COMPARISON OF TRAFFIC LOAD MODELS BASED ON SIMULATION AND MEASURED DATA

Mayrai Gindy[1] and Hani H. Nassif[2]

ABSTRACT

The effect of using simulated truck records to forecast future return levels is examined. Statistical models are based on weigh-in-motion (WIM) data collected from thirty-three different sites in the State of New Jersey over an 11-year period. For each observed truck record, the maximum midspan bending moment for an 18.3 m (60-ft) simple span is calculated. It is found that this effect is best represented by a bimodal Inverse Gaussian distribution.

Truck moments, expressed as a ratio of the 1989 American Association of State Highway and Transportation Officials (AASHTO 1989) live load moment, are extrapolated using two very different mathematical models. The Normal Probability Paper (NPP) approach, used in the calibration of the current AASHTO Code, and the models of the extreme value theory (EVT) are considered. The results indicate that EVT models provide a more rational and objective method for return level estimates. It is also shown that, although simulated truck traffic may adequately predict near-future levels, simulation does not reflect the variability associated with far-future estimates.

KEY WORDS

simulation, Monte Carlo, extrapolation, extreme value theory, live load

INTRODUCTION

The current practice of highway bridge design in the United States is based on the AASHTO Load and Resistance Factor Design (LRFD) Bridge Design Specifications (AASHTO 2002). The 75-year maximum bending moments and shears were estimated based on a 2-week truck weigh survey from Ontario, Canada containing less than 10,000 truck records (Nowak 1994). Oftentimes, however, a larger dataset is desirable for predictions over a long time period. This can be accomplished in one of three ways, namely by observation, simulation, or extrapolation.

Observation, alone, is often too expensive, time consuming, and generally unrealistic. As a result, truck load effects are often simulated based on a short time history of observed data and used for extrapolation. In this paper, the Monte Carlo method is used to simulate truck effects, up to 1 year, based on one month of observed data. Return level estimates of the simulated records are compared with those from measured data for the same time period.

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Two very different extrapolation methods are considered, namely the NPP and the EVT. Advantages and disadvantages of each method are discussed.

Measured truck traffic data is collected from over 33 WIM sites over an 11-year period. This extensive database provides a unique opportunity to assess the accuracy of various prediction methods. Data from 1993 is used as the basis for simulation and extrapolation and results are compared with known 11-year levels (2003).

WEIGH-IN-MOTION DATABASE

WIM technology has been extensively used by highway and bridge engineers to monitor truck traffic since the introduction of federal programs such as the Long-term Pavement Performance (LTPP) program, created as an element of the Strategic Highway Research Program (SHRP) in the mid 1980s. WIM systems are capable of measuring vehicle gross weights, axle weights, axle spacings, and vehicle class of actual truck traffic at full highway speeds. WIM sensors, typically a piezoelectric strip, load cell, or bending plate, are directly installed in the roadway surface. As a result, the sensors are relatively undetectable by roadway users and provide unbiased truck weight data (Moses et al. 1987, Kim et al. 1996, Laman and Nowak 1997, Katz and Rakha 2002).

WIM data collected from thirty-three (33) different sites located throughout the State of New Jersey (NJ) over an 11-year period (1993-2003, with some gaps) is included in the present study. The WIM sites represent a variety of location-specific characteristics, including truck volume, roadway type (major/minor arterials), area type (urban/rural), and number of lanes as shown in Figure 1. Due to the size of the database, approximately 1 million truck records per month, WIM data is statistically analyzed to evaluate the truck traffic characteristics. Results presented herein are for Interstate 195, a 4-lane (EB/WB) principal arterial located in a rural part of Monmouth County. The recording period extends from 1-October 1993 through 30-June 2003 and includes 2,628,556 truck records.

