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Growth of truck traffic volume for mechanistic-empirical pavement design

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Pavement design is moving towards the mechanistic-empirical approach, which requires very detailed truck traffic information, including truck traffic volume. This paper focuses on analysis of truck traffic volume growth, specifically in three areas: characteristics of the growth pattern, sensitivity of pavement responses to the growth rate, and prediction of the growth rate based on road way characteristics and socio-economic data. The truck traffic data collected by weigh-in-motion (WIM) stations on California highways were used in the analysis. Results showed that both linear and compound growth models well fit the truck traffic growth trends. Growth rates estimated from less than six years data may have large variation, which can lead to significant errors in pavement response prediction. Various truck classes have distinct growth patterns and are affected differently by roadway and socio-economic characteristics.

Keywords: truck traffic; mechanistic-empirical design; weigh-in-motion; growth rate; sensitivity analysis

1. Introduction

1.1 Background

Truck traffic is the most important factor leading to pavement deterioration and damage. Traditionally, truck traffic has been aggregated into equivalent repetitions of a standard axle load (ESAL) for pavement design. Recent developments in pavement distress models, high-speed personal computers and sophisticated test equipment have advanced pavement design to the mechanistic-empirical procedures.

The newly developed NCHRP 1-37A Mechanistic-Empirical Pavement Design Guide (ME-PDG) requires very detailed truck traffic information, including the hourly and monthly variation and annual growth pattern of traffic volume, axle load spectra of different axle types for different truck classes, tyre pressure, axle spacing, traffic wander and other general traffic data. With such large amount of information, the wheel load at a specific pavement location at any time can be simulated reasonably well, so that the incremental damage in pavements due to the combined effects of different traffic and climate can be computed sequentially and summed to give the accumulated damage over the design life of a pavement. Traffic information of such details, however, is often unavailable to most highway agencies. Correspondingly, ME-PDG uses three levels of traffic inputs, with Level 1 being the most accurate (project specific) and Level 3 being regional or state defaults. Recently, considerable effort has been spent to characterise and model axle load spectra and to develop regional defaults (Prozzi and Hong 2005, Lu and Harvey 2006), but less work has been done to analyse the growth pattern of truck traffic, particularly for different vehicle classes, and to develop guidelines for determining the default inputs for locations where historical traffic data are unavailable or insufficient. In a follow-up NCHRP research 1-39, which was intended to be used as a direct input for NCHRP 1-37A traffic data, a simple procedure was proposed to forecast the rates of change in traffic volumes (Cambridge *et al*. 2005). This procedure aggregates trucks into two groups (single-unit trucks and combinations), uses truck traffic data from similar sites for regression analysis, and judgementally adjusts the results based on macroeconomic and site-specific factors. This procedure seems to be reasonable for pavement sections without historical traffic data. Many operational questions, however, were not well explored or explained in that research, such as whether different truck classes have similar growth rates, how to determine the similarity among project sites and how to adjust the results.

California Department of Transportation (Caltrans) has been installing weigh-in-motion (WIM) stations and collecting truck traffic data on the state highways since 1987. It has maintained a very detailed database of historical truck traffic information for over 80 highway sites across the state. Examination of these microscopic-level (site-specific) data can provide insights into the truck traffic flow pattern and help answer the aforementioned questions.

Accurate estimation of truck traffic flow pattern and growth rate is not only crucial for design of new pavements, but also valuable for ME-PDG users to estimate absent traffic history for predicting the performance of existing pavement sections. Moreover, it is also important

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for many other research and operation needs, such as air quality modelling, highway safety control, transportation planning, and other highway infrastructure designs.

1.2 Objectives

This paper focuses on analysis of the truck traffic growth pattern in California, sensitivity of pavement responses to errors in growth rate estimation, and potential contributing predictors that can be used to predict truck traffic growth rates, using the truck traffic data collected by WIM stations on California highways. Results from this study are intended to provide better understanding of truck traffic growth patterns for users of the mechanistic-empirical pavement design procedures.

2. Data source

The WIM data collected during the period from 1991 to 2003 were obtained from Caltrans Office of Truck Services for all the 98 WIM stations installed before 2001. Caltrans typically selects one-week data from each month for each station and performs a check on such data for proper operation of the WIM system, calibration drift, and proper coding of vehicle records containing questionable data elements. All the data that had passed the routine check were used for analysis.

Introduction of California WIM system can be found in the literature (Lu *et al.* 2002). One thing to note is that Caltrans implemented the FHWA vehicle classification system with slight modifications, which added two more truck classes: Class 14 (five-axle truck trailer) and Class 15 (irregular trucks and/or unclassified trucks due to system error). Both truck classes account for small percentages of the total traffic. If deemed necessary to match the FHWAs 13 Class system, the Class 14s could be reclassified as Class 9s and the Class 15s could be either dropped or moved into other classifications based upon axle counts and weights.

3. Characterisation of truck traffic flow patterns

3.1 Estimation of average annual daily truck traffic (AADTT)

Human economic activities, where truck traffic originates, have distinct cycles with different periods such as day, week and year. Correspondingly, truck traffic volumes would also show strong cyclic variations. This temporal variation has been confirmed by many observations and studies (Lu and Harvey 2002, Prozzi and Hong 2006). As an example, Figure 1 shows the daily truck traffic volume observed from 1991 to 2003 on interstate Route 5 in San Joaquin County. It is obvious that the truck traffic volume on Sundays is significantly lower than that on Saturdays, which itself is significantly lower than that on weekdays. Seasonal variation is also clear in this figure, with high volume in the summer and low volume in the winter. In addition, there are a few weekdays showing low volumes similar to those on Sundays. Backtracking revealed that they are state holidays. Knowing the temporal variation is important for correctly estimating the AADTT, which is the key traffic volume variable for pavement design.

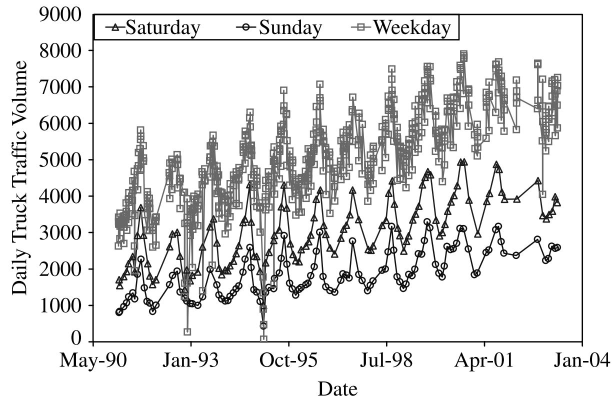

Figure 1. Daily truck traffic volume at WIM station 001 (Highway 5 Northbound, San Joaquin).

