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Load Truncation Approach for Development of Live Load Factors for Bridge Rating

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Abstract

Various local governments have developed state-specific vehicular live load factors for bridge rating. However, a significant computational demand is often associated with such an effort. This is due to the large size of the weigh-in-motion (WIM) databases frequently used in the procedure. In this study, a method is proposed that can significantly reduce the computational cost of the analysis, while still maintaining reasonable accuracy. The proposed approach develops approximate live load random variable statistics by truncating the WIM database based on gross vehicle weight, then a complete reliability analysis is conducted to develop new live load factors that meet AASHTO-specified rating standards. Two WIM databases, one based on typically legal vehicles and another based on unusually heavy vehicles, are considered for evaluation. Results of the proposed approach are compared to an exact assessment as well as to a simplified method suggested by AASHTO. It was found that the proposed approach may provide very large reductions in computational cost with minimal loss of accuracy, whereas significant inaccuracies were found with the existing simplified approach.

Author Keywords:

Weigh-in-motion, WIM, Gross Vehicle Weight, Bridge, Load model, Rating, Design

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Introduction

In the US, bridge load rating is required by the US Department of Transportation (DOT) to assure that structures within each state inventory are sufficiently safe for vehicular traffic. Bridge rating procedures are specified in the Manual for Bridge Evaluation (MBE) (AASHTO 2018), where rating for design, legal, and permit loads is discussed. Bridge rating has been based on an assessment of structural reliability since 2003 with the publication of the Manual for Condition Evaluation and Load and Resistance Factor Rating (LRFR) of Highway Bridges (AASHTO 2003). The MBE was later released in 2008, replacing the initial LRFR specifications as well as the alternative 1998 Manual for Condition Evaluation of Bridges (based on allowable stress and load factor rating (LFR), which was not reliability-based, but still allowed for use to assess structures designed under older, non-reliability based design provisions (AASHTO 1998). The purpose of the LRFR version was to provide a more consistent level of safety than that achieved under the previous LFR procedure. As part of LRFR calibration, the appropriate vehicular live load statistics used in the reliability assessment to establish live load factors for rating were developed. These factors were later again revised in 2011 (Sivakumar and Ghosn 2011) using weigh-in-motion (WIM) data from truck traffic collected in 2005 and 2006 from six states including New York, Mississippi, Indiana, Florida, and California. The recalibrated MBE rating process was formulated based on a 5-year return period for load rating to achieve a minimum target reliability index (β) of 1.5 for any particular girder, with an average target level of 2.5 across the bridge inventory.

As expected, significant improvement in load modeling over previous versions was achieved due to the use of current (at the time) WIM data. However, the WIM data collected from the six states noted above does not necessarily well-represent traffic data in other states that were not included in the MBE calibration effort. Therefore, various states have initiated efforts to develop unique live load models that better represent traffic data specific to their region. Some of these states include Oregon (Pelphrey and Higgins 2006), New York (Ghosn et al. 2011; Anitori et al. 2017), Michigan (Eamon et al. 2014; Eamon and Siavashi 2018), Missouri (Kwon et al. 2010), and Illinois (Fu et al. 2019) where the live load factors for bridge design and rating were developed based on state-specific WIM data. Similar efforts to better characterize vehicle load effects based on WIM data were conducted by Lee and Souny-Slitine 1998 (Texas) and Tatabai et al. 2009 (Wisconsin).

Although substantially conservative load modeling can be conducted with minimal effort, the cost associated with conservatively rating existing bridges is significantly higher than conservatively designing new structures. While conservative designs may lead to slightly larger component sizes or reinforcement levels, conservative rating may lead to unnecessary posting, rehabilitation, or replacement. Posted bridges that restrict traffic limit commercial vehicles from fully utilizing the transportation network, which may negatively affect local economies. Therefore, DOTs prefer to limit bridge posting as much as possible while not jeopardizing the level of safety.

Various models have been proposed to develop load models for bridge design and rating (Miao and Chan 2002; O'Brien et al. 2010; Nowak and Rakoczy 2013, etc.). Although these various methods of live load model development using WIM data may differ substantially in approach, they each share a significant drawback if accurate results are desired: high computational cost. This is primarily a result of the large database of vehicle records typically used for load effect assessment, which can often range from tens to hundreds of millions of vehicles (Sivakumar and Ghosn 2011, Nowak and Rakoczy 2013; Eamon et al. 2014, Eamon and Siavashi 2018). Each truck record in the database, representing a unique multi-axle configuration, is typically analyzed for the maximum load effects that it causes across multiple bridge spans and in some cases different bridge types. At present, a considerable amount of WIM data is available from numerous states. Although utilizing a large database may increase load modeling accuracy, it correspondingly increases computational cost. Although not theoretically problematic, this computational cost may render WIM-based solutions undesirable, if not practically inaccessible, depending on the time and resources available.

Various studies has proposed the use of gross vehicle weight (GVW) as a surrogate for a more rigorous analysis of vehicular load effects, such as for development of simplified methods to estimate load factors (Fu and Hag-Elsafi 2000; Moses 2001), as well as an indicator of the magnitude of load effect (O'Brien and Enright 2012), among others. In this study, a different approach is proposed, where the objective is to develop an approximate live load random variable based on selectively eliminating the large majority of vehicles from the WIM database based on GVW. Using the approximate live load random variable, a full reliability assessment is then conducted to establish live load factors for rating. To illustrate the proposed approach, an example state-specific analysis is conducted to determine live load factors for the Strength I limit state (i.e. normal use vehicles, such as legal and routine permit) within the framework of the AASHTO MBE.

WIM Data Considered

Prior to load effect analysis, a WIM database for consideration must be identified. For evaluation of the method proposed in this study, data from twenty WIM stations in the State of Michigan were used. The WIM stations selected record data at a frequency of 1,000 Hz, a sampling rate that can accurately capture vehicle configurations and relative vehicle positioning. Data were collected with quartz piezoelectric sensor systems permanently embedded in and flush to the roadway surface. The system consists of weight sensors and inductive loops placed on either side of the sensors. The loop before the sensors detects a vehicle and activates the WIM system, while the loop after the sensors tracks the time that vehicle axles cross between the loops, information which is used to determine vehicle speed and axle spacing. Each lane has its own sensor system, which are linked together to record simultaneous multiple lane events. WIM stations are monitored and periodically calibrated to test vehicles of known axle weight and configuration by DOT personnel to ensure accuracy. During this calibration process, possible dynamic effects are removed such that the pseudo-static axle weights are captured. Sixteen of these sites are on major interstate routes (I-94, I-69, I-75, and I-96) while four are on lower-volume state highways (US-127, US-2, and M-95). The data were collected for 34 months from February 2014 to January 2017 (excluding April and May 2014, which were unavailable). The average daily truck traffic (ADTT) varied from approximately 360 to 16,500 with ten stations greater than 5,000, five stations with roughly 3,500, three near 1,500, and two with approximately 400 ADTT. Each WIM station automatically filters noncritical lightweight vehicles with GVW less than 67 kN from the database, resulting in approximately 101 million vehicle records. However, due to possible errors in WIM data collection, additional data filtering was used to remove potentially erroneous records from the database. These filtering criteria included feasible limitations on axle spacing, weight, speed, and length (Eamon and Siavashi 2018). A typical frequency histogram of GVW is primarily bi-modal, with peak frequencies at approximately 334 kN and 156 kN, which represent the most common loaded and unloaded 5-axle truck weights in Michigan. Nearly all sites are represented with similar multi-modal frequency plots, though peaks shift somewhat as a function of differences in local traffic density. Approximately 80% of trucks at all sites were of the five-axle (3S2) type. To further confirm the reasonableness of the WIM data, various checks were implemented as recommended in NCHRP 683 (Sivakumar et al. 2011), such as comparing the GVW frequency histograms, mean and modal axle spacing, GVW, and axle weights to generally expected values (Eamon and Siavashi 2018). These quality checks reduced the database to approximately 89.5 million. The database was then further analyzed to consider only state (Michigan) legal and routine (annual or extended) permit vehicles which are used by Michigan Department of Transportation (MDOT) for Strength I limit state evaluation (i.e. normal use of the bridge) within the legal load rating framework. As discussed in further detail below, Strength I live load statistics are correspondingly based on this pool of legal and routine permit vehicles, although no specific limit is imposed on the probability density model and thus the possibility of sampling a vehicle exceeding the legal limit in the subsequent reliability analysis is maintained. Following the MBE calibration approach, it is assumed that even heavier vehicles (i.e. special permit and potentially extreme illegal overloads) are to be accounted for in the Strength II limit state. A summary of the criteria used to categorize a record as MI-Legal or Extended Permit vehicles (MI-LEP) is given in Table 1. Approximately 88.9 million vehicles fell into this category. As Michigan has unusually high legal vehicle weights, up to approximately twice the Federal limit for some configurations, a vehicle pool representative of most other states that follow the Federal limit was also developed. This alternative database was created by imposing more restrictive limits based on the Code of Federal Regulations Part 658.17 (1994), which represents a simplified version of the axle weight and spacing rule commonly known as the “Bridge Formula”. This is labeled in Table 1 as the “Simplified CFR” category. Approximately 78.4 million vehicles fell into this group. From the different data pools as described above, load effects (maximum moments and shears) were calculated by incrementing the measured vehicles across hypothetical simple bridge spans (from 6-60 m in length) in increments of 300 mm.