TRUCK TRAFFIC COMPOSITION

The truck traffic composition for October 1993 is presented in detail. Similar results are observed for other months. It is found that truck traffic is almost evenly divided among 5-axle trucks and 2, 3, and 4-axle trucks with 53% and 45%, respectively. The site contains very few trucks with more than five axles, accounting for only 2% of the total truck traffic. A gross weight distribution of the truck traffic is shown in Figure 2 along with the legal limit of 356 kN (80 kips) and the effective gross weight (W_{eq}) of 249 kN (56 kips). The latter, given by Equation 1, provides a convenient measure of the total weight of the truck population (Chotickai and Bowman 2006). It is also observed that approximately 17% of the truck traffic exceeds the legal total load limit, although there is currently no mechanism in place to verify whether some of these trucks are permit vehicles and therefore legal trucks.

$$W_{\mathrm{eq}} = \left(\sum f_i W_i^3 \right)^{1/3} \tag{1}$$

where f_i = frequency of occurrence of trucks with a gross vehicle weight of W_i.

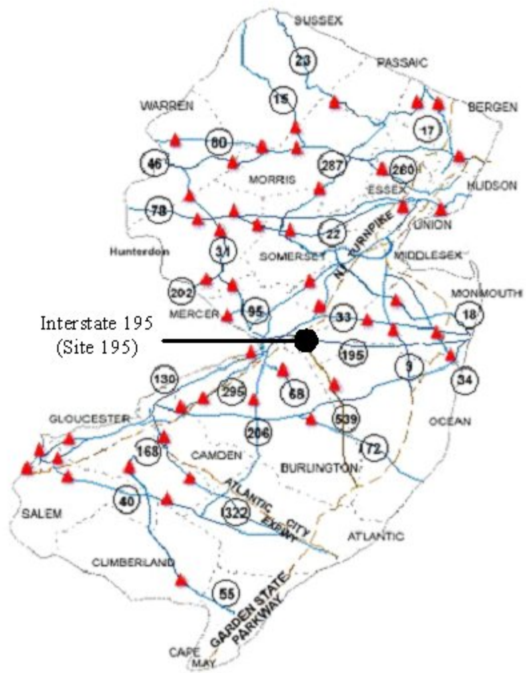


Figure 1: Map of Weigh-in-Motion (WIM) Sites Located in the State of New Jersey (courtesy of the New Jersey Department of Transportation)

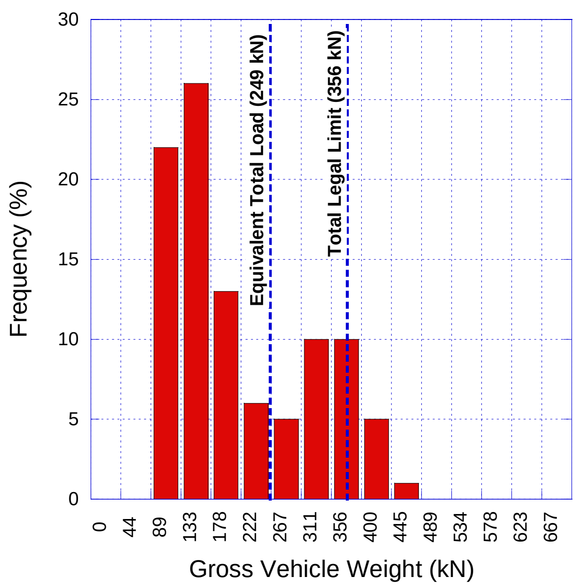


Figure 2: Histogram of Gross Truck Weight for Site 195 (October 1993)

TRUCK TYPE

Truck traffic is often categorized into one of thirteen FHWA classes based on the number of axles and number of power and trailer units. Often, however, many different vehicle or body types may exist within a single class, depending on the axle configuration, truck use, and axle weight restrictions. As a result, truck traffic is further classified into more specific groups referred to as vehicle types (VTs). The New Jersey VT classification scheme, similar to that used by Caltrans (Lu et al. 2002), is used in this study. Table 1 presents the dominant VTs identified in the October 1993 WIM data of Site 195, along with the axle spacing restrictions. These five body types represent 91% of the total truck traffic. By considering individual vehicle types (VTs) rather than vehicle classes, the statistical description of truck traffic is greatly improved.