Fundamentally, AADTT is calculated by the following equation:

$$AADTT_y = \frac{1}{N_y}\sum_{i=1}^{N_y} DTT_i, \qquad (1)$$

where $AADTT_y$ is the AADTT in Year y, N_y is the number of days in Year y equal to 365 or 366, DTT_i is the truck traffic in Day i. It is rare to have the complete daily traffic volumes in a year, so $AADTT_y$ has to be estimated from sampling. Because DTT_i follows different distributions on weekdays, weekends, holidays and in different months, the estimator of $AADTT_y$ from simple random sampling will have large variance, and has the jeopardy of being biased if the sampling is not completely random, which is often the case due to small sample sizes. A reasonable way of estimation is so-called stratified sampling, in which the population is partitioned into homogeneous groups and a sample is selected within each group. The days in a year can be grouped into weekdays, Saturdays, Sundays, and holidays in each month, and $AADTT_y$ can be estimated by the following equation:

$$AA\hat{D}TT_y = \frac{1}{N_y}\sum_{j=1}^{4}\sum_{m=1}^{12}\left(n_{mj}MADTT_{mj}\right), \qquad (2)$$

where $AA\hat{D}TT_y$ is the estimator of $AADTT_y$, j is an index for group (e.g. $j = 1$ represents weekdays, $j = 2$ represents Saturdays), m is an index for month, n_{mj} is the number of days in jth group in mth month, and $MADTT_{mj}$ is the average daily truck traffic volume in jth group in mth month. $MADTT_{mj}$ can be estimated by simple random sampling in each group. This sampling scheme is similar to the procedure recommended by the 2001 traffic-monitoring guide (TMG), except that TMG does not sample the traffic volume on holidays (FHWA 2001). Equation (2) fails when data are absent in any of the $4 \times 12 = 48$ groups. Fortunately, the monthly variation pattern of traffic volume is generally stable across years (Prozzi and Hong 2006). Knowing the monthly adjustment factors and one or more monthly average daily traffic volumes for each group, the estimation of $AADTT_y$ can be further simplified to the following equation:

$$A\hat{ADTT}_y = \frac{1}{N_y}\sum_{j=1}^{4}\left(n_j \frac{\sum_m MADTT_{mj}}{\sum_m MAF_{mj}}\right), \tag{3}$$

where n_j is the number of days in jth group in one year, MAF_{mj} is the monthly adjustment factor for jth group in mth month. MAF_{mj} can be computed from all historical data in years when 12-month data are available, by the following equation:

$$MAF_{mj} = \frac{\sum_y MADTT_{mjy}}{\sum_y AADTT_y}, \tag{4}$$

where y is an index for year.

Separating holidays from weekdays is necessary because they show much lower traffic volume. The floating (unfixed) nature of many holidays may easily make them treated as weekdays in some sloppy sampling and propagate large errors to the estimation of AADTT, particularly when the sample size is small. On the other hand, it is observed that the daily traffic volume in holidays is similar to that on Sundays, so Equation (3) can be further simplified by combining Sundays and holidays into one group, which was adopted in this study.

3.2 Function fitting of AADTT growth trend

The AADTT was calculated with Equation (4) for all WIM stations in California using valid data available from each WIM station's start of use to the year of 2003. Figure 2 shows the typical growth trends of AADTT in California. As can be seen, truck traffic generally increases with time in the whole state, but with different rates, and fluctuates along the growth trends.

In the ME-PDG, three traffic growth functions are allowed: No Growth, Linear Growth, and Compound Growth (NCHRP 2006):

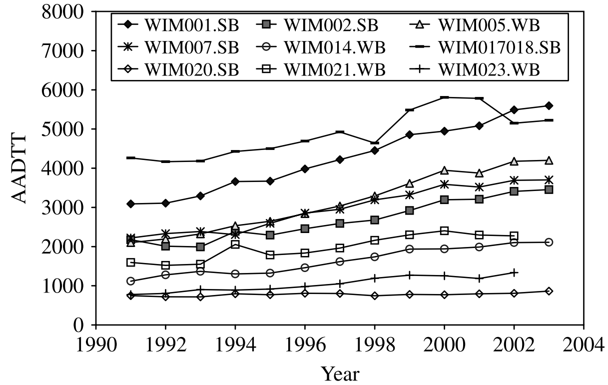

Figure 2. AADTT growth trends at typical WIM stations in California during 1991 through 2003.

no Growth:

$$AADTT_t = 1.0 \times AADTT_{BY}, \tag{5a}$$

linear Growth:

$$AADTT_t = AADTT_{BY} + AADTT_{REF} \times GR \times t, \tag{5b}$$

compound Growth:

$$AADTT_t = AADTT_{BY} \times (1 + GR)^t, \tag{5c}$$

where $AADTT_t$ is the annual average daily truck traffic at age t, GR is the traffic growth rate in percentage, $AADTT_{BY}$ and $AADTT_{REF}$ are the annual average daily truck traffic at the base year and the reference year, respectively. Usually, the base year equals the reference year.

It is worthwhile to investigate which function best fits the AADTT data in California and the appropriate range of growth rate. Because function (5a) is essentially a special case of functions (5b) and (5c) when $GR = 0$, only the latter two functions were used to fit the historical AADTT data for each truck class at each WIM station. Linear and nonlinear regressions were used to estimate parameters ($AADTT_{BY}$ and GR) in functions (5b) and (5c), respectively. The goodness-of-fit of each model was measured by R^2 as defined below:

$$R^2 = 1 - \sum(o_i - p_i)^2 \Big/ \sum(o_i - o_{avg})^2, \tag{6}$$

where o_i is observed AADTT, p_i is predicted AADTT, and o_{avg} is average of all observed AADTT.

The average R^2 from each model for each truck class is shown in Table 1. A paired t-test was used to compare the R^2 from both models. Before running the test, a logit transformation, $\text{logit}(R^2) = \ln[R^2/(1 - R^2)]$, was applied to make the response variable approximately normally distributed. The P-values from the paired t-test are shown in the last column of Table 1. It can be seen that for truck Classes 5, 9 and the aggregated trucks, both the

Table 1. Comparison of R^2 from linear and compound growth models.