Correlation of Vehicle Parameters and Load Effect

Once load effects are determined for the entire vehicle database of interest, the typical approach used for load factor development is to form the cumulative distribution function (CDF) for a particular bridge span and load effect of interest. Then, various approaches are available to estimate the statistical parameters (typically limited to the first two statistical moments; mean and standard deviation) from the CDF needed to characterize the maximum load effect as a random variable representing a return period of interest, which is taken as 5 years for Strength I rating in AASHTO MBE (AASHTO 2018). This live load random variable is then used in a reliability analysis to obtain the required rating live load factors, as described in more detail below. In most procedures used to develop the live load random variable statistical parameters, only the very upper tail of the load effect CDF is used, which might range from 20% to less than 1% of the data, depending on the approach (Moses 2001; Sivakumar et al. 2011; Nowak and Rakoczy 2013, Eamon et al. 2014, Eamon and Siavashi 2018). As such, the large majority of vehicle load effects that are calculated are not needed. This represents a considerable waste of computational effort. For example, to calculate vehicle moments for a single bridge span of 18 m using the database of 89 million MI-LEP vehicle records discussed above required approximately 45 hours on a modern personal computer (Intel Core i7 2.7/3.6 GHz CPU with 32 GB of RAM). Realize this analysis must be repeated for various different bridge spans, different bridge types in some cases, and for shear effects as well, resulting in a rather substantial computational effort requirement. If the number of vehicles considered could be reduced to only those that will form the upper tail of the load effect CDF used for the live load model, say, to 1/10th of the original database, this time would be similarly reduced to approximately 1/10th of that originally required, representing a substantial savings of computational effort.

With regard to computational demand, here it should be noted that there are three types of vehicle positioning scenarios to be considered: a single vehicle on the bridge; multiple vehicles in a single lane ("following" vehicles); and vehicles in more than one lane (multiple-lane load effects). In practice, single and following vehicle effects are combined to construct a database of single lane load effects, then two types of load effect analysis are conducted: one for the single lane loaded case and the second for the multiple lane loaded case. Although a bridge may have many lanes of traffic, the MBE calibration, and hence the comparisons presented in this study, consider up to two-lane effects, which encompass the most probable multi-lane events and for which most WIM data are available. Both analyses are required for all hypothetical structures considered to develop final live load factors as there is often no clear pattern, in terms of bridge span and girder spacing, as to which type of load effect (i.e. one-lane or two-lane) will govern. With regard to computational effort, the single-lane, single vehicle load effects are of most concern, as these typically make up the vast majority of load effects generated. Although proportions vary with bride span, ADTT, location, and classification method, various studies have found that single vehicle effects make up greater than 95% of load effects in most instances (Sivakumar et al. 2011, Eamon et al. 2014, Eamon and Siavashi 2018). For example, for the MI-LEP database mentioned above, considering the 6-60 m span range, the ratio of multiple presence vehicles to single vehicles was approximately 1:70 to 1:1000 (with longer spans having a greater likelihood of multiple presence). Such results are typical. Therefore, this study is focused on reducing the computational effort only related to single vehicle load effects, although it would be possible to apply the proposed method to multi-lane data as well in the same manner that it is applied here to one lane load effects.

To reduce computational effort, the relationship between single vehicle load effect and directly available vehicle parameters within the WIM data can be studied, to determine if such a parameter can be used to include only the vehicles which will have significant impact on the load effect statistics. This approach could thus eliminate the need to compute load effects for the large majority of vehicles. An obvious parameter to consider is GVW. However, although it may appear intuitive that only the heaviest trucks are important, the effectiveness of using GVW as a direct surrogate for load effect is quantitatively unknown. One complication is the effect of vehicle length, where heavier vehicles are often longer, and may produce lower load effects than a lighter, shorter vehicle. Another factor is bridge span length, where the effect of vehicle length may be expected to become less important as span length increases. As such, the vehicle parameters selected for consideration were: GVW; length; number of axles; GVW/length; and GVW x length. These parameters are either directly available from the WIM data or readily calculated from two available parameters with minimal computational effort. The correlation coefficient (ρ) of each of these parameters to load effect was computed across various span lengths for the MI-LEP and Simplified CFR vehicle databases described above. Results for moment effects are shown in Figures 1 and 2. Shear results are nearly identical and are thus not shown.

As shown in the figures, in general, as span length increases, the correlation between load effect and all considered parameters except GVW / length increases. GVW is shown to have the highest correlation, with values varying from about 0.9 to nearly 1.0 for both vehicle databases. As these values of ρ are high, the use of GVW to eliminate a large portion of vehicles from consideration appears promising. In fact, a simplified method to estimate live load factors for rating based on GVW is already given in the MBE, based on NCHRP 454 (Moses 2001), and is taken as (for single lane loading):

$$\gamma_L = 1.8\left[\frac{W^*+t_{(ADTT)}\sigma^*}{120}\right] \geq 1.80 \qquad \text{Eq. 1}$$

where W^* and σ^* are the mean truck weight and standard deviation of the top 20 percent of the vehicle sample (kips), and $t_{(ADTT)}$ is a fractile value appropriate for the maximum expected loading event, taken as 4.9, 4.5, and 3.9 for ADTT values of 5000, 1000, and 100, respectively. The accuracy of this existing AASHTO method, however, is not clearly documented. The effectiveness of the AASHTO approach, as well as the alternative approach proposed in this study, is later quantified.

To clarify the difference between the "exact", AASHTO, and proposed approaches for live load factor development, first consider the exact procedure. In the exact method, load effects from all vehicles in the appropriate WIM database are first computed. As noted above, a different set of load effects is needed for each span length considered in the analysis. Once all load effects are computed for a given span, the CDF of load effects for that span is formed. For rating, from this CDF, the mean maximum load statistics for a 5-year return period are developed. As noted above, alternative procedures are available to do this. An investigation of these various possibilities is beyond the focus of this study. However, a common method that was used in the reliability calibration of the MBE (Sivakumar and Ghosn 2011) as well as in subsequent studies (Sivakumar et al. 2011, Eamon et al. 2014, Eamon and Siavashi 2018) models the live load using extreme value theory. This model can be accurately used if the extreme (high) values of the load effect CDF well-fit a normal distribution. If so, the mean maximum load effect ($\bar{L}_{max}$) and its standard deviation ($\sigma_{L\,max}$) are given as:

$$\bar{L}_{max} = \mu_N + \frac{0.5772157}{\alpha_N} \qquad \text{Eq. 2}$$

$$\sigma_{L\,max} = \frac{\pi}{\sqrt{6}\,\alpha_N} \qquad \text{Eq. 3}$$

where

$$\mu_N = \bar{x} + \sigma\left(\sqrt{2\ln(N)} - \frac{\ln(\ln(N)) + \ln(4\pi)}{2\sqrt{2\ln(N)}}\right) \qquad \text{Eq. 4}$$

$$\alpha_N = \frac{\sqrt{2\ln(N)}}{\sigma} \qquad \text{Eq. 5}$$

In these expressions, N is the total number of trucks expected during the return period (i.e. in 5 years) and $\bar{x}$ and σ within Eqs. 4 and 5 are found from the slope (m) and intercept (n) of a line fit to the upper tail of the CDF when plotted on normal probability paper (i.e. when the vertical axis is taken as the inverse standard normal CDF), where parameters $\bar{x}$ and σ are given by $\bar{x} = -\frac{n}{m}$ and $\sigma = \frac{1-n}{m} - \bar{x}$, respectively. For illustration, example CDFs for simple moments considering the very heaviest vehicles (top 0.1%) of the MI-LEP database for spans of 6-60 m and accompanying best-fit regression lines suitable for use in Eqs. 2-5 are shown in Figure 3. The resulting vehicle load statistics ($\bar{L}_{max}$ and $\sigma_{L\,max}$) are then used along with other load effect uncertainties, as discussed further below, to form a random variable for live load which can be used in reliability analysis to determine appropriate live load factors for rating.

In contrast, the AASHTO approach (Eq. 1), represents a substantial computational savings from the exact approach, as no load effects need to be calculated, nor does any reliability analysis need to be conducted; only the mean and standard deviation of the top 20% of GVW of vehicles in the database are computed. As quantified later, however, as perhaps expected, some accuracy concerns exist with this simplified approach. Here it should be noted that although Eq. 1 appears in the MBE, it was not used in the latest calibration effort and does not necessarily produce load factors representing the currently intended level of reliability. Rather, it was the exact procedure (i.e. using “all” WIM data) that was used to determine target reliability levels and set corresponding load factors. As discussed in the MBE, although Eq. 1 is offered as an alternative to reduce computational effort for site-specific cases (as further discussed below), intended reliability targets are achieved with the exact approach, and it was thus recommended for state-wide use (AASHTO 2018; Sivakumar and Ghosn 2011).

The alternative approach proposed in this study follows the same framework of the exact approach. The only difference is the number of vehicles used to calculate load effects that are used to form the CDF. Rather than use the entire vehicle database, load effects are computed only from the heaviest vehicles. Here, regardless of the size of the reduced database, the fundamental requirements of the extrapolation procedure described above are maintained in all cases; i.e. a best-fit regression line is fit to the upper linear tail of data (where the length of the tail may vary, depending on the proportion of data on the CDF that are linear in standard normal space), then Eqs. 2-5 are used to estimate vehicle load effect statistics. Because other vehicle characteristics such as vehicle length, axle spacing, and axle weight influence load effect, basing the load effect CDF only on maximum GWV vehicles is an approximation. The effectiveness of this approximation, based on what proportion of maximum GWV vehicles are considered, is quantified later in this study. It should be noted that the reliability analysis (which requires a separate analysis for each girder type, spacing, and span length considered) used in the exact and proposed approaches actually involves an insignificant amount of effort, in terms of computational time, beyond the AASHTO approach (less than several seconds for the entire reliability analysis for all cases). Rather, it is the calculation of load effects needed to form the CDF which requires the vast majority of computational effort.

