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Development of Traffic Live Load Models for Bridge Superstructure Rating with RBDO and Best Selection Approach

Sasan Siavashi[1] and Christopher D. Eamon[2]

Abstract

Reliability-based design optimization (RBDO) is frequently used to determine optimal structural geometry and material characteristics that can best meet performance goals while considering uncertainties. In this study, the effectiveness of RBDO to develop a rating load model for a set of bridge structures is explored, as well as the use of an alternate Best Selection procedure that requires substantially less computational effort. The specific problem investigated is the development of a vehicular load model for use in bridge rating, where the objective of the optimization is to minimize the variation in reliability index across different girder types and bridge geometries. Moment and shear limit states are considered, where girder resistance and load random variables are included in the reliability analysis. It was found that the proposed Best Selection approach could be used to develop rating model as nearly as effective as an ideal RBDO solution but with significantly less computational effort. Both approaches significantly reduced the range and coefficient of variation of reliability index among the bridge cases considered.

Author Keywords:

Optimization, Reliability-based design optimization, Load rating, Load model

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Introduction

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. Generally, it is desired by the DOTs to limit bridge posting as much as possible, as restrictions prevent the general public, as well as commercial vehicles, from fully utilizing the transportation network. Typically, the design load rating evaluates the ability of the bridge to carry the HL-93 design load specified in the American Association of State Highway and Transportation Officials Load and Resistance Factor Design Specifications (AASHTO LRFD 2017) and is used to complete the Federal inventory rating. The design load is also used to evaluate the bridge at the Federal operating level, where capacity associated with a lower level of reliability is assessed. Structures are also rated for state-specific legal loads at the operating level, to determine if traffic restriction is required.

Since 2003, with the publication of the Manual for Condition Evaluation and Load and Resistance Factor Rating (LRFR) of Highway Bridges (AASHTO 2003), bridge rating has been implicitly based on an assessment of structural reliability. 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 Load Factor Rating, which was not reliability-based). The purpose of the LRFR version was to provide a more consistent level of safety than that achieved under the previous procedure. Part of the LRFR calibration effort was to develop appropriate vehicular live load statistics used in the reliability assessment to establish live load factors for rating. These factors were later revised in 2011 (Sivakumar and Ghosn 2011) using weigh-in-motion (WIM) data from truck traffic collected from six states. Based on a 5-year return period for load rating, the recalibrated MBE rating process was formulated to result in an average target reliability index (β) of 2.5, with a minimum level of 1.5 for any particular structure.

Although the WIM data collected to develop the live load factors in the MBE represented a significant improvement in load modeling over previous versions, understandably, it does not necessarily well-represent the traffic loads in various other states that were not included in the MBE calibration effort. However, a number of states initiated efforts to develop unique live load models to better represent local traffic data. Some of these include Missouri (Pelphery et al. 2006), Oregon (Kwon et al. 2010), and New York (Ghosn et al. 2011; Anitori et al. 2017), where state-specific WIM data were used to develop new live load factors for bridge design and rating. Similar work includes that implemented by Texas (Lee and Souny-Slitine 1998) and Wisconsin (Tatabai et al. 2009), which used WIM data to better characterize vehicle load effects.

More recently, Eamon and Siavashi (2018) revised the Michigan DOT (MDOT) bridge rating procedure based on a reliability-based analysis of WIM data. It was found that use of existing rating vehicles produced significant inconsistencies in reliability. That is, for a given rating factor, one structure had a significantly different level of reliability than another. This inconsistency varied depending on bridge geometry, girder material type, and mode of failure. One way to resolve this problem would be to vary the live load factor on the rating vehicle as necessary to match the required reliability level. However, this approach would be impractical, requiring many hundreds of different load factors, one for each bridge type and geometry. An alternative possible solution is to simply apply the largest live load factor required across all cases, such that the minimum specified reliability level is always achieved. From the perspective of the DOT, this simpler approach is highly undesirable, as it would result in a large number of under-rated structures, potentially leading to unnecessary traffic restriction. Because the pattern of required load factor variation is complex, the development of an appropriate live load model for rating is not obvious. For such problems, reliability-based design optimization (RBDO) may be an appropriate solution approach.

In a typical RBDO procedure, geometric (or material) design parameters are taken as design variables (DVs), where an optimal set is determined that best meets specified performance criteria when subjected to reliability-based constraints. Various research efforts have used this approach to optimize hypothetical bridge designs for different performance goals, such as cost minimization (Thoft 2000; Turan and Yanmaz 2011; Behnam and Eamon 2013; Saad et al. 2016; Garcia-Segura et al. 2017); weight (Nakib 1991; Yang et al. 2011; Thompson et al. 2006), and resistance to extreme loads (Negaro and Simoes 2004; Basha and Sivakumar 2010; Kusano et al. 2014).

In this study, rather than taking design variables as geometric characteristics of a bridge to develop an optimal design, DVs are taken as representative parameters of the rating model itself. That is, RBDO is not used to develop an optimal structural design, but rather an optimal live load model to be used for bridge rating. As such, the first objective of this study is to examine the viability of using RBDO to develop a rating live load model, with the objective to minimize the inconsistencies in rating factor and corresponding reliability level among many different types of bridge girders. Kamjoo and Eamon (2018) recently proposed a similar approach for development of a load model for design.