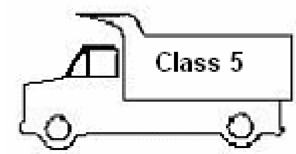
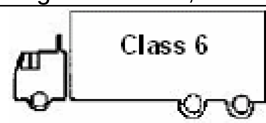
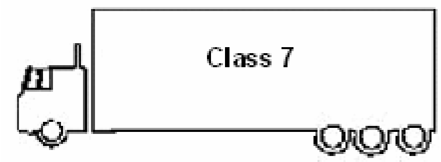
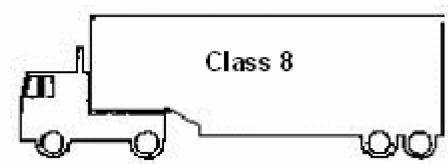
For statistical consideration of the axle weights, the first axle is always considered as the steering axle while axles separated by a distance of 1.8 m (5.8 ft) or smaller are considered as tandem (two axles) or tridem (three axles). Otherwise, the axle is considered as a single axle. Axle weight distributions for the dominant VTs are presented in Figure 3 on normal probability paper (NPP). In Figure 3, axle weights for tandem and tridem axles are presented as combined weights.

SIMULATION

Unlike the 11-year WIM database used in this study, oftentimes there is limited observed data (i.e. weeks). As a result, in an attempt to imitate a real-life system, truck traffic is mathematically simulated over a longer time period. The Monte Carlo (MC) method is used to generate truck effects based on the observed data and according to the observed probability distributions.

For each truck record, the maximum midspan bending moment for an 18.3 m (60-ft) simply-supported span, expressed as a ratio of the 1989 AASHTO (AASHTO 1989) design moment, is computed. The 1989 Code is selected to be consistent with prior LRFD Code calibration procedures. Statistical models are developed for a 1-month base dataset and used to estimate the 1-, 5-, and 10-year return levels. Model estimates are subsequently compared with actual observed maxima for the same time periods. The 11-year duration of the measured data provides a unique opportunity to assess model accuracy and improve the predictive credibility for even longer return periods (i.e. 75 years).

Table 1: Dominant Vehicle Types Identified for Site 195 (October 1993)

Vehicle Type		**Axle Spacing (min/max, m)**	**Percentage (%)**
VT03	 Single unit truck, 2 axles	AXS1 (1.8/6.4)	10
VT11	 Single unit truck, 3 axles	AXS1 (0/6.1) AXS2 (0/1.8)	16
VT17	 Single trailer, 4 axles	AXS1 (0/12.2) AXS2 (0/3) AXS3 (0/1.8)	6
VT19	 Single trailer, 4 axles	AXS1 (0/12.2) AXS2 (0/12.2) AXS3 (0/1.8)	10
VT22	 Single trailer, 5 axles	AXS1 (0/12.2) AXS2 (0/1.8) AXS3 (0/12.2) AXS4 (0/1.8)	49

The observed maximum midspan bending moment for a 1-month period (October 1993) is shown in Figure 4. It is found that the distribution is best represented by a bimodal Inverse Gaussian distribution, as indicated by a nearly linear quantile-quantile (QQ) plot in Figure 4b. The bimodal mixing function, with a mixing proportion (p) of 0.87 for values below the trough of 1.0, is given by

$$f(x) = p\left[I_1\left(x|\mu_1, \lambda_1\right)\right] + (1-p)\left[I_2\left(x|\mu_2, \lambda_2\right)\right] \tag{2}$$

where, $f(x)$ is the bimodal probability density function and $I(x)$ is the Inverse Gaussian probability density function with location μ and scale λ and expressed by

$$I(x) = \left[\frac{\lambda}{2\pi x^3}\right]^{1/2} \exp\left\{\frac{-\lambda(x-\mu)^2}{2\mu^2 x}\right\} \tag{3}$$

This distribution is subsequently used as the basis for the MC simulation. Assuming no growth in truck volume, the simulated truck effects for a 1-year period are shown in Figure 4c. These effects are compared with actual observed trucks over a 1-month period, the base period originally used to construct the distribution, and a 1-year period. It is observed that although the correlation between simulated and observed is quite good, the simulated records tend to more closely imitate the records of the base period. This may be reasonable for simulation of near-future periods such as one year, but may not reflect the level of variability that is undoubtedly present for simulation of far-future periods such as 75 years.