Reliability Analysis

For the exact and proposed procedures, a reliability analysis is required to determine rating load factors. These factors, the ultimate product of interest, will be used to compare the accuracy of the three alternate methods considered (exact, AASHTO, proposed). For comparison, the analysis was conducted for bridges which make up the majority of most state inventories: those that are constructed of composite steel and prestressed concrete I-girders, prestressed concrete box beams (both spread and side-by-side), and reinforced concrete girders. Simple span structures of these girder types were analyzed with spans from 6 to 60 m at increments of 6 m for all girders except for reinforced concrete, which is limited to 30 meters. Girder spacing was varied from 1.2 to 3.6 m at 0.6 m increments, while for side-by-side box beams, two widths (0.9 m and 1.2 m) were considered. Bridges were assumed to support a 230 mm thick reinforced concrete deck, 65 mm wearing surface, and additional typical nonstructural items (primarily barriers and diaphragms) relevant to dead-load calculation. Thus, considering all combinations of length (10) and girder spacing (5) increments results in 50 geometries each for prestressed concrete, steel, and spread box beam bridge types; 25 for reinforced concrete; and 20 side-by-side box beams, for 195 cases. The range of these geometries and types covers nearly all girder bridges in the state of Michigan as well as other state inventories. Although the consideration of alternative designs, such as non-girder type bridges, longer spans, curved or skewed decks, and other features are important, such structures represent somewhat unique cases not directly considered in the MBE calibration, and are thus beyond the scope of the comparisons presented here. Moreover, it is not currently possible to assess potential differences between the methods compared in this study considering many of these bridge features, since WIM data are generally taken from stations placed on the roadway rather than directly on bridge decks. Thus, the effects that many interesting features of bridge geometry (such as curvature, skew, etc.) might have on traffic pattern are typically not available. However, the authors would currently propose no adjustment to the method proposed in these circumstances.

Random variables used for reliability assessment are girder resistance *(R)*, dead load, and live load. Dead load includes prefabricated (D_p) site-cast (D_s) and deck wearing surface (D_w) components, while live load consists of vehicle live load *(L_{max})* and dynamic load *(I_M)*. In addition, uncertainty in the distribution of vehicular live load to an individual girder is considered *(DF)*. Bias factor (ratio of mean to nominal value) and coefficient of variation (COV) of these random variables are presented in Table 2.

The live load random variable statistical parameters are not only a function of the uncertainty in projected maximum vehicle load effect, characterized here by coefficient of variation $V_{projection}$, with parameters determined by Eqs. 2 and 3 (where $V_{projection} = \frac{\sigma_{L\,max}}{\bar{L}_{max}}$), but other uncertainties as well. These uncertainties include those of site location (V_{site}), characterizing the variation in mean maximum load effect from one site to another; the dynamic load effect, (V_{IM}), taken as 9% for one lane effects (Sivakumar et al. 2011); the uncertainty in WIM data collection at a particular site (V_{data}), taken as 2% for the database considered (Eamon and Siavashi 2018); and uncertainty in vehicular live load distribution to the girder (V_{DF}), which varies as a function of girder type as shown in Table 2 (Sivakumar et al. 2011). The resulting COV of total live load effect can be thus approximated as:

$$V_{max\,L} = \sqrt{V_{projection}^2 + V_{site}^2 + V_{data}^2 + V_{IM}^2 + V_{DF}^2} \qquad \text{Eq.6}$$

This final value was found to vary from 0.16-0.30, depending on the bridge type and vehicle database considered.

With the exception of live load, all random variable statistical parameters used in the AASHTO LRFD (Nowak 1999) and MBE calibrations (Sivakumar and Ghosn 2011) are used in this study. To be consistent with the reliability model used in these previous calibration efforts, it is also assumed that girder resistance is lognormal whereas the sum of load effects is taken as normally distributed.

Once random variables are defined, the general limit state function g_i for each bridge girder i can be written as:

$$g_i = R - (D_p + D_s + D_w) - DF(L_{max} + I_M) \qquad \text{Eq. 7}$$

with random variables D_p, D_s, D_w, DF, I_M, and L_{max} defined above. Limit states are formed for simple span load effects for moment and shear.

The minimum requirements of acceptability need to be identified in order to establish nominal values for girder resistance R to be used in the reliability analysis. In the case of rating, the rating factor is the metric used to determine the minimum level of acceptability (i.e. if rating factor is ≥1.0, no traffic restriction is required). In the MBE, rating factor (RF) is defined as:

$$RF = \frac{\phi R_n - 1.25DC - 1.5DW}{\gamma_{LL}(LL + IM)} \qquad \text{Eq. 8}$$

In Eq. 8, resistance factor ϕ varies as a function of girder type and failure mode; R_n is the nominal resistance of the component; DC and DW are respectively the dead loads of the structure and the wearing surface; LL is the rating vehicle live load effect; IM is specified as 0.33*LL; and γ_{LL} is the rating vehicle load factor. Note that the parameters given in Eq. 8 can be calculated according to the MBE specifications based on the bridge geometry and other code-specified factors. The uncertainties in these parameters are represented as random variables in the limit state function. In particular, uncertainties in nominal resistance R_n and weight of the wearing surface

DW in Eq. 8. are represented by directly corresponding random variables R and D_w in Eq. 7. The remaining dead load effect *DC* in Eq. 8 is represented as the sum of two random variables D_p and D_s, and the live and dynamic load effects on the girder *LL* and *IM* are represented by random variables L_{max} and I_M, respectively, in addition to a random variable accounting for the uncertainty in load distribution to the girder, *DF*.

Considering legal and routine permit vehicles, the MBE considers two limits for target girder reliability index β: a minimum of β =1.5 for any girder as well as an average of β =2.5 across all girders in the inventory. Both limits are applied to the specific case when RF = 1.0 which represents the boundary of acceptability (i.e. just before traffic requires restriction). Therefore, by setting RF = 1.0 in Eq. 8 and solving for R_n, the required nominal resistance at these target reliability levels can be determined as follows:

$$R_n = (1/\phi)(1.25DC + 1.5DW + \gamma_{LL}(LL + IM)) \qquad \text{Eq. 9}$$

In Eq. 9, R_n can be found from the dead load (*DC, DW*) and live load (γ_{LL}, *LL, IM*) effects. Once R_n is found, using the bias factors λ shown in Table 2, the mean value $\bar{R}$ of the girder resistance random variable R can be calculated ($\bar{R} = \lambda \times R_n$). As a result, the reliability index associated with the limits state given by Eq. 7 can be computed. Note that, as typical for code calibration efforts, the target reliability indices developed for the MBE (i.e. β = 1.5, 2.5) are notional values calculated based on various simplifying and often highly conservative assumptions, and are used for calibration purposes only. That is, the corresponding theoretical failure probabilities (i.e. $p_f = \Phi(-\beta)$) should not be thought to represent actual bridge girder safety levels.

As mentioned earlier, this study concerns reducing the computational effort required to develop a live load model using WIM data while maintaining an acceptable level of accuracy. Developing a live load model may involve forming a new nominal rating vehicle and associated load effect (*LL*), new live load factors for existing rating vehicles (γ_{LL}), or both. Regardless of the approach taken, in this process, the total live load effect needed to be produced by the rating model ($\gamma_{LL}(LL+IM)$) begins as an unknown. However, since the target reliability index limits are known (minimum of 1.5 and average of 2.5), the minimum value of $\gamma_{LL}(LL+IM)$ needed to produce an R_n (and in particular, the mean value of *R*) that will satisfy the reliability target can be established. For convenience, the quantity $\gamma_{LL}(LL+IM)$ is referred to as the required load effect (RLE) in this study. In other words, RLE is the total load effect required by the live load rating model such that for any girder, when RF = 1, a minimum reliability index of 1.5 for any girder, with an average of 2.5, is met. Note that the RLE is a deterministic factor used to represent the total live load effect in the AASHTO rating equation (Eqs. 8, 9); it is not itself a random variable nor does it appear in the limit state function (Eq. 7), although uncertainties in load components *LL* and *IM* within the RLE are represented by individual random variables L_{max} and I_M in the reliability analysis.

The reliability process is summarized as follows. First, based on values used for similar bridges considered in the previous reliability-based AASHTO code calibration efforts, nominal and mean (using the bias factors given in Table 2) values for dead load random variables (D_p, D_s, D_w) and live load distribution factor (*DF*) are calculated for a selection of typical bridge designs.

Second, the mean value of *R*, needed for reliability analysis, is expressed as $\bar{R} = \lambda \times R_n$, where R_n is given by Eq. 9 and bias factor (λ) given in Table 2 for the type of girder and failure mode considered. Note that R_n, and as a result $\bar{R}$, is a function of the unknown RLE value ($\gamma_{LL}(LL+IM)$).

Then, by setting the required reliability target to 1.5 for a given girder and considering the limit state function given by Eq.7, reliability index becomes a function of random variables R, D_p, D_s, D_w, DF, I_M, and L_{max} within Eq. 7 (where the precise relationship depends on the specific reliability analysis method chosen) Note that the mean girder resistance $\bar{R}$ remains a function of the unknown RLE. Finally, since the reliability index is known in the calculation of β, the RLE, which is the only unknown, can be solved for. Therefore, the live load effect that meets the minimum reliability target and needed to be produced by the rating live load model (RLE) can be established. From all results, the average reliability index is then computed to check this second requirement ($\beta_{ave} \geq 2.5$).

Due to the large number of bridges considered in this study, the reliability analysis was conducted using the closed form first-order, second moment (FOSM) procedure, such that reliability index (β) can be computed directly. The FOSM method assumes all random variables are normal, which typically produces conservative assessments of reliability when resistance is lognormal as in this study. However, Eamon et al. (2016) found that when reliability index approaches 1.5, no significant difference exists between the FOSM and exact solution when the limit state function and random variable parameters discussed above are considered. For verification, a sample of girder reliability indices were computed with Monte Carlo Simulation (MCS) with $1\text{x}10^6$ simulations. It was found that the indices estimated with the FOSM approach within 1% of the "exact" MCS values. For other problem types, alternative efficient reliability algorithms can be considered (e.g. Acar et al. 2010).

