asphalt Institute Method

Single-unit trucks			Tractor semi-trailers		
2-axle 4-tire	2-axle 6-tire	3-axle or more	3-axle	4-axle	5-axle or more
0.01-0.07	0.15-0.32	0.29-1.59	0.33-0.78	0.43-1.32	0.63-1.53

Note: Equivalent axle load = $\sum (\text{Truck traffic volume} \times \text{Truck factor})$

TABLE 8 ESAL Computation: Constant-Percentage Axle Load Method

Vehicle Class	Axle Load as a Percentage of Gross Vehicle Weight
4A	HMAX = 0.67 W ; HMIN = 0.33 W
4B	HMAX = 0.54 W ; HMIN = 0.46 W
5	X1 = 0.44 W ; X2 = 0.56 W
6	X1 = 0.31 W ; X23 = 0.69 W
7	X1 = 0.24 W ; X2 = 0.40 W ; X3 = 0.36 W
8A	X1 = 0.28 W ; X2 = 0.29 W ; X34 = 0.43 W
8B	X1 = 0.25 W ; X2 = 0.30 W ; X34 = 0.45 W
9A	X1 = 0.23 W ; X2 = 0.26 W ; X345 = 0.51 W
9B	X1 = 0.24 W ; X23 = 0.35 W ; X34 = 0.41 W

Note: (i) ESAL factor is obtained from AASHTO table [5] after axle load is computed.
(ii) Definitions of all symbols are given in Table 4.

pore traffic. The total ESAL values obtained from these two methods were each more than three times the actual values.

2. The three methods that made use of axle load distributions, namely, the constant-percentage method, the polynomial regression model, and the power model, all yielded ESAL estimates of the same order of magnitude as the actual value. In order of decreasing accuracy in their predictions, the polynomial method produced the best results, followed by the power model, and the constant-percentage method.

3. The actual ESAL for buses (Classes 4A and 4B) and two-axle, single-unit trucks (Class 5) fell within the range given by the Asphalt Institute method. For all other classes of heavy vehicles, the actual ESAL values were much lower than the lower limits of the Asphalt Institute method. The

big differences in ESAL values in Classes 6 and 9 could possibly be explained by the fact that the Asphalt Institute method classifies these two classes under three axles or more and five axles or more, respectively, thereby tending to overestimate the ESAL by including the effects of other multiple-axle vehicles not included in Classes 6 and 9. In general, the large discrepancy between the ESAL loading on Singapore roads and those predicted by the U.S. and the U.K. methods can be attributed to the differences in the operational characteristics of the freight industry. Being a small island state, Singapore does not have large volumes of long-haul truck fleets. The trip distances of freight movements are very short compared with those in the United States and the United Kingdom.

TABLE 9 Values of ESAL Computed by Various Methods

CLASS	NUMBER OF VEHICLES	ACTUAL ESAL	ESAL BY AXLE LOAD DISTRIBUTION METHOD			ESAL BY VOLUME BASED METHOD		
			CONSTANT PERCENTAGE METHOD	POLYNOMIAL REGRESSION L-MODEL	POWER L-MODEL	ASPHALT INSTITUTE METHOD		U.K. ROAD NOTE 29 METHOD
						LOWER LIMIT	UPPER LIMIT	
4A	1418	79.88	89.23	72.35	73.58	14.18	99.26	-
4B	852	20.51	19.81	18.46	18.52	8.52	59.64	-
5	3103	87.26	64.74	59.86	59.56	31.03	217.21	-
6	4040	217.01	191.26	231.24	224.13	1171.6	6423.6	-
7	870	107.71	80.27	101.43	124.78	287.1	678.6	-
8A	1049	59.37	55.73	69.06	68.25	451.07	1384.7	-
8B	747	78.46	70.25	121.01	146.89	321.21	986.04	-
9A	323	38.39	29.29	31.997	32.37	203.49	494.2	-
9B	236	4.68	4.62	5.345	5.544	148.68	361	-
TOTAL	12638	693.27	605.2	710.752	753.62	2636.88	10704.3	5687