Truck class	Average R^2 from compound growth model	Average R^2 from linear growth model	P-value from paired t-test on logirt(R^2)
All classes	0.819	0.824	0.061
Class 4	0.639	0.631	0.155
Class 5	0.823	0.815	0.098
Class 6	0.457	0.463	0.245
Class 7	0.364	0.353	0.297
Class 8	0.291	0.293	0.498
Class 9	0.786	0.800	0.000
Class 10	0.487	0.517	0.000
Class 11	0.300	0.299	0.596
Class 12	0.315	0.309	0.195
Class 13	0.287	0.277	0.449
Class 14	0.359	0.338	0.000
Class 15	0.305	0.301	0.483

linear and compound growth functions fit the truck traffic trend well, with the linear model slightly better. Based on the paired t-test, linear growth fitting is better than the compound growth fitting at 99 and 90% confidence levels for truck Class 9 and the aggregated trucks, respectively, while for truck Class 5 the compound growth fitting is marginally better than the linear growth fitting at 90% confidence level. For other truck classes, although the average R^2s from both models are similar, they all have small values, which indicates that neither of the models explained well the growth trends. This suggests that the actual truck traffic volumes did not have clear growth trends, only fluctuated with time. This will be illustrated later in the paper.

Table 1 shows that the average R^2 from both models is around 0.82 for the aggregate truck traffic ('All Classes'), indicating that some variation in the traffic data series is not explained by either the linear or the compound growth model. This unexplained variation can be treated as the intrinsic fluctuations in traffic trends due to some unknown factors. Knowledge of this fluctuation is useful in sensitivity analysis. This fluctuation can be measured by the residual standard error (RSE) from regression analysis, which is defined as:

$$RSE = \sqrt{\sum (o_i - p_i)^2 \Big/ (n-p)}, \quad (7)$$

where n is the number of observations and p is the number of parameters. Figure 3 shows a plot of RSE from the linear growth fitting versus AADTT in 2000 for all truck classes on a log–log scale. The RSE from the compound growth fitting has the similar plot. As we see, there is a good correlation between ln(RSE) and ln($AADTT$). By linear regression, RSE can be estimated from AADTT with the following formula:

$$RSE = a \cdot AADTT^b \cdot \exp(\varepsilon), \quad (8)$$

where a and b are parameters to be estimated, ε is a normally distributed random variable with mean 0 and variance σ^2. For the linear and compound growth models, the estimated parameters (a, b and σ) are (0.3487, 0.7266 and 0.7112) and (0.3027, 0.7531 and 0.7139), respectively. These parameters will be used later in the sensitivity analysis of this study.

3.3 *Effect of number of observations on estimated growth rates*

In several past studies on truck traffic, significantly large growth rates have been reported, such as 28% (Papagiannakis *et al.* 2006) and 22% (Prozzi and Hong 2006). Although it is not impossible, such large annual growth rates should be rare. This is realised in the ME-PDG software, in which a warning message pops out whenever a growth rate larger than 8% is entered. Examination of the source data in those studies revealed that the growth rates were all estimated from traffic data collected in a period less than six years (two and five years,

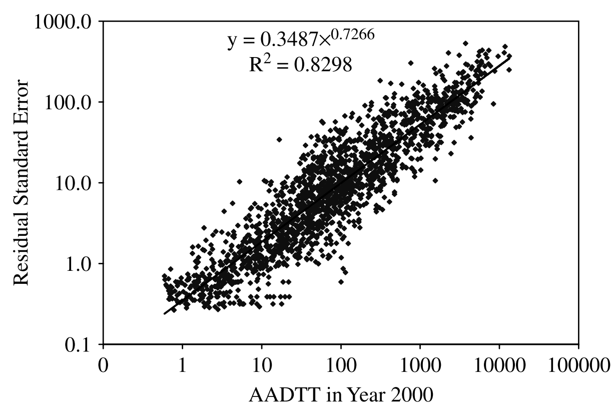

Figure 3. Relationship between residual standard error of AADTT and AADTT in 2000.

respectively, in the above two references), which is possibly the reason why large estimates were obtained. The following analysis supports the above conjecture.

To investigate the effect of number of observations on the estimated growth rates, the growth rate of all trucks at each WIM station was estimated with 2-, 3-, ..., and up to 13-year data. The linear growth model was used because it fits aggregated truck data better than the compound growth model. The AADTT in the year of 2000 is used throughout the rest of the paper as the reference value for the linear growth rate. The growth rates estimated from different numbers of observations are shown in Figure 4a, based on WIM stations with nine or more years' observations. The plot reveals that large growth rates may occur when the number of observations is less than six years, but they converge to a smaller value when the number of observations increases. Given the pavement design life is typically 15–30 years, the growth rate estimated from less than six years data would significantly over- or under-estimate the truck traffic volume in the design life of pavements. Therefore, it is recommended that traffic volume data in at least six consecutive years should be used to estimate the AADTT growth rate.

The variation of growth rate due to small number of observations can be roughly measured by the standard deviation (*SD*) as calculated below:

$$SD_k = \sqrt{\frac{\sum_{i=1}^{n}\left((GR_{ki} - GR_{Mi}) - \frac{1}{n}\sum_{i=1}^{n}(GR_{ki} - GR_{Mi})\right)^2}{n-1}}, \tag{9}$$

where k represents the number of observations, GR_{ki} is the growth rate at WIM station i estimated from k observations, GR_{Mi} is the converged growth rate at WIM station i estimated from maximum number of observations (13 in this study), and n is the number of WIM stations. Figure 4b shows the calculated *SD* versus the number of observations for the aggregated trucks in California. As can be seen, the standard deviation of growth rate is very large for small number of observations. This helps to explain the unusually large growth rates appeared in some studies.