Using this typical process for rating live load model development, the effect of reducing the size of the vehicle database based on GWV; i.e. the proposed approach, will be compared to results of the exact approach using all vehicle data, as well as results of the AASHTO simplified procedure.

Effect of Data Reduction on Live Load Random Variable Statistical Parameters

The purpose of the proposed approach is to reduce computational effort by computing load effects for only a portion of the total vehicle database. A key issue to be addressed is how much of the database can be practically removed while maintaining acceptably accurate results.

As discussed earlier, reducing the amount of data used to generate load effects will alter the statistics of the live load random variable used in the reliability analysis needed to develop live load factors for rating. Altering the data pool will affect the following statistical parameters: the mean maximum live load effect ($\bar{L}_{max}$); coefficient of variation of the mean maximum load ($V_{projection}$); and the coefficient of variation with respect to WIM site location (V_{site}); see Eqs. 6 and 7.

Using the two databases described earlier (MI-LEP and Simplified CFR), various portions of vehicle data were removed such that the top 50, 20, 10, 5, and 1 percent of single vehicle records by GVW were retained. The load effects from these reduced single vehicle pools were then calculated, and combined with all load effects constituting multiple vehicles in the same lane (i.e. the "following" vehicle effects) to produce reduced databases of single lane load effects, as is typically done. Recall from the discussion above that the following vehicle load effects, as well as multiple-lane load effects generally account for only a very small proportion of the total load effects, and thus these are not of interest in this study for consideration of alteration to reduce computational effort. Once the reduced single lane load effects were calculated, the three affected live load random variable statistics ($\bar{L}_{max}$, $V_{projection}$, V_{site}) were similarly recomputed and used to determine $V_{max\ L}$ (Eq. 6), the total variation in live load effect. $V_{max\ L}$ results for the reduced datasets are shown in Figures 4 and 5 for MI-LEP vehicles and are compared to the unreduced database ("All"). Note that for construction of these figures (but not in subsequent reliability calculations, where the exact values are used), from the range of possible values for V_{DF} given in Table 2, V_{DF} is taken as the minimum possible in all cases (0.11, which actually only corresponds to the shortest 6 m span which allows for the resulting $V_{max\ L}$ value to become most sensitive to changes in the potentially altered parameters $V_{projection}$ and V_{site}.

As shown in the figures, for all data considered, $V_{max\ L}$ decreases as span increases. This result is typical (Nowak 1999, Sivakumar and Ghosn 2011, Kamjoo and Eamon 2018), and occurs because load effects on smaller spans are more sensitive to variations in truck axle spacing and weights. Consistent across all span lengths, however, for both moment and shear, $V_{max\ L}$ was found to slightly increase as the dataset is reduced. This is a result of a combination of a decreasing $V_{projection}$ and increasing V_{site} as the data are reduced, with the increase in V_{site} slightly dominating. Here $V_{projection}$ decreases for a particular site because there is less variability in the remaining data as the wider range of (lighter) load effects are removed. Conversely, V_{site} increases because removing these lighter vehicles, which are common to all sites, emphasizes differences in the remaining heavy vehicles between sites due to local traffic patterns (for example, one site may be close to a gravel pit or an industrial center, resulting in a certain type of heavy vehicle and accompanying load effects not reflected at another site). However, the resulting difference in $V_{max\ L}$ is so small (with a typical increase factor in $V_{max\ L}$ of 1.01 and maximum increase factor of 1.04) that it is inconsequential. Similar results were observed for the simplified CFR dataset (not shown for brevity).

More significant is the effect of data reduction on mean maximum load effect, $\bar{L}_{max}$ (Eq. 2). The ratio of $\bar{L}_{max}$ for a reduced dataset to the exact case using all data ($\bar{L}_{\max r}/\bar{L}_{\max e}$) for the

MI-LEP and Simplified CFR databases for moment and shear are given in Figure 6. As shown in the figure, for all cases, reducing the data set results in an over-estimation of $\bar{L}_{max}$. This is not surprising, as the reduced database becomes more severely biased towards heavier vehicles as it is reduced. In general, the degree of over-estimation increases as span length increases. As shown in the figure, for both databases and load effects, depending on span length, the $\bar{L}_{\max r}/\bar{L}_{\max e}$ ratio ranged from 1.0-1.02 when reducing the data to 50%; 1.0-1.04 when reduced to 20%; 1.0-1.06 when reduced to 10% and 5%; and 1.0-1.07 when reduced to 1%. Thus, when using only 1/100th of the original database, at most, a 7% overestimation of mean maximum load effect was found.

Effect of Data Reduction on Required Load Effect and Girder Reliability

Of primary concern is how using a GVW-reduced database will affect the ultimate product of interest, the required live load effect (RLE) to be used for rating; i.e. the quantity $\gamma_{LL}(LL+IM)$ in Eq. 9, and the corresponding computed reliability levels of the bridge girders. Using the revised live load random variable statistical parameters discussed above, RLE values were recomputed for the reduced data set cases. Ratios of the RLE for the reduced data to the exact (i.e. all data) case, (RLE_r / RLE_e), are given in Table 3. Note that if the vehicle model itself is left unchanged, as is typical, the (RLE_r / RLE_e) ratio represents the fractional increase in the live load factor (γ_{LL}). As seen in the table, the (RLE_r / RLE_e) ratios are all greater than unity. This implies that the RLE values, or practically, the live load factors γ_{LL} calculated using the reduced data sets produce conservative results. Given that both live load random variable statistics $V_{max\,L}$ and $\bar{L}_{max}$ increase for the reduced data sets, this result is inevitable. This is because increasing either parameter results in an under-estimation of the true reliability index, requiring an increase in live load factor γ_{LL} to restore reliability index to the minimum acceptable level.

Table 3 provides values for the minimum, maximum, and mean ratios from the 195 bridge girder cases described earlier. As shown in Table 3, the average RLE_r / RLE_e ratio of all cases using datasets reduced to 10% varies from 1.02 – 1.07. Note that in some cases, the maximum ratio found from any of the cases is quite high; for example, again considering the 10% dataset, the Simplified CFR vehicles produces a maximum ratio of 1.19 (this occurs for the case of a 18 m reinforced concrete girder (3.6 m spacing); other high ratio cases that approach this value are a 54 m prestress concrete I-girder (1.2 m spacing) as well as spread box beam spans greater than 30 m. Although few in number and conservative, these outlying cases appear to be significantly discrepancies, perhaps unacceptable. Due to how rating models are typically implemented in common practice, however, using load factors rather than girder-specific RLE values, the actual deviation from using the exact dataset is actually much smaller. This issue is discussed in further detail below.

The resulting minimum, maximum, and mean rating reliability indices of the girders are given in Table 4. These are computed using the RLE_r values found from the GWV-reduced data pools to rate the girders, then assessing reliability using the exact live load statistics found from all of the data. Thus, the values in Table 4 indicate actual resulting rating reliability indices if the GVW-reduced data were used to develop the load model. As shown, as the data used to construct the live load random variable is reduced, results become more conservative and the actual reliability index increases. Also shown on the table is the resulting reliability index if the suggested AASHTO approach (Eq. 1) is used. That is, girders are rated by calculating the mean and standard deviation of the top 20% of GVWs and then the load factor (γ_{LL}) found from Eq. 1 is applied to develop the RLE ($\gamma_{LL}(LL+IM)$). As shown, results are extremely conservative, in most cases greatly exceeding the minimum required reliability target of 1.5. Here the "mean" results in Table

4 may appear problematic, as the MBE specifies a minimum reliability target of 1.5 for any case, but that the average of all cases should be no lower than 2.5. For the best comparison of the effect of the reduced data sets, this average limit was not imposed in the solutions presented in Tables 3 or 4 (imposing the higher average limit would obscure the differences in results between the sets). A more practical comparison based on how rating models are commonly implemented is given in the section below, in which both the minimum and average MBE criteria are met.

Effect of Data Reduction on Load Factors

The previous comparisons shown in Tables 3 and 4 were based on theoretically ideal, girder-specific RLE values. That is, the effect of using the reduced database was compared to an exact case where different RLE values were specifically computed for each individual girder. In practice, this ideal result would amount to using a different load model or load factor that was developed specifically for each bridge girder. Although useful for theoretical assessment, in practice, this approach, and the corresponding resulting discrepancies, is unrealistic. Thus, rather than using ideal RLE values that are girder-specific, as in the previous comparisons, here the effect of reduced data sets on generalized rating live load factors is considered. In a typical DOT rating model, similar to design, a constant live load factor γ_{LL} is used to rate all girders in the bridge inventory. To determine the appropriate inventory-wide rating live load factor, first girder-specific live load factors are determined. These are found by calculating the rating vehicle load effect (*LL*) specific to each hypothetical girder considered, then determining the needed live load factor γ_{LL} to be used such that the RLE ($\gamma_{LL}(LL+IM)$) is met such that no girder has a reliability index less than 1.5, and the average reliability index of all cases considered is no less than 2.5. The maximum of all girder-specific γ_{LL} values needed for any girder to meet $\beta \geq 1.5$ is then chosen to be used with the rating vehicle(s) for all girders, provided that the required average $\beta_{ave} \geq 2.5$ is met.