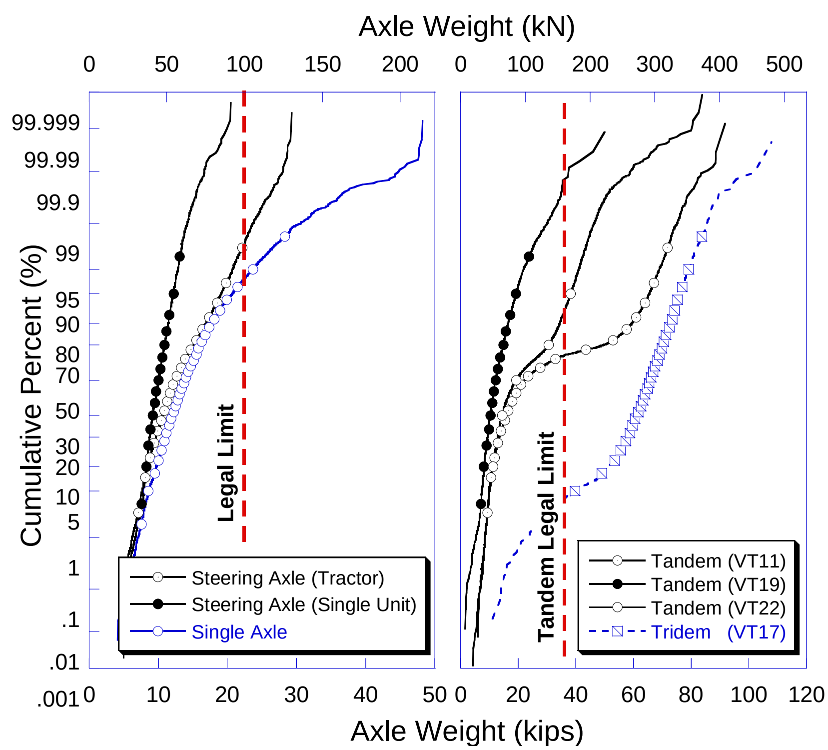


Figure 3: Axle Weight Distributions for Dominant Vehicle Types Idenftified for Site 195 (October 1993)