Although an RBDO result may represent a theoretically ideal solution, it is accompanied by several notable drawbacks: high computational cost, a somewhat complex problem formulation, and a resulting load model that may bear little resemblance to any realistic vehicle configuration. Thus, the second, and primary objective of this study is to evaluate the effectiveness of a simple and much less costly alternative approach which provides not an optimal solution, but the best solution available based only on measured actual vehicle configurations.

Traffic Data Collection

As noted above, various agencies have collected state-specific WIM data and have used those data to refine bridge rating models. To evaluate the viability of the two approaches for rating load model development considered in this study, traffic data collected from Michigan are considered as an example. The WIM data used here were obtained from consideration of approximately 40 Michigan stations with high-speed (1000 Hz) sampling necessarily to accurately record vehicle configurations and positioning. Of these sites, a selection of 20 representative locations throughout the State were chosen in different average daily truck traffic (ADTT) categories ranging from approximately 400 to 16000. These stations are generally on major routes (State and Interstate roadways). The WIM data used were collected over 34 months from February 2014 to January 2017, excluding April and May 2014, which were unavailable. Since WIM data is often associated with collection errors, data filtering criteria were employed to eliminate unrealistic records from the 101 million vehicle database, such as feasible limitations on axle spacing, weight, speed, and length (for example, truck axles spaced closer than 1 m; heavy trucks with speeds over 160 kph; axle weights over 312 kN, etc.; see Eamon et al. 2016 for a complete description of these criteria). To further confirm the reasonableness of the WIM data, several checks were implemented as recommended in NCHRP 683, such as comparison of the gross vehicle weight (GVW) frequency histograms, mean and modal axle spacing, GVW, and axle weights to generally expected values (Eamon and Siavashi 2018). The database was then further reduced to consider only legal and routine (annual) permit vehicles, which MDOT groups together for Strength I limit state evaluation (i.e. normal use of the bridge) within the legal load rating framework. A summary of the criteria used to categorize a record as a legal or routine permit vehicle is given in Table 1. After applying the filtering criteria, about 89 million vehicle records remained and were considered for later load effect analysis, as described below.

Reliability-Based Design Optimization

Probability theory is most commonly used to model uncertainty in reliability-based design optimization. Correspondingly, an RBDO problem defines a set of *NDV* design variables $\boldsymbol{Y} = \{Y_1, Y_2, \ldots, Y_{NDV}\}^T$ to be determined that minimizes or maximizes given performance criteria, as well as a set of *n* random variables $\boldsymbol{X} = \{X_1, X_2, \ldots, X_n\}^T$ that describe load, resistance, and other uncertainties. Given a probabilistic limit state function $g(\boldsymbol{X}, \boldsymbol{Y})$ for consideration, failure can be defined as $g(\boldsymbol{X}, \boldsymbol{Y}) \leq 0$, and correspondingly, $g(\boldsymbol{X}, \boldsymbol{Y}) > 0$ implies safety while $g(\boldsymbol{X}, \boldsymbol{Y}) = 0$ represents the boundary between the failed and safe regions.

Various methods of formulating and solving RBDO problems have been proposed (Enevoldsen and Sorensen 1995; Tu et al. 1999; Rais-Rohani and Xie 2005; Kharmanda and Olhoff 2007; Aoues and Chateauneuf 2010, etc), including numerous approximate methods for assessing probabilistic constraints to reduce computational effort (Enevoldsen and Sorensen 1995; Tu et al. 1999; Du and Chen 2004; Qu and Haftka 2004). In this study, an RBDO approach is used to develop a live load rating model that should result in a requirement for traffic restriction to occur on any structure when it reaches a minimum specified level of reliability. In other words, the variation in reliability level among different structures, at the point at which traffic restriction is imposed, is minimized (ideally zero).

With this approach in mind, the optimization problem is described as:

$$\min f(\boldsymbol{X},\boldsymbol{Y})$$

$$\text{s. t. } \beta_i \geq \beta_{\min}; i = 1, N_p \qquad (1)$$

$$Y_k^l \leq Y_k \leq Y_k^u; k = 1, NDV$$

where $f(\boldsymbol{X}, \boldsymbol{Y})$ is an objective function quantifying variability in structural reliability among the different bridge girders considered for rating, as described below; β_i is the reliability index constraint for girder i among N_p structures considered; β_{min} is the minimum acceptable reliability index; and Y_k is the k^{th} design variable among NDV design variables, with lower and upper bounds given as Y_k^l and Y_k^u.