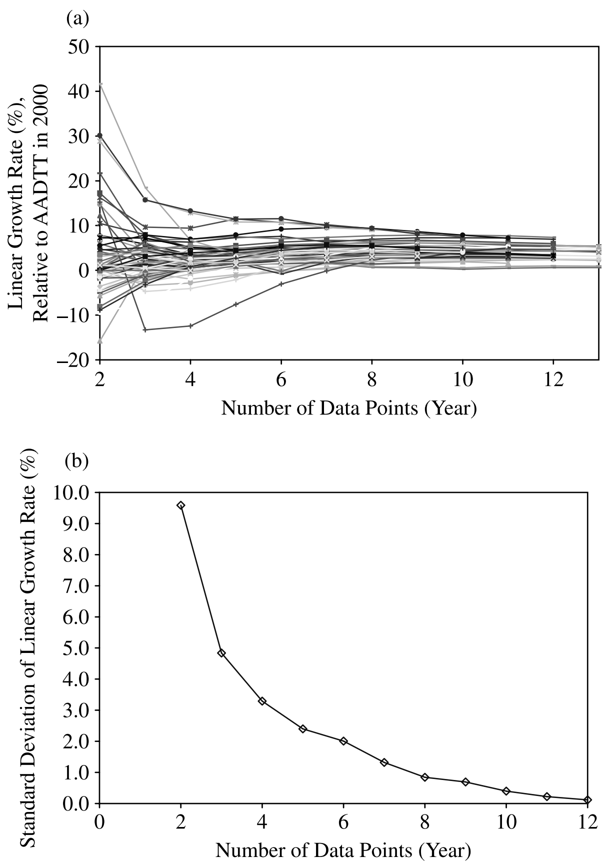

Figure 4. (a) Overview of linear growth rates estimated with different numbers of observations for various WIM stations. (b) Standard deviation of linear growth rate estimated with different number of observations.

3.4 Distribution of truck traffic growth rate in California

Knowledge of the state-wide truck traffic growth rate is useful in aiding highway agencies to choose the default values for the ME-PDG software when historical traffic data are unavailable or insufficient. Figure 5 shows the distribution of the linear growth rate (relative to the AADTT in 2000) of each truck class and the aggregated trucks, calculated from WIM stations with six or more years' data.

The results show that the growth rate distribution of aggregated trucks is in a narrow range with a mean of 3.97%, which is very similar to that of Class 9 trucks. This is expected because Class 9 trucks account for over 50% of the truck flow in the state (Lu and Harvey 2006). The average growth rate of aggregated trucks is also very close to the default value (4.0) adopted in the ME-PDG software, indicating the very appropriateness of this default value.

Truck traffic is correlated to economic activities. It is of interest to compare the truck traffic growth trend and the economy growth trend. Using the US gross domestic product (GDP) as an index for the economic activity, its growth trend was estimated from the last 15-year real GDP data (Johnston and Williamson 2006). The estimated linear growth rate of real GDP is 3.65% (relative to the real GDP in 2000), which is slightly lower than the truck traffic growth rate. The implication from the similarity between truck traffic and GDP growth trends is that some economic indices may be used along with historical traffic data to predict the truck traffic growth trend.

The growth rate distributions of other truck classes have a broader range of variation and different means.

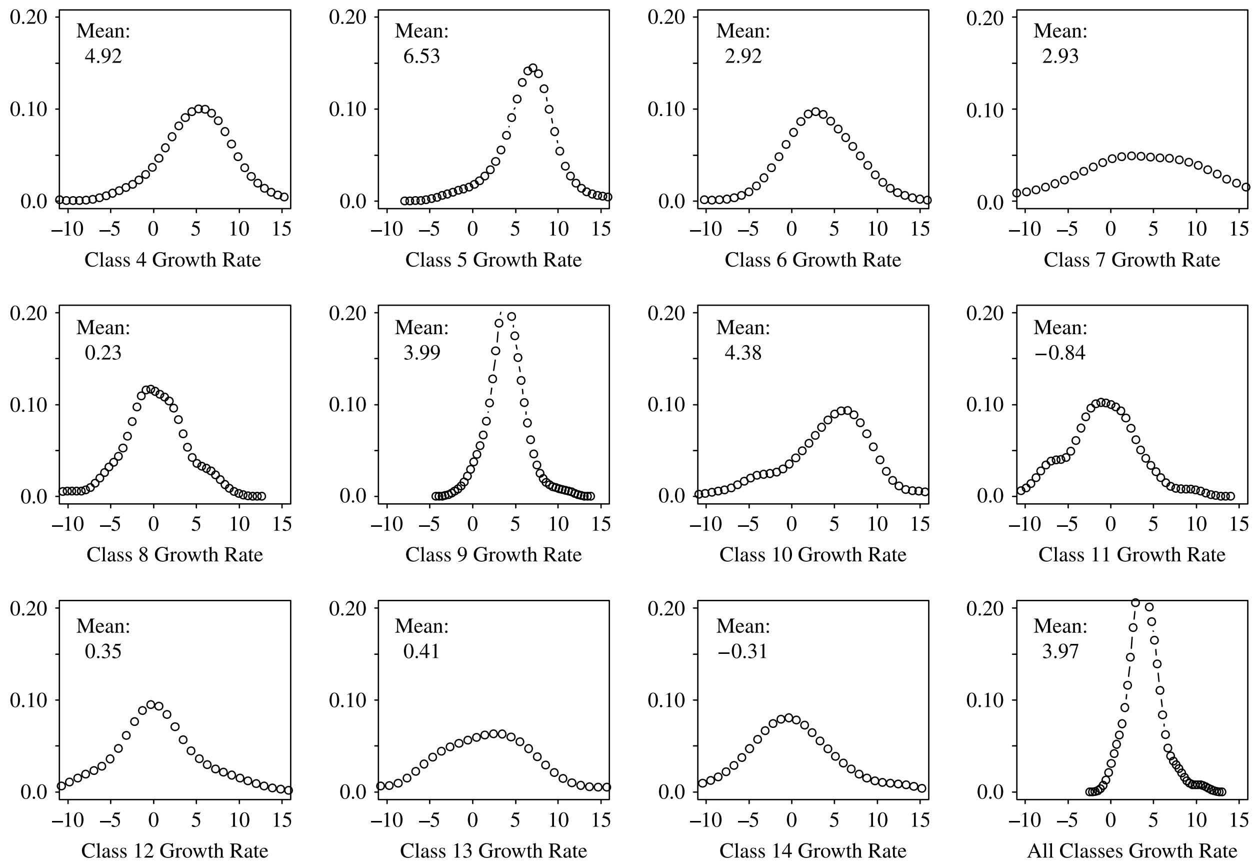

Figure 5. Probability distrubution of linear growth rate for each truck class and aggregate trucks.