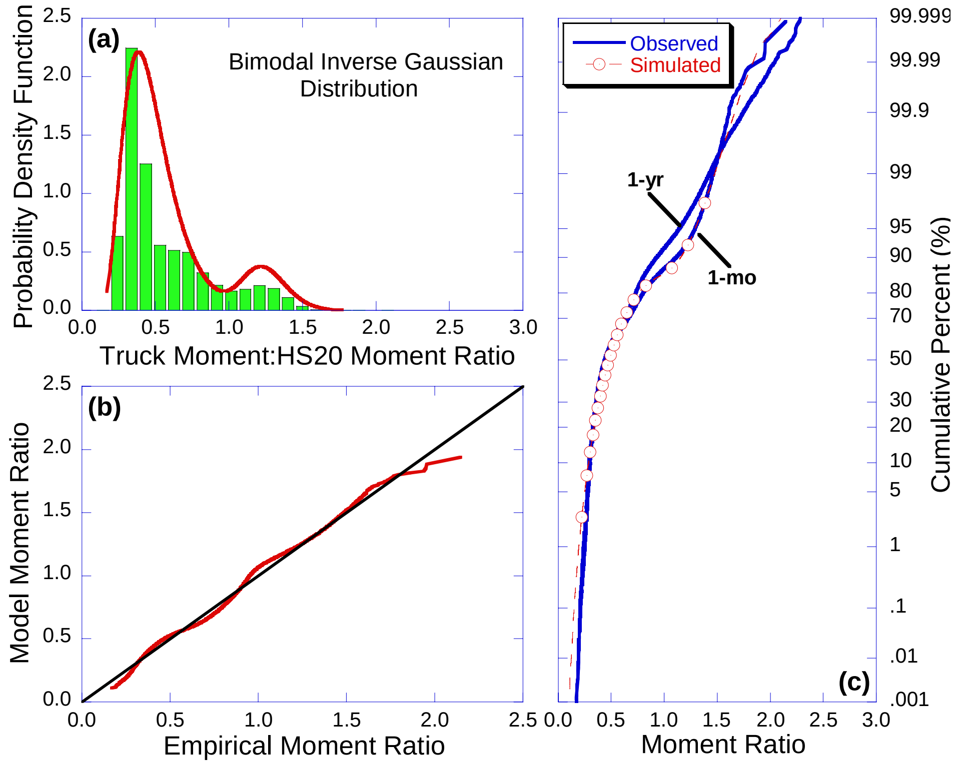


Figure 4: Distribution of the Observed Truck Moment Ratios for Site 195 (a) Fitted Bimodal Inverse Gaussian Distribution (b) Quantile-Quantile Plot of Fitted Distribution (c) Comparison of 12-month Simulated and 1- and 12-months Observed Truck Effects

EXTRAPOLATION

The current edition of the AASHTO LRFD Code (AASHTO 2002) was calibrated based on a 2-week truck weigh survey from Ontario, Canada containing 9,250 records. The data was plotted on NPP and assumed to follow a normal distribution. Return levels corresponding to longer time periods were then estimated based on the expected number of trucks and the inverse normal probability distribution (Nowak 1993 and 1994, Nowak and Hong 1991). Although this approach is relatively straightforward, it relies heavily on the judgment and experience of the researcher and does not provide a measure of the uncertainty associated with future estimates. Additionally, this approach only serves to describe the central region of the data and may not adequately describe the upper or lower tail beahvior.

Conversely, the models of the extreme value theory (EVT), although significantly more complicated, offer a statistically sound, mathematically robust, and objective approach for studying the behavior of maximum and minimum events. EVT has been extensively used to model the occurrence of natural phenomena but has also been recently extended to other areas as well. Two EVT models are considered in this study, namely the generalized extreme value (GEV) distribution and the generalized Pareto distrution (GPD). The GEV distribution models block maxima according to

$$G(z;\mu,\sigma,\xi)=\begin{cases}\exp\left\{-\left[1+\xi\left(\dfrac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}, & \xi\neq 0\\ \exp\left\{-\exp\left[-\left(\dfrac{z-\mu}{\sigma}\right)\right]\right\}, & \xi\to 0\end{cases} \tag{4}$$

defined on $\left\{z:1+\xi\left(\dfrac{z-\mu}{\sigma}\right)>0\right\}$, $-\infty<\mu<\infty, \sigma>0$ and $-\infty<\xi<\infty$, where $\mu, \sigma,$ and ξ are the location, scale, and shape parameters, respectively and z is the block maxima. On the other hand, the GPD model considers only those records that exceed a specified level or threshold (u). The GPD model is given by the following probability distribution function

$$\Pr\{X\geq x \mid X>u\}=\begin{cases}\left[1+\xi\left(\dfrac{x-u}{\sigma *}\right)\right]^{-1/\xi}, & \xi\neq 0\\ \exp\left(-\dfrac{x-u}{\sigma *}\right), & \xi\to 0\end{cases} \tag{5}$$

provided that $x>u$ and defined on $\left\{x:1+\xi\left(\dfrac{x-u}{\sigma *}\right)>0\right\}$, where $\sigma *$ and ξ are the scale and shape parameters, respectively.

Return level estimates for the 1-, 5-, and 10-year periods are estimated using the NPP and EVT models. Figure 5a presents the extrapolations of the NPP using the observed 1-month base dataset (October 1993). It is shown that many different linear extrapolations may be drawn with a maximum error of 33% among estimates and observed values.

In comparison, the EVT model return level estimates are shown in Figure 5b. It is found that, once variability is considered, both EVT models provide accurate return level estimates, with a maximum error of 15%. Additionally, the uncertainty in estimates is shown to increase for levels of longer return periods. This is intuitive since more variability is associated with predicting far-future events (i.e. 10 years) compared with near-future events (i.e. 1 year). It has been found that improved EVT model predictions may be obtained by using at least 5 months for the GEV model and 3 months for the GPD model (Gindy and Nassif).

The effect of using simulated truck records for extrapolation is examined in Figure 5b. A 1-month dataset simulated using the previously described bimodal Inverse Gaussian distribution is used. It is found that the reduced variability in the simulated records, as shown in Figure 4, also translates to reduced variability in return level estimates for both the EVT and NPP models. This is undesirable, especially for predicition of far-future levels, because the true variability in truck traffic is not reflected in the prediction.