Clearly, imposing the single governing load factor on all girders will provide a conservative rating for all types of girders except the single governing case. Minimizing this conservatism can be accomplished by refining the rating vehicle model (*LL*) to better match the RLEs, a topic which has been addressed elsewhere (see Siavashi and Eamon 2019, for example). However, to examine results using the reduced datasets, the above procedure is followed to determine the required live load factor (γ_{LL}). In this analysis, existing rating vehicles are used for the live load effect (*LL*), which are taken to be those currently used by MDOT (Curtis and Till 2008, MDOT 2009) for the MI-LEP database and the AASHTO rating vehicles described in the MBE for the Simplified CFR database. These results are given in Figure 7. Note that the figure provides different required load factors for moment and shear, but the single governing factor for either would be used in practice. Also shown in the figure are the load factors found from using the suggested AASHTO procedure (Eq. 1). As expected based on previous results, it was found that a higher load factor resulted as the datasets were reduced. Reducing the dataset to 10% of the heaviest vehicles resulted in a ratio of reduced to exact live load factors ($\gamma_{LL\ r}$ / $\gamma_{LL\ e}$) of 1.05 and 1.04 for moment and 1.04 and 1.03 for shear for the MI-LEP and Simplified CFR databases, respectively. Only using 1% of the heaviest vehicles in the database resulted in ($\gamma_{LL\ r}$ / $\gamma_{LL\ e}$) ratios of 1.10 and 1.06 for moment and 1.06 and 1.05 for shear for the two respective databases. In contrast, the AASHTO procedure produced load factor ratios of 2.67 and 1.36 for moment and 2.06 and 1.03 for shear for the two databases. It should be again noted that the load factors shown in Fig.7 include results only from the single-lane load effects, and thus represent worst-case discrepancies using the reduced data sets. That is, because some of the bridge geometries considered are governed by two lane load effects, and the proposed reduction method does not affect two lane results, the final load factor, taken as the maximum of either the single lane or two-lane load effect, may in fact be completely unaffected. Whether this may occur or not is database dependent. For example, considering the MI-LEP database, approximately 58% of the girder cases for moment and 13% of the cases for shear were dominated by two-lane effects. From these results, it was found that the two-lane 6 m side-by-side spread box (0.9 m width) load factor governed overall for shear and the one-lane 6 m side-by-side spread box (0.9 m width) governed for moment, resulting in maximum load factors of 1.07 for shear and 1.11 for moment, respectively. Also note that, although moment and shear load factors are separated for illustration in the figure, the single governing load factor for moment or shear would be used in practice (and thus in this case, the single-lane effect dominated overall). The reliability indices associated with the use of the inventory-wide load factors given in Figure 7 are shown in Table 5. Notice in the table, that even using the exact procedure that considers all data, a large variation in reliability among the different girder cases exists. A large variation is not atypical (Nowak 1999, Kamjoo and Eamon 2018), and is due to an inadequacy of the existing rating live load model, via the load effects caused by the idealized rating trucks used (*LL*), to capture the actual load effects. Again considering the exact result using all data, note that either the minimum reliability index (for MI-LEP Moment and Shear, and for Simplified CFR Shear), or the average reliability index (for Simplified CFR Moment) will govern the load factor required. Which will govern is case dependent and depends on both the database and rating trucks used. Also notice as the size of the database is decreased, both the minimum and mean reliability index increase, due to the increased level of conservatism that results. Similar to the results of Figure 7, in general, only modest increases in conservatism result for rather large reductions in the database size. For example, reducing the database by an order of magnitude (i.e. to the Top 10%) causes an average increase in girder reliability index from 3.63 to 3.77 for moment and from 3.40 to 3.50 for shear considering the MI-LEP case, and from 2.50 to 2.60 for moment and 2.72 to 2.78 for shear considering the Simplified CFR case. However, much larger discrepancies in reliability are found from the AASHTO procedure, as shown in the table.

In fairness, although there are no specific limitations given to the use of Eq. 1, a suggested scenario for use of this expression given in the code commentary is to develop live load factors for a localized, low-volume road carrying heavy trucks. Therefore, to see if Eq. 1 might provide better results in this situation, rather than combine all traffic data to produce state-wide load factors, as done for all previous results presented, the analyses above were repeated individually for 14 different WIM sites, with varying ADTT from 360-16,500. These results are shown in Figures 8 and 9 for both the MI-LEP and Simplified CFR databases, respectively (note in these site-specific analyses, V_{site} in Eq. 6 is set to zero). Although Eq. 1 suggests a minimum load factor of 1.80; this minimum is not directly imposed in the result of Eq. 1 in the figures, which would result in greater discrepancies. As shown in the figures, using site-specific data rather than state-wide data has little impact on the effectiveness of using the GVW-reduced dataset as proposed, as well as the larger discrepancy generally found from the AASHTO Method.

Considering the Simplified CFR moment, assessing all 14 sites individually, the reduced to exact load factor ratio ($\gamma_{LL\ r}$ / $\gamma_{LL\ e}$) varies from 1.02 to 1.11 considering the top 10% of data, with an average of 1.06 (reduced to ratios from1.01 to 1.06 with an average of 1.03 if the top 20% is considered), while the AASHTO simplified procedure produced ratios from 1.18 to 1.50 with an average of 1.34. Considering shear, the WIM site-specific ($\gamma_{LL\ r}$ / $\gamma_{LL\ e}$) ratios varied from 1.01 to 1.09 considering the top 10%, with an average of 1.05 (reduced to ratios from 1.00 to 1.04 with an average of 1.02 considering the top 20%) , while the AASHTO resulted in ratios from 1.02 to 1.33 with an average of 1.23.

For the MI-LEP database, the effectiveness of the proposed procedure remains similar, while the results of the AASHTO method significantly worsened. Considering the Simplified CFR moment, assessing all 14 sites individually, the reduced to exact load factor ratio ($\gamma_{LL\,r}$ / $\gamma_{LL\,e}$) varies from 1.04 to 1.10 considering the top 10% of data, with an average of 1.07 (reduced to ratios from 1.01 to 1.07 with an average of 1.04 if the top 20% is considered), while the AASHTO simplified procedure produced ratios from 1.60 to 3.06 with an average of 2.50. Considering shear, the WIM site-specific ($\gamma_{LL\,r}$ / $\gamma_{LL\,e}$) ratios varied from 1.03 to 1.11 considering the top 10%, with an average of 1.07 (reduced to ratios from 1.02 to 1.06 with an average of 1.04 considering the top 20%) , while the AASHTO resulted in ratios from 1.72 to 3.24 with an average of 2.66.

Although the results given in Tables 3-5 concern Strength I vehicles associated with rating, a common concern for state DOTs, the method was also evaluated on a vehicle pool unfiltered with regard to GVW, that would perhaps represent a combined Strength I/Strength II calibration for design (Eamon et al. 2016) containing the very heaviest vehicles, with an associated target reliability level of 3.5 (Nowak 1999). It was found that the proposed method was equally effective in this case, where ratios of RLE_r/RLE_e (i.e. values shown in Table 3) as well as differences in reliability index (i.e. Tables 4 and 5) were no greater than those presented for rating.

Although only simple span results are presented, 2-span continuous bridges otherwise identical to the simple span cases were also investigated for the MI-LEP database. In general, it was found that GVW is equally well correlated to continuous span shear and moment load effects. It was also found that differences in reliability when using the reduced datasets and the exact case (i.e. all data) were very similar to those found with the simple spans. A few exceptions were: shears at the top 1% data reduction case for girder-specific load factors (per Table 4) were more conservative than for the simple spans; and for the single governing load factor analysis (per Table

5) for the top 5% case, continuous moments provided less discrepancy but continuous shears more discrepancy as compared to the simple span cases, while for the top 1% case, continuous moments provided more discrepancy and continuous shears less discrepancy than for simple spans.

Conclusion

In this study, the effects of using a GVW-based load truncation approach to develop State-specific live load factors for rating was evaluated. Two different traffic datasets representative of unusually heavy as well as typically legal vehicles were considered. A strong correlation was found between GVW and load effects, with correlation coefficient varying from about 0.9 to nearly 1.0 for both vehicle databases. Reducing the datasets to as little as 1% of the top GVW data generally resulted in insignificant increases in COV of mean maximum load effect, whereas reducing the data to as much as the top 10% resulted in an increase in mean maximum load effect from 1-6%, depending on span length. Reducing the data to the top 5% increased idealized (i.e. girder-specific) average required load factors to 4-5% considering the MI-LEP database and up to 8% for the Simplified CFR, with associated increases in mean minimum reliability index from 1.5 to approximately 1.6. This is in comparison to the suggested simplified AASHTO procedure, which produced mean minimum indices of about 3-5.

If used as commonly implemented in DOT rating practice, when the same rating live load factor(s) is used for all girders in the bridge inventory, reducing the dataset to the top 10% increased live load factors from 3-5%, while only using 1% of the heaviest vehicles approximately doubled these discrepancies. In contrast, the simplified AASHTO procedure increased load factors by factors of 1.36 and 2.67 for moment and 1.03 and 2.06 for shear, depending on the database considered. Similar results were obtained for WIM site-specific rather than statewide consideration of traffic data. In all cases, use of the reduced databases produced conservative results.

It thus appears that the use of the load truncation approach to develop State-specific live load rating factors appears highly promising, where large reductions in computational effort can be achieved with minimal loss of accuracy. Although what amount of computational effort and error are acceptable must be determined by the analyst, using approximately the top 10% by GWV appears to be a reasonable starting point, where an order of magnitude of reduced computational effort consistently produced less than a 5% (conservative) discrepancy in inventory-wide load factor.

Data Availability Statement

Some or all data, models, or code used during the study were provided by a third party (weigh-in-motion data). Direct requests for these materials may be made to the provider as indicated in the Acknowledgements.

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Table 1. Vehicle Filtering Criteria.

Vehicle Type	Criteria
Legal, GVW > 356 kN	For axles spaced ≥ 2.75 m, axles ≤ 80 kN For axles spaced from 1 – 2.7 m, axles ≤ 58 kN For axles spaced < 1 m, axles ≤ 40 kN 2 ≤ Number of axles ≤ 11 Vehicle Length ≤ 29 m
Legal, GVW < 356 kN	Any individual axle ≤ 89 kN Sum of tandem axles ≤ 151 kN 2 ≤ Number of axles ≤ 11 Vehicle Length ≤ 29 m

MI-Legal and Extended Permit (MI-LEP)	Permit (Construction)*	Any axle $\leq$ 107 kN GVW $\leq$ 667 kN 2 $\leq$ Number of axles $\leq$ 11 Vehicle Length $\leq$ 26 m
Simplified CFR		GVW $\leq$ 356 kN Any axle $\leq$ 89 kN For axles spaced from 1 – 2.4 m, Sum of tandem axles $\leq$ 151 kN

*Various types of permits exist, depending on vehicle use category and cargo type. Permits for construction vehicles are generally most permissive and govern load effects.