Class 5 trucks have the highest average growth rate (6.53%) while truck classes 8, 11, 12, 13 and 14 have near-zero average growth rates. Obviously, it is inappropriate to use a uniform growth rate for all truck classes in pavement design.

4. Sensitivity analysis of pavement response to traffic volume prediction

One of the significant differences of the newly developed ME-PDG from the traditional pavement design procedures is that it requires much more input parameters. These parameters affect the analysis outputs in a complex and interactive way. The sensitivity of the design guide outputs to these inputs needs to be determined to establish requirements for efficient data collection. Recent studies have begun to investigate the sensitivities of ME-PDG to traffic input (Papagiannakis *et al.* 2006, Zaghloul *et al.* 2006). There is, however, very limited work on the sensitivity of the ME-PDG to truck traffic volume prediction. One may think that sensitivity analysis is not necessary because change in the traffic volume simply means proportional change in pavement life. This is true in the traditional pavement design procedures, in which pavement life is interchangeable with the number of repetitions of an equivalent single axle load (ESAL). In the ME-PDG, however, this is not the case because pavement damage is calculated incrementally and the damage rate changes nonlinearly with varying climate, axle load, and pavement conditions.

The estimated traffic volume may differ from the true value due to several reasons. The first one is significant change in traffic trend due to unpredictable changes in external factors, such as economy recession/boom and technology development in other transportation modes. Probability of this type of error is small, but is intrinsic to all types of predictions and is difficult to predict. Correction for this type of error is outside the scope of this paper. Error in traffic volume prediction may also originate from causes that can be prevented or minimised, such as the use of a small number of observations for modelling and inappropriate selection of parameters in traffic volume calculation.

This section investigates the effects of variation in parameters of the linear growth model on pavement responses predicted by ME-PDG. There are two parameters in the linear growth model Equation (5b): the base year annual average daily truck traffic $AADTT_{BY}$ and the linear growth rate GR ($AADTT_{REF}$ is a reference value that can be selected arbitrarily).

Variation of $AADTT_{BY}$ mainly comes from an often over-looked fact: when using a fitted model for prediction, the estimated parameters should be used for best prediction. That is, the estimated base-year AADTT instead of the observed base-year AADTT should be used to predict future traffic volume. Use of the observed AADTT virtually introduces a random error term. The SD of this error term can be measured by the residual standard error (RSE) from regression analysis, as in Equation (8). If ε is replaced with σ, RSE can be computed by the following formula for the linear growth model:

$$RSE = 0.3487 \cdot AADTT^{0.7266} \cdot \exp(0.7112), \qquad (10)$$

Replacing ε with σ indicates that there is approximately 0.16 probability that the actual RSE will be larger than the value calculated by Equation (10) at a given AADTT level.

Variation of GR mainly originates from the use of insufficient number of observations for parameter estimation, as shown in Figure 4b. In this study, the standard deviation of GR corresponding to three-year observations, which is about 4.4%, is used in the sensitivity analysis.

Nine combinations of changes in $AADTT_{BY}$ and GR are used to investigate the responses of both asphalt concrete pavements (ACPs) and joint plain concrete pavements (JPCPs) in two climate regions in California, as shown in Table 2. The variations in traffic parameters can be grouped into four scenarios: GR changes by 1.96 standard deviations while $AADTT_{BY}$ is kept at its mean (Scenario 1); $AADTT_{BY}$ changes by 1.96 standard deviations while GR is kept at its mean (Scenario 2); both $AADTT_{BY}$ and GR change by 1.96 standard deviations (Scenario 3); both $AADTT_{BY}$ and GR change by one standard deviation (Scenario 4). Because negative growth rates are not allowed in the ME-PDG software, they were converted to zero during the analysis.

The software ME-PDG Version 1.00 was adopted for the analysis. Results are summarised in Table 3. As can be seen, variation in the two growth model parameters has significant effect on all responses of both pavement types in both climate regions. Using pavement responses in the base case as references, the results in Table 3 are normalised and plotted in Figure 6a and b.

Figure 6a (i) and b (i) show that error in the linear growth rate estimates, primarily due to small number of observations, can change the cumulative truck traffic volume in pavement design life to 30 through 330% of the base value with a probability of 0.95 (assuming the

Table 2. Factor levels used in the sensitivity analysis.

Traffic inputs	Case 0 (Base case): $AADTT_{BY}$, GR Case 1 (Scenario 1): $AADTT_{BY}$, $GR + 1.96\hat{\sigma}_2$ Case 2 (Scenario 1): $AADTT_{BY}$, $GR - 1.96\hat{\sigma}_2$ Case 3 (Scenario 2): $AADTT_{BY} + 1.96\hat{\sigma}_1, GR$ Case 4 (Scenario 2): $AADTT_{BY} - 1.96\hat{\sigma}_1, GR$ Case 5 (Scenario 3): $AADTT_{BY} + 1.96\hat{\sigma}_1, GR + 1.96\hat{\sigma}_2$ Case 6 (Scenario 3): $AADTT_{BY} - 1.96\hat{\sigma}_1, GR - 1.96\hat{\sigma}_2$ Case 7 (Scenario 4): $AADTT_{BY} + \hat{\sigma}_1$, $GR + \hat{\sigma}_2$ Case 8 (Scenario 4): $AADTT_{BY} - \hat{\sigma}_1$, $GR - \hat{\sigma}_2$ $\hat{\sigma}_1 = RSE = 0.3487 \cdot AADTT^{0.7266} \cdot \exp(0.7112)$, $\hat{\sigma}_2 = 4.4\%$ $AADTT_{BY}$, GR, and all other traffic inputs were estimated from site-specific WIM stations
Climate regions	Central Valley, Northern Coast Climate inputs were generated from weather stations in each region
Pavement structures	*AC pavement:* Design life: 20 years Reliability level: 90% AC layer: 9.7-in. thick, PG76-16 binder (Central Valley), 6-in. thick, PG64-16 binder (Northern Coast) Granular base: 8-in. thick, A-1-a type (Central Valley), 6-in. thick, A-1-a type (Northern Coast) Subgrade: clayey sand (A-2-6) *PCC pavement (JPCP):* Design life: 30 years Reliability level: 90% PCC layer: 10-in. thick (Central Valley), 8-in. thick (Northern Coast) CTB layer: 6-in. thick (Central Valley), 4-in. thick (Northern Coast) Aggregate base: 4-in. thick, A-1-a type Subgrade: clayey sand (A-2-6) All other inputs were MEPDG Version 1.0 software defaults

1 in. = 25.4 mm.