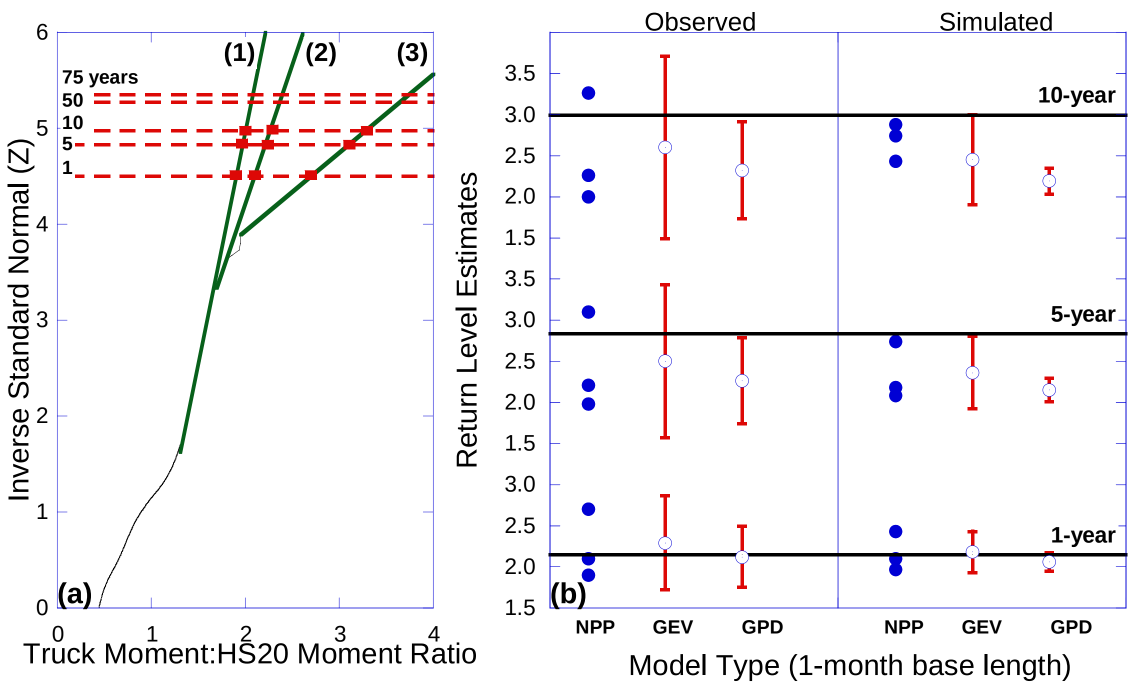


Figure 5: Return Level Estiamtes based on 1-month base period using (a) NPP and (b) EVT

CONCLUSIONS

A WIM database, containing truck traffic information collected from over thirty-three WIM sites over an 11-year period (1993-2003, with some gaps) is used for this study. The database represents a variety of location-specific characteristics and contains approximately one million truck records per month. This extensive database provides a unique opportunity to assess the accuracy of simulation and extrapolation methods and improve the predictive credibility of models for long return periods. Generally, data from 1993 is used as the base dataset and forecast estimates are compared with known 11-year levels.

Truck traffic for the month of October 1993 is statistically analyzed for Site 195. Five dominant vehicle types are identified based on axle configuration, truck use, and axle weight restrictions. Probability distribution of the maximum midspan bending moment ratio is described. It is found that a bimodal Inverse Gaussian distribution with a mixing proportion of 0.87 best describes the observed live load effect. The Monte Carlo method is used to simulate truck records for a 1-year period. Good correlation is observed between the simulated and measured live load effects.

Two very different forecasting methods are considered for estimating the 1-, 5-, and 10-year return levels. The NPP approach proved to be subjective and sensitive to the portion of the data considered during the extrapolation. On the other hand, the EVT approach, although mathematically more complicated, provides estimates in agreement with observed levels. Results also indicate that while simulated records are adequate for predicting near-future levels, they generally underestimate far-future levels. This is because the variability associated with longer return periods is not reflected in the simulation.

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