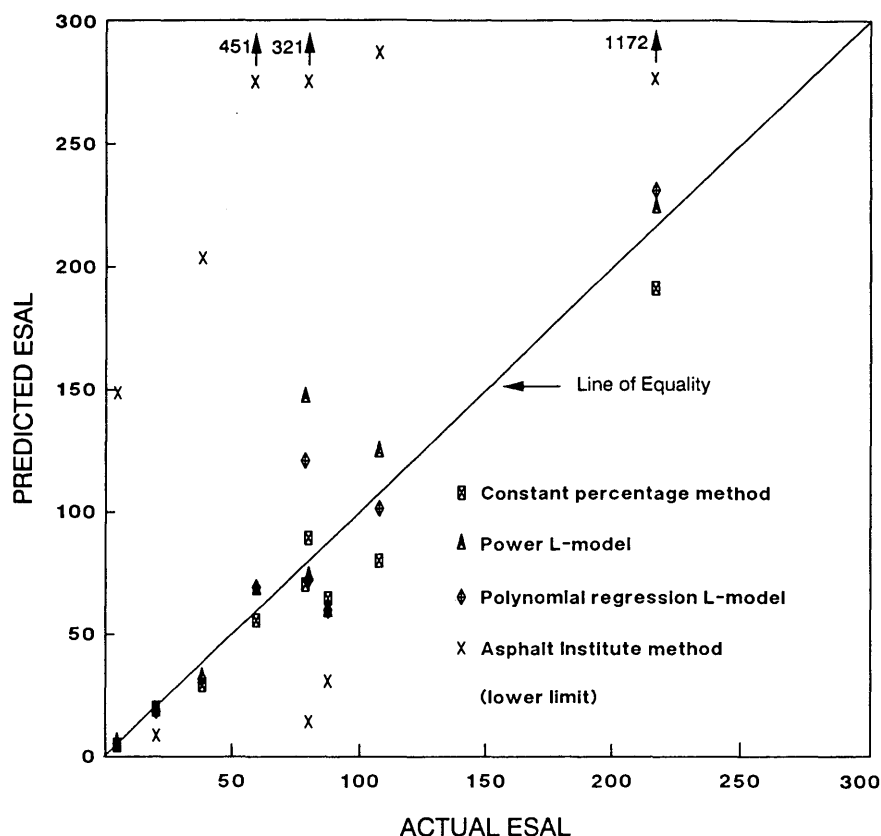


FIGURE 5 Comparison of ESAL values computed by various methods.

These results clearly demonstrate the need to conduct axle load studies to evaluate traffic loading in countries or regions not covered by established pavement design manuals such as the Asphalt Institute manual or the U.K. Road Note. This is because the characteristics of freight transportation are likely to vary from country to country. Overestimation of traffic loading leads to wasteful design in terms of layer thickness for new pavements and to underestimation of remaining pavement life in road network management systems.

CONCLUSIONS

On the basis of field data on axle loads of heavy vehicles, mathematical models were derived for vehicle weight and axle load distributions for the major vehicle classes in Singapore. It was shown that the vehicle weight distributions of individual vehicle classes could be described closely by Weibull distribution functions. In the case of axle load distributions, either second-order polynomial regression models or power models could be used. Second-order polynomial regression models were found to give the closest estimation of the actual ESAL of the measured axle loads. The use of general-purpose, volume-based procedures developed for U.S. or U.K. traffic loading conditions resulted in grossly overestimated ESAL values for Singapore.

The approach adopted in this study can be easily applied elsewhere to characterize vehicle weight and axle load distri-

butions for use in pavement or bridge design, and in traffic loading estimation for pavement performance monitoring. The coefficients in the vehicle weight and axle load models can be calibrated to suit local traffic conditions.

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Publication of this paper sponsored by Committee on Flexible Pavement Design.