Table 3a. Outputs of sensitivity analysis for AC pavements.

Location	Case	Longitudinal cracking (ft/mi)	Alligator cracking (%)	Subtotal AC rutting (in.)	Total rutting (in.)	IRI (in./mi)	Cumulative trucks
Central Valley	Case 0	69.8	4.5	0.409	0.639	100.2	3.770E + 08
	Case 1	149.0	8.1	0.538	0.785	107.9	1.191E + 09
	Case 2	39.1	3.2	0.345	0.565	96.6	9.203E + 07
	Case 3	106.0	6.2	0.475	0.714	104.1	4.168E + 08
	Case 4	43.0	3.5	0.355	0.578	97.2	3.373E + 08
	Case 5	128.0	7.4	0.513	0.757	106.3	1.316E + 09
	Case 6	46.3	3.6	0.364	0.587	97.7	8.233E + 07
	Case 7	81.0	5.0	0.429	0.662	101.3	8.151E + 08
	Case 8	58.8	4.0	0.388	0.615	99.0	1.416E + 08
Northern Coast	Case 0	2000.0	4.7	0.083	0.321	87.1	3.148E + 07
	Case 1	4220.0	9.4	0.115	0.373	91.7	1.018E + 08
	Case 2	1450.0	3.5	0.073	0.301	85.6	1.141E + 07
	Case 3	3060.0	6.7	0.098	0.347	89.2	3.735E + 07
	Case 4	1670.0	3.9	0.077	0.308	86.1	2.562E + 07
	Case 5	3580.0	7.9	0.106	0.359	90.3	1.207E + 08
	Case 6	1880.0	4.3	0.08	0.314	86.5	9.288E + 06
	Case 7	2450.0	5.6	0.09	0.333	88.0	6.588E + 07
	Case 8	1540.0	3.8	0.075	0.308	86.0	1.318E + 07

1 mile = 1.6093 km. 1 foot = 0.3048 m.

error in the linear growth rate estimates follows a normal distribution). On the other hand, error in the base-year AADTT estimates can change the cumulative trucks by ±20% of the base value when the base-year AADTT varies with a probability of 0.95. Combination of the two errors will further expand the varying range.

Other plots in Figure 6a and b suggest that the change in pavement responses due to errors in traffic volume prediction is different in various climate regions for different pavement types, and the percentage change in pavement responses is not proportional to the percentage change in cumulative trucks. Pavement cracking seems to be most affected by changes in the truck volume prediction. At the 95% confidence level, the predicted alligator cracking in AC pavements can increase up to 70% of the base case (Case 0) value due to the error in growth rate estimation (Scenario 1) and up to 20% due to the error in base-year AADTT estimation (Scenario 2), while the predicted percentage of cracked slabs in PCC pavements can increase up to 400% due to the error in growth rate estimation (Scenario 1) and up to 30% due to the error in base-year AADTT estimation (Scenario 2). Predicted faulting in PCC pavements is also significantly affected by changes in the growth model parameters, while

Table 3b. Outputs of sensitivity analysis for PCC pavements.

Location	Case	Faulting (in)	Slabs cracked (%)	IRI (in./mi)	Cumulative trucks
Central Valley	Case 0	0.076	0.3	122.2	7.691E + 08
	Case 1	0.104	1.2	137.7	2.570E + 09
	Case 2	0.061	0.1	114.5	1.380E + 08
	Case 3	0.080	0.4	124.4	8.501E + 08
	Case 4	0.071	0.3	119.7	6.881E + 08
	Case 5	0.110	1.4	140.8	2.841E + 09
	Case 6	0.057	0.1	112.4	1.235E + 08
	Case 7	0.093	0.8	131.8	1.736E + 09
	Case 8	0.060	0.1	113.7	2.514E + 08
Northern Coast	Case 0	0.009	0.0	86.8	6.156E + 07
	Case 1	0.017	0.0	91.4	2.172E + 08
	Case 2	0.008	0.0	86.3	1.712E + 07
	Case 3	0.010	0.0	87.7	7.302E + 07
	Case 4	0.007	0.0	85.8	5.009E + 07
	Case 5	0.020	0.1	93.0	2.577E + 08
	Case 6	0.006	0.0	85.4	1.393E + 07
	Case 7	0.014	0.0	89.5	1.369E + 08
	Case 8	0.007	0.0	85.9	2.182E + 07