Table 2. Random Variables.

Random Variable		Bias Factor	COV
Resistance RVs	R		
Prestressed Concrete, Moment		1.05	0.075
Prestressed Concrete, Shear		1.15	0.14
Reinforced Concrete, Moment		1.14	0.13
Reinforced Concrete, Shear[1]		1.20	0.155
Steel, Moment		1.12	0.10
Steel, Shear		1.14	0.105
Load RVs			
Vehicle Live Load, Moment	L_{max}	1.14-1.73[2]	0.14-0.21[3]
Vehicle Live Load, Shear	L_{max}	1.14-1.64[2]	0.15-0.19[3]
Vehicle Dynamic Load	I_M	1.13[4]	0.09
Vehicle Load Distribution Factor	DF	0.72-0.79	0.11-0.16
Dead Load, Prefabricated	D_p	1.03	0.08
Dead Load, Site-Cast	D_s	1.05	0.10
Dead Load, Wearing Surface	D_w	mean 89 mm	0.25

1. Assumes shear stirrups present.
2. Bias factor is given for the MI-LEP data as the ratio of mean load effect to the governing nominal Michigan legal rating truck load effect. For the Simplified CFR data, bias factor is 1.50-1.95 for moment and 1.59-1.90 for shear, and is given as the ratio of mean load effect to the governing nominal AASHTO legal rating truck load effect.
3. Includes uncertainties from data projection, site, WIM data, impact factor, and load distribution.
4. Bias factor is given as a multiple of static LL, such that the total vehicular load effect is LL*bias $_{IM}$.

Table 3. Required Load Effect Ratios.

Reduced Dataset	RLE_r/RLE_e	MI-LEP Moment	MI-LEP Shear	Simplified CFR Moment	Simplified CFR Shear
Top 50%	maximum	1.04	1.04	1.07	1.09
	mean	1.01	1.01	1.03	1.02
	minimum	1.00	1.00	1.00	1.00
Top 20%	maximum	1.07	1.07	1.16	1.14
	mean	1.03	1.03	1.06	1.04
	minimum	1.02	1.01	1.00	1.01
Top 10%	maximum	1.08	1.08	1.19	1.18
	mean	1.05	1.03	1.07	1.06
	minimum	1.03	1.01	1.01	1.02
Top 5%	maximum	1.09	1.10	1.21	1.23
	mean	1.05	1.04	1.08	1.08
	minimum	1.04	1.01	1.01	1.03
Top 1%	maximum	1.10	1.13	1.27	1.26
	mean	1.06	1.05	1.10	1.10
	minimum	1.04	1.01	1.01	1.03

Table 4. Reliability Results for Different Vehicle Database Sizes, Girder-Specific Load Factors.

Reduced Dataset	Reliability Index (β)	MI-LEP		Simplified CFR	
		Moment	Shear	Moment	Shear
Top 50%	maximum	1.56	1.59	1.64	1.67
	mean	1.52	1.52	1.54	1.53
	minimum	1.51	1.50	1.51	1.50
Top 20%	maximum	1.61	1.63	1.73	1.75
	mean	1.57	1.54	1.57	1.56
	minimum	1.52	1.51	1.51	1.51
Top 10%	maximum	1.67	1.69	1.81	1.84
	mean	1.60	1.57	1.59	1.58
	minimum	1.53	1.51	1.51	1.52
Top 5%	maximum	1.84	1.71	1.91	1.91
	mean	1.62	1.58	1.60	1.59
	minimum	1.53	1.52	1.52	1.53
Top 1%	maximum	1.95	1.74	2.03	1.97
	mean	1.68	1.61	1.63	1.53
	minimum	1.54	1.54	1.52	1.61
AASHTO	maximum	8.84	4.85	4.52	3.74
	mean	4.95	3.65	3.25	2.78
	minimum	6.89	2.78	2.70	1.63

Table 5. Reliability Results for Different Vehicle Database Sizes, Single Governing Load Factor.

Reduced Dataset	Reliability Index (β)	MI-LEP		Simplified CFR	
		Moment	Shear	Moment	Shear
All	maximum	4.91	4.75	3.01	3.64
	mean	3.61	3.40	2.50	2.72
	minimum	1.50	1.50	1.87	1.50
Top 50%	maximum	4.93	4.78	3.06	3.70
	mean	3.63	3.42	2.53	2.75
	minimum	1.52	1.53	1.91	1.57
Top 20%	maximum	5.03	4.82	3.15	3.72
	mean	3.71	3.45	2.58	2.76
	minimum	1.64	1.57	1.99	1.59
Top 10%	maximum	5.09	4.88	3.20	3.74
	mean	3.77	3.50	2.60	2.78
	minimum	1.72	1.64	2.03	1.61
Top 5%	maximum	5.19	4.91	3.24	3.76
	mean	3.85	3.52	2.62	2.79
	minimum	1.84	1.68	2.07	1.64
Top 1%	maximum	5.27	4.95	3.26	3.78
	mean	3.92	3.56	2.63	2.81
	minimum	1.94	1.73	2.10	1.66
AASHTO	maximum	8.80	6.82	4.58	3.87
	mean	4.95	5.04	3.25	2.87
	minimum	6.89	3.81	2.70	1.62

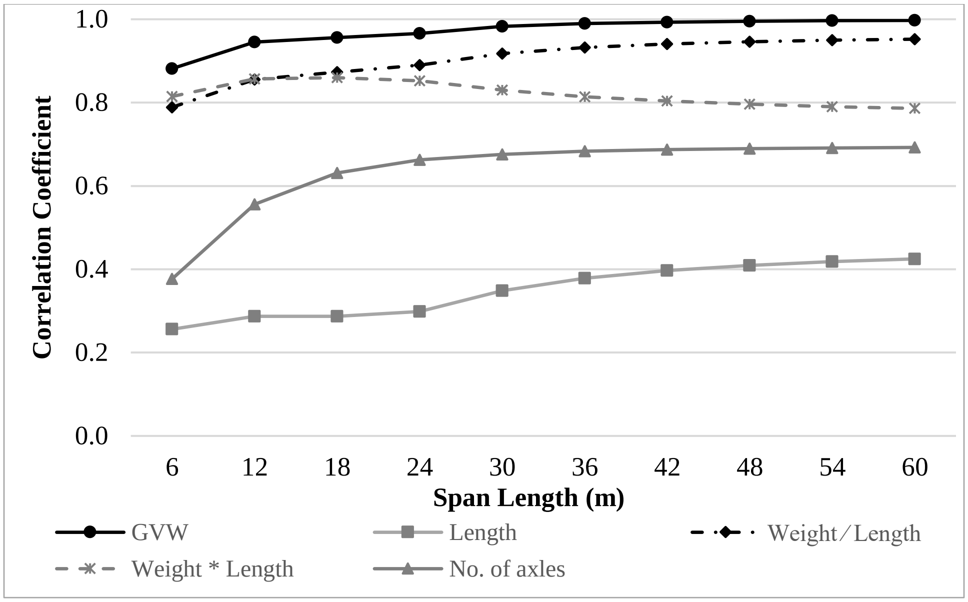

Figure 1. Correlation Between Vehicle Parameter and Moment, MI-LEP.

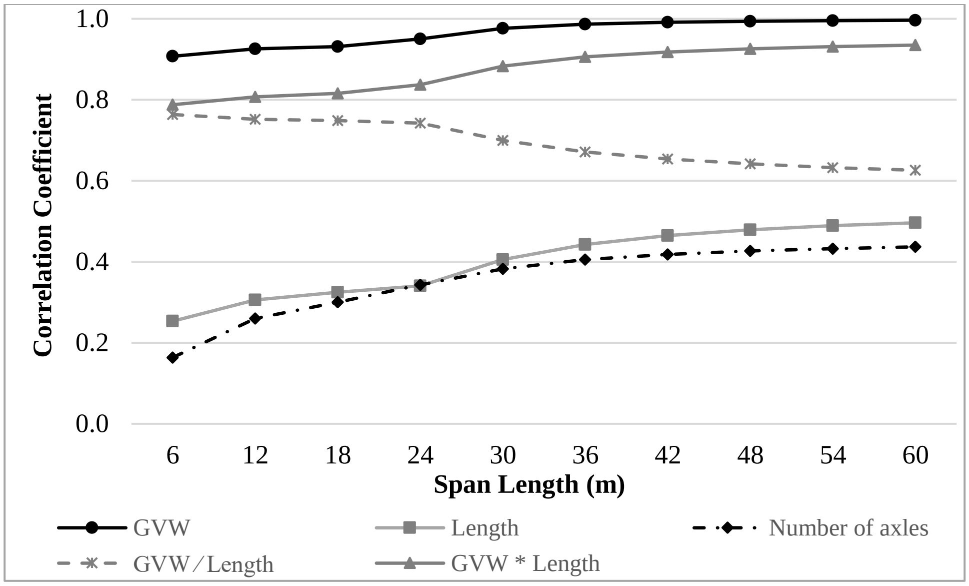

Figure 2. Correlation Between Vehicle Parameter and Moment, Simplified CFR.