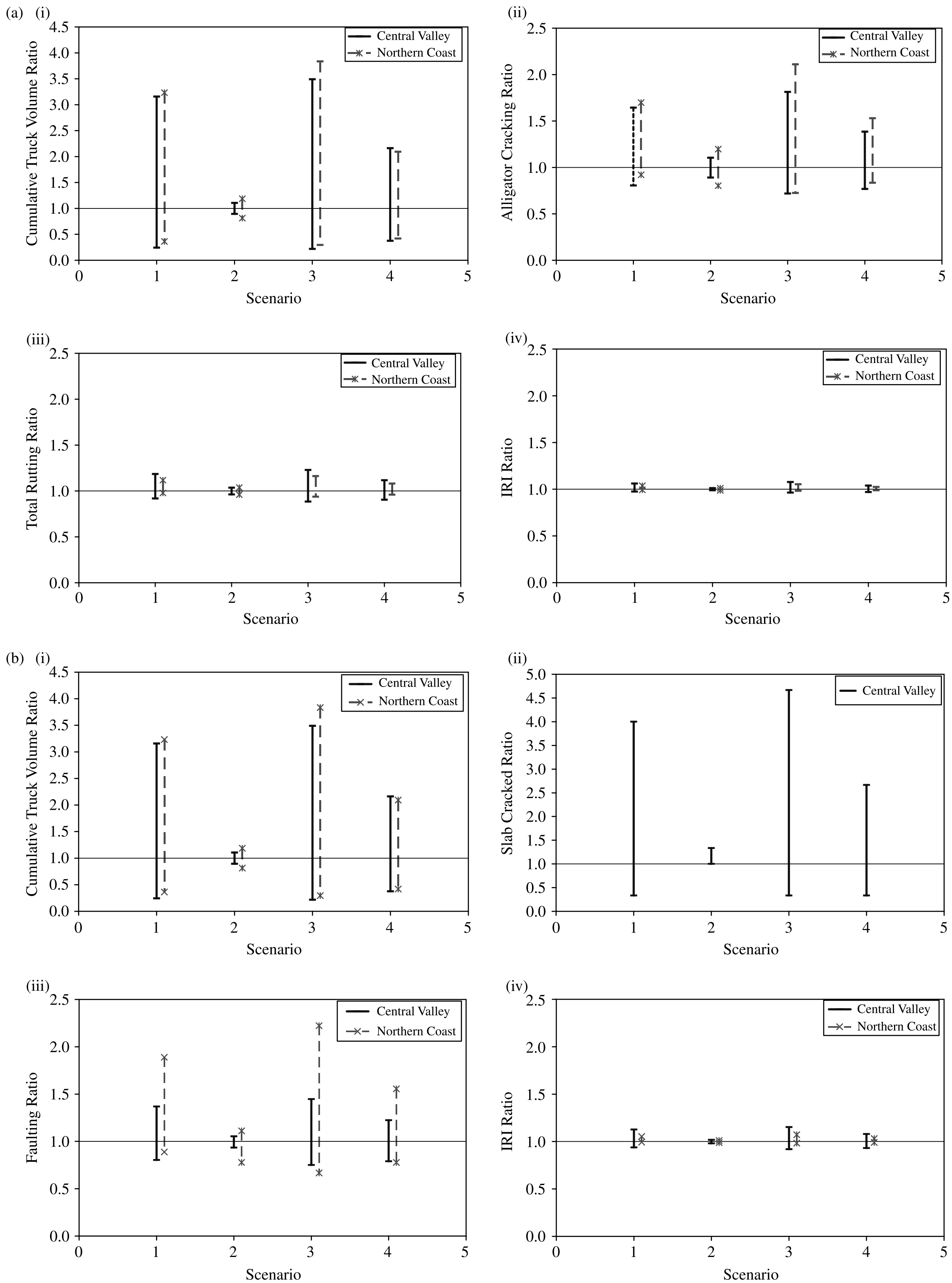

Figure 6. (a) Effects of variation in base-year AADTT and growth rate on AC pavement responses (i, cumulative truck traffic ratio; ii, alligator cracking ratio, iii, total rutting ratio; iv, IRI ratio). (b) Effects of variation in base-year AADTT and growth rate on PCC pavement responses (i, cumulative truck traffic ratio; ii, slab cracked ratio; iii, faulting ratio and iv, IRI ratio).

predicted rutting in AC pavements is less affected. On the other hand, the International Roughness Index (IRI) is insensitive to changes in the growth model parameters.

5. Forecast of truck traffic growth rate

Although a combination of data acquisition technologies is now available for traffic data collection, such as the weigh-in-motion (WIM) system, automated vehicle classification (AVC), and automated traffic recorder (ATR), and there are databases containing traffic information, such as the long-term pavement performance (LTPP) database and pavement management system (PMS) databases, truck data collection is still an expensive and time-consuming process and currently available data are far from enough to cover every highway. In addition, for new pavement construction, there is no historical traffic data for modelling. In order to explore alternative methods for estimation and to provide a better understanding of the truck traffic-growing trend on highways, an attempt was made in this study to correlate truck traffic growth rate with some potential explanatory variables such as roadway characteristics and socio-economic factors. Socio-economic factors have been used by some state agencies (e.g. West Virginia and Arizona) to help develop traffic growth factors (Cambridge Systematics, Inc. 2005).

Extrapolation of truck traffic characteristics to other locations has been explored in a previous study (Lu and Harvey 2006), in which a cluster analysis was performed. The cluster analysis seems to work for most traffic inputs, such as hourly and monthly distribution factors, truck class distribution and axle load spectra. Initially, cluster analysis was tried in this study, but its results revealed no useful information regarding the structure of traffic growth trends. Therefore, as an alternative, effort was focused on other statistical techniques.

Multiple-year volume data at each WIM station can be treated as repeated measures on the same highway section over the course of time. Advanced statistical models (e.g. linear mixed-effect models) are available for this type of data to incorporate potential correlation between consecutive observations, but in practice these data are often analysed by a two-stage procedure. This procedure first fit the repeated measures from one subject by a regression function, then the estimated parameters are treated as the response variables and another regression analysis is performed to explore the relationship between the estimated parameters and other explanatory factors. Because the two-stage analysis is conceptually and computationally simple and a preliminary analysis showed that the linear mixed-effect model produced similar results for the data analysed here, the two-stage procedure is adopted in this study. The first stage analysis has been completed in the previous section, so details are given to the second stage in this section, to develop a multiple linear regression model.

The growth rate estimated from the linear growth model is treated as the response variable. The explanatory variables are chosen from those that represent the roadway characteristics and socio-economic activities. Variables for the roadway characteristics include the number of lanes, highway functional classification, truck traffic volume and area types. Highway functional classification has three levels: interstate highway, US highway and state highway. The AADTT in the year of 2000 is used to represent the truck traffic volume at each WIM location. Area types have two levels: Urban and Rural. Urban area is a territory that has a population density over 1000 per square mile and a minimum population of 50,000 people. Variables for the socio-economic activities include nearby population density, housing density, change in population density from 1990 to 2000, change in housing density from 1990 to 2000, and land use. Land use has two levels; agriculture/forest and other uses. Land use is considered because agricultural and logging activities typically incur truck traffic. Data for these explanatory variables were all extracted from California Spatial Information Library.

Pearson's correlation matrix of these explanatory variables revealed that the number of lanes and area types, population density and housing density, population density change and housing density change are each highly correlated, so the number of lanes, housing density and housing density change were removed from the analysis. In addition, the population density change over ten years was normalised by the population density in the year of 2000, so essentially a population density growth rate was used as an explanatory variable.

Table 4 summarises the estimation results for the aggregate trucks and each truck class. As can be seen, R^2 is small for all model estimations, indicating that the fitted regression models cannot be used to predict truck traffic growth rate with high precision. For the null hypothesis that the regression function is a constant term, the *P*-value is larger than 0.05 for truck classes 4, 6, 7, 8, 10 and 13, indicating that at a 95% confidence level the multiple linear regression model is no better than taking a simple average. In other words, none of the explanatory variables have significant effects on the growth rates of these truck classes. On the other hand, the *P*-value for the constant term hypothesis is smaller than 0.05 for truck classes 5, 9, 11, 12, 14 and aggregated trucks, indicating that the multiple regression models can explain to some extent the variation of growth rate.

The *P*-values for estimated parameters show that for the aggregated trucks, population density, population density growth rate and land use are significant at a 90% confidence level. The signs of estimated parameters suggest that the growth rate of truck traffic is higher in areas with smaller population density, or higher population density growth rate, or in agriculture/logging areas. For Class 5 trucks, truck traffic volume

Table 4. Multiple regression analysis results.

Parameter	All		Class 4		Class 5		Class 6		Class 7		Class 8	
	Estimate	*P*-value	Estimate	*P*-value	Estimate	*P*-value	Estimate	*P*-value	Estimate	*P*-value	Estimate	*P*-value
(Intercept)	4.125	0.000	6.573	0.000	7.626	0.000	2.627	0.000	1.473	0.291	-0.134	0.835
US Rte-Interstate Rte	−0.364	0.192	0.581	0.349	0.193	0.682	0.678	0.330	−1.957	0.145	0.168	0.753
State Rte-Interstate Rte	0.106	0.420	0.039	0.901	−0.203	0.382	0.336	0.319	0.069	0.914	0.584	0.028
AADTT2000	0.000	0.519	−0.022	0.099	−0.001	0.099	0.003	0.205	0.031	0.543	0.007	0.029
Urban−rural	−0.150	0.453	0.701	0.137	−0.309	0.408	0.180	0.723	1.530	0.102	0.160	0.693
PD2000[a]	−0.001	0.108	0.001	0.261	0.000	0.782	0.000	0.981	0.001	0.748	−0.001	0.243
NDPD[b]	0.025	0.023	−0.030	0.212	0.027	0.142	0.050	0.069	0.079	0.192	−0.018	0.382
LandUse[c]	0.457	0.023	0.846	0.064	0.844	0.016	0.943	0.067	1.637	0.081	0.694	0.080
R^2	0.204	–	0.087	–	0.193	–	0.112	–	0.118	–	0.102	–
P-value for constant[d]	0.001	–	0.179	–	0.001	–	0.067	–	0.093	–	0.101	–

Parameter	Class 9		Class 10		Class 11		Class 12		Class 13		Class 14	
	Estimate	*P*-value	Estimate	*P*-value	Estimate	*P*-value	Estimate	*P*-value	Estimate	*P*-value	Estimate	*P*-value
(Intercept)	3.672	0.000	3.640	0.000	−1.789	0.011	−0.040	0.962	0.670	0.602	−2.390	0.016
US Rte-Interstate rte	−1.535	0.000	0.407	0.588	−0.834	0.148	−1.432	0.053	1.221	0.317	−0.731	0.384
State Rte-Interstate Rte	0.537	0.000	0.618	0.084	0.312	0.260	0.889	0.009	−0.293	0.609	0.206	0.616
AADTT2000	0.000	0.758	0.028	0.136	0.002	0.237	0.008	0.646	0.209	0.319	0.012	0.178
Urban−rural	−0.168	0.373	−0.040	0.939	−0.885	0.031	−1.132	0.023	0.332	0.699	1.618	0.009
PD2000[a]	−0.002	0.003	0.001	0.525	−0.003	0.010	−0.004	0.002	−0.002	0.331	−0.001	0.514
NDPD[b]	0.008	0.454	0.036	0.219	0.055	0.015	0.084	0.005	−0.011	0.811	0.084	0.012
LandUse[c]	0.382	0.048	0.624	0.248	0.088	0.831	0.775	0.126	0.047	0.957	0.052	0.933
R^2	0.383	–	0.092	–	0.206	–	0.235	–	0.031	–	0.133	–
P-value for constant[d]	0.000	–	0.152	–	0.001	–	0.000	–	0.864	–	0.027	–

[a]Population density in the year of 2000.
[b]Population density change from 1990 to 2000, normalised by PD2000.
[c]Agriculture/logging land use reference to other land uses.
[d]*P*-value for the null hypothesis that the regression function is a constant term.

(AADTT2000) and land use are significant at a 90% confidence level. The signs of estimated parameters suggest that the growth rate of Class 5 trucks is higher in areas with less truck traffic, and is higher in agriculture/logging areas than in other land use areas. For Class 9 trucks, highway functional class, population density and land use are significant at a 90% confidence level. Specifically, the growth rate of Class 9 trucks is lowest on US highways and highest on state highways, lower in counties with higher population density, and higher in agriculture/logging areas. For truck classes 11, 12 and 14, the growth rate is significantly associated with rural/urban areas and population density growth rate. Specifically, their growth rates are higher in the rural area and in areas where population density growth rate is higher.

6. Conclusions

This paper focuses on analysis of the truck traffic growth pattern in California, sensitivity of pavement responses to variation in growth rates, and potential contributing predictors that can be used to predict truck traffic growth rates. Main findings are summarised as following:

(1) Truck traffic generally increases over years. Different truck classes have distinct growth trends. Both compound growth and linear growth functions can model the growth trends. When the linear growth rate in percentage is used, the reference year must be clearly stated. If another year with different AADTT is used as the reference year, the growth rate has to be adjusted accordingly. For California highways, a 4% linear growth rate (relative to the traffic volume in the year of 2000) can be used as the default value for truck traffic.

(2) Results from the sensitivity analysis illustrate the importance of careful selection of parameters used in the truck traffic growth models. Instead of being directly observed, the base-year AADTT should be estimated from the growth model that is to be used in the design procedure. Small number of observations significantly affects the estimated growth rate, which itself has significant effect on pavement responses over the design life of pavements. To reduce variance in truck volume prediction, it is recommended that at least six-year traffic observations should be used for parameter estimation. As a supplementary tool, the regional economy growth rate can be used to check the reasonability of estimated truck traffic growth rate.

(3) Roadway characteristics and socio-economic factors cannot be used to directly predict truck traffic growth rate with high accuracy, but some factors are significantly associated with traffic growth, which can assist pavement designer in selecting appropriate defaults for traffic growth rates. These factors include population density, population density growth rate, land use, and highway functional classification.

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