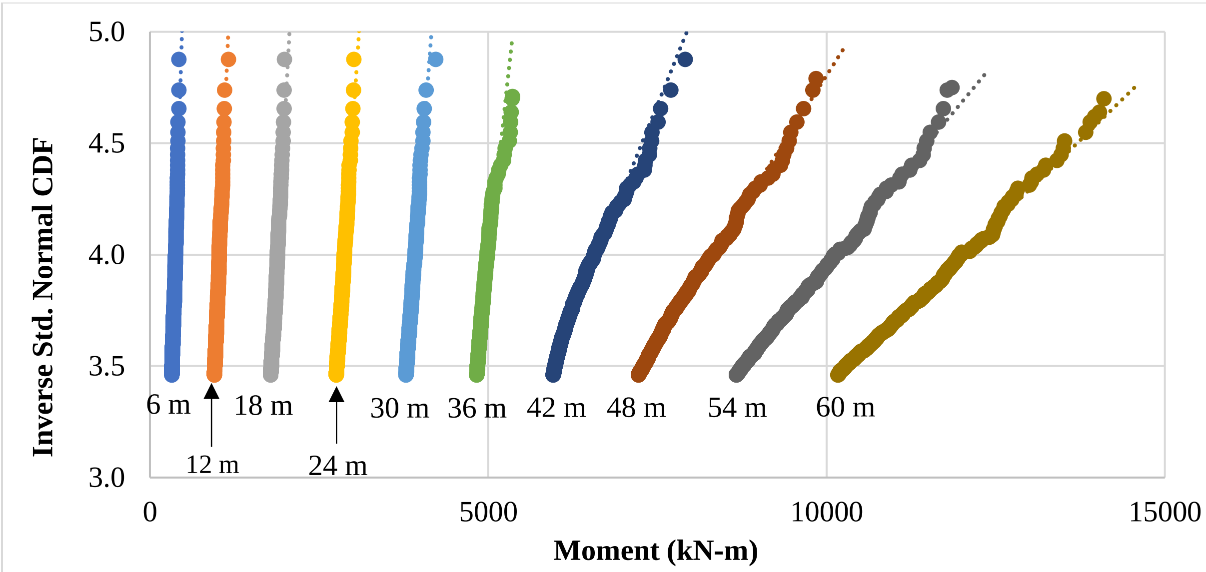

Figure 3. Example CDF of 6-60 m Span Moments.

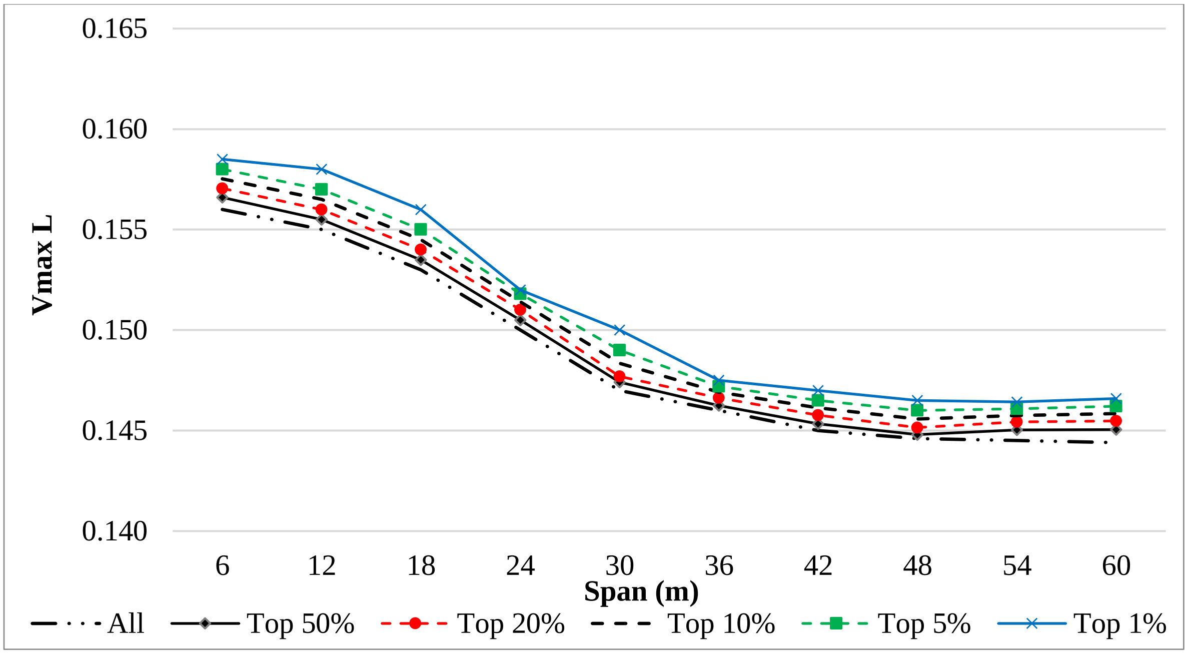

Figure 4. Effect of Database Reduction on V_{maxL} for Moment, MI-LEP Vehicles.

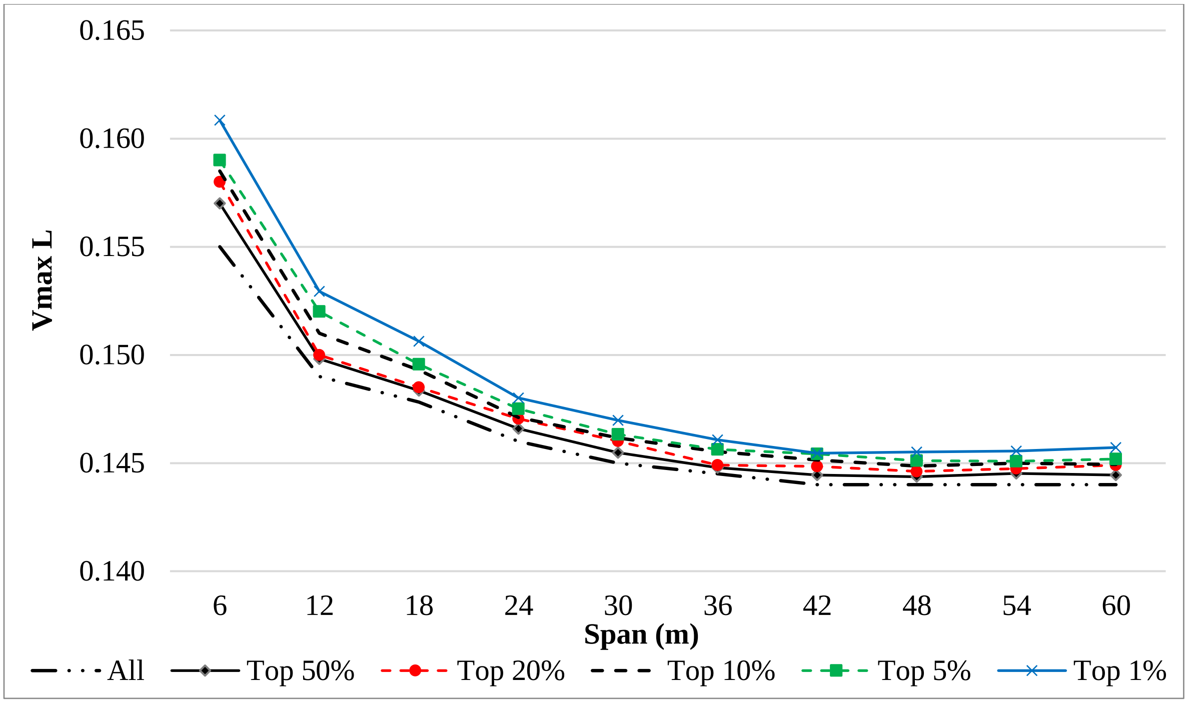

Figure 5. Effect of Database Reduction on V_{maxL} for Shear, MI-LEP Vehicles.

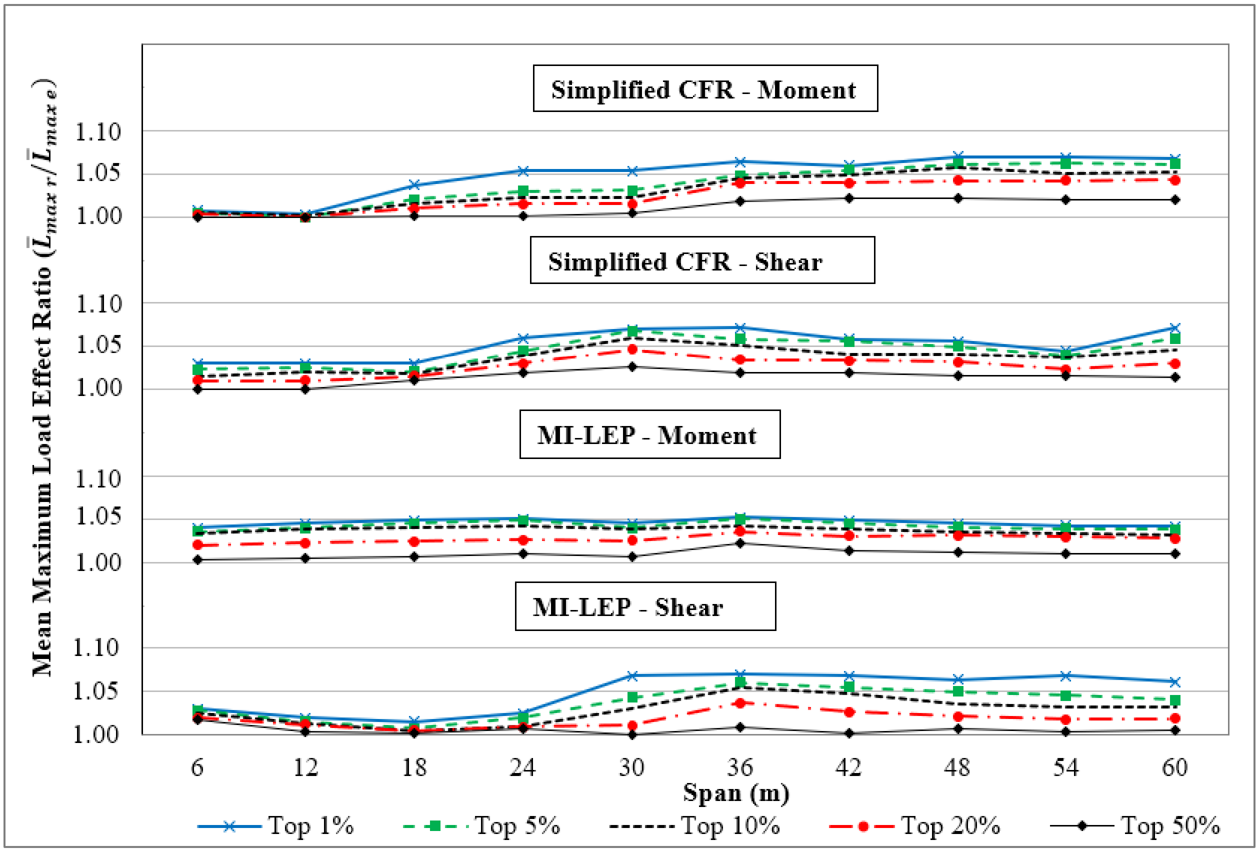

Figure 6. Effect of Database Reduction on Mean Maximum Load Effect.

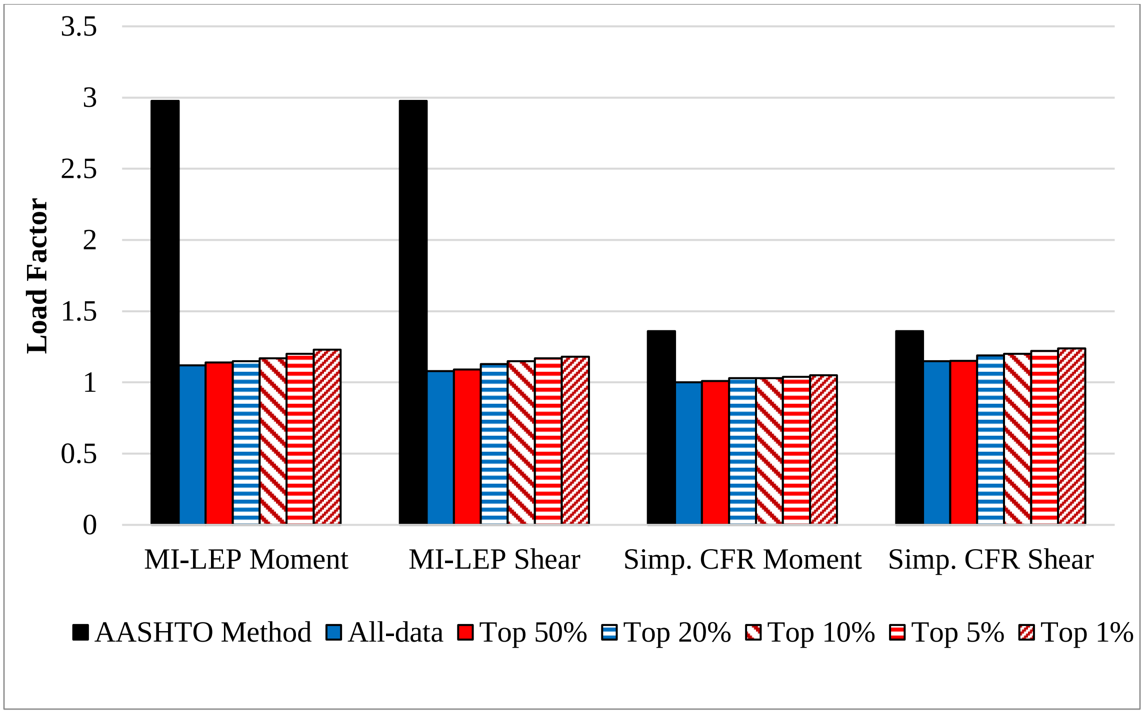

Figure 7. Comparison between AASHTO and Proposed Procedure.

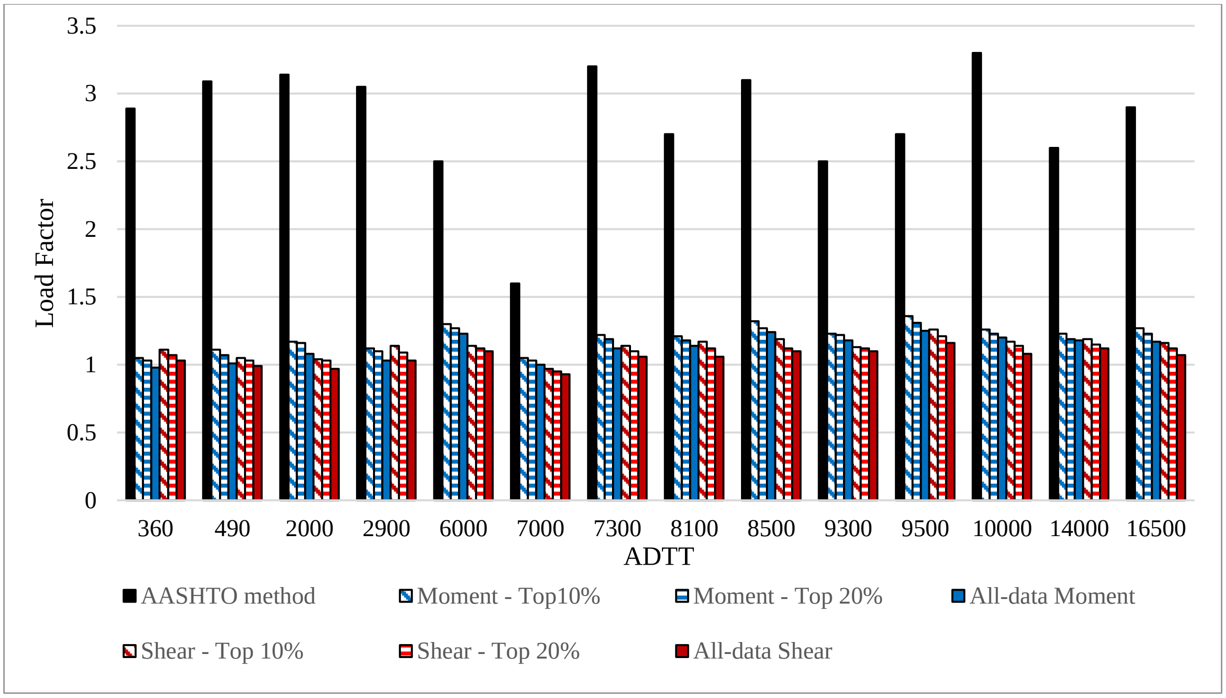

Figure 8. Comparison between AASHTO and Proposed Procedure, MI-LEP.

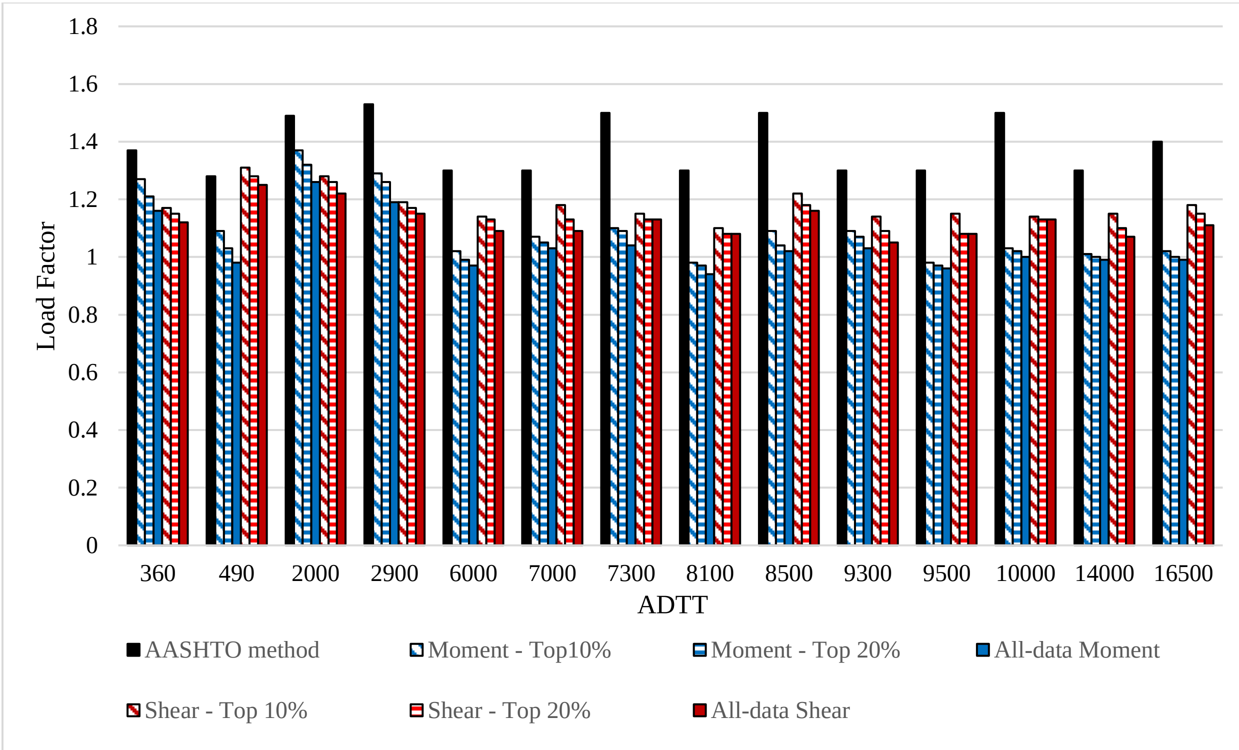

Figure 9. Comparison between AASHTO and Proposed Procedure, Simplified CFR.