As discussed earlier, objective functions for bridge-related RBDO problems have been most commonly expressed in term of weight or cost, such that these performance measures can be minimized. Here, the desire is to minimize variation in reliability among different girders, and thus $f(\boldsymbol{X}, \boldsymbol{Y})$ must be formulated to quantify this variation. It follows that if all girders match the desired reliability index at the same reference value for rating factor, variation from the target reliability level (β_T) is zero and an ideal solution results. Variation from a target level can of course be quantified in numerous ways, such as mean squared error, root mean squared error, R-squared, mean absolute error, and many others. Mean squared error is used in this study, which results in an objective function formulated as:

$$f(X,Y) = \sum_{\mathrm{i}=1}^{N_p} \frac{(\beta_i - \beta_T)^2}{N_p} \quad (2)$$

Reliability Analysis

Random variables ***X*** used for reliability assessment are girder resistance *(R)* and load effects, the latter of which include vehicle live load *(LL)*, dynamic load *(IM)*, and dead load from prefabricated (D_p) and site-cast (D_s) components, as well as from the deck wearing surface (D_w). Uncertainty in the distribution of vehicular live load to an individual girder is also considered *(DF)*. Bias factor (ratio of mean to nominal value) and coefficient of variation (COV) for random variables are given in Table 2. With the exception of live load *(LL)*, which is calculated from Michigan-specific data, all random variable statistical parameters are based on those used in the AASHTO LRFD (Nowak 1999) and MBE calibrations (AASHTO 2018). For reliability assessment, girder resistance is considered lognormal whereas the sum of load effects is taken as normally distributed, as assumed in previous calibrations for consistency (Nowak 1999; Sivakumar et al. 2011).

As reported by Eamon and Siavashi (2018), vehicular live load statistics were developed from the 89 million records of WIM data collected from Michigan as described above, where load effects were calculated by incrementing trains of measured vehicles across various hypothetical bridge spans from 6-60 m and recording maximum moment and shears. In this process, the total load effect to a girder caused by the actual vehicle locations relative to one-another in single and adjacent lane placements were maintained. Live load effects were proportioned to the girder based on mean values of *DF*, where nominal values are specified in AASHTO LRFD as a function of bridge geometry. Vehicle live load is then projected to an assumed 5-year rating period as specified in the MBE (corresponding to the maximum assumed time between inspections) for legal and routine permit rating, using an Extreme Type I extrapolation, which was found to well-fit the Michigan data (Eamon et. al 2016). These live load effects were found to have significant variation from the existing Michigan as well as MBE rating models, as shown by the varying bias factor and COV for *LL* in Table 2. In particular, a bias factor of unity and COV of zero would indicate that the mean maximum value for live load exactly matches the load effect caused by the existing (Michigan) rating model with no uncertainty. As noted earlier, this difference was identified as the cause of the significant discrepancy in girder rating reliability on Michigan bridge structures (Eamon and Siavashi 2018).

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

$$g_i = R - (D_p+D_s+D_W) - DF(LL+ IM) \qquad (3)$$

with random variables R, D_p, D_s, D_w, DF, IM, and LL defined above. Limit states are formed for simple span load effects (moment and shear) for prestressed concrete I-shaped girders, composite steel girders, reinforced concrete girders, and spread and side-by-side prestressed concrete box beams. Bridges are assumed to support a reinforced concrete deck and have a wearing surface and additional items such as barriers and diaphragms relevant for dead load calculation. Dead loads are based on those used in the MBE calibration (NCHRP 683). Bridges are taken as two lane, with span lengths from 6-60 meter in increments of 6 m (limited to 30 m for reinforced concrete). Girder spacing varied from 1.2 to 3.6 meter at 0.6 m increments, while for side-by-side box beams, two widths (0.9 meters and 1.2 meters) were considered. 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 inventory.

The target reliability index associated with the MBE is $\beta_T = 2.5$, which represents the average required reliability level across all girders considered (AASHTO 2018). Although during the MBE calibration the reliability index of any particular girder was allowed to fall as low as 1.5, this represents a very low level of nominal reliability that not all DOTs may be comfortable with (β=2.5 corresponds to failure probability $p_f \approx$ 1:160 whereas β=1.5 corresponds to $p_f \approx$ 1:15, an order of magnitude of difference; however, these reliability targets are notional values and corresponding failure probabilities should not be taken literally). In this study, a higher minimum level is imposed such that the minimum (β_{min}) as well as the target (β_T) indices are taken as 2.5, although this creates a more challenging problem for the solution methods considered to address.

To establish nominal values for girder resistance for use in the reliability analysis, the minimum requirements of acceptability must be identified, to avoid biasing reliability results upward by analyzing conservatively-designed components. For example, in the case of design, for LRFD in general, this criteria is expressed as: $\phi R_n = \sum \gamma_i Q_i$, (where γ_i are load factors and Q_i are load effects), and thus the minimum acceptable value for R_n, which is to be used in the reliability analysis, can be established if load effects Q are known.

In the case of rating, acceptability is expressed in terms of rating factor, for which the minimum acceptable value (i.e. without requiring traffic restriction) is 1.0. Rating factor (RF) is given in the MBE by:

$$RF = \frac{\phi R_n - 1.25DC - 1.5DW}{\gamma_{LL}(LL + IM)} \quad (4)$$

In this expression, 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 the dead loads of the structure and the wearing surface, respectively; IM is specified as 1.33, LL is the rating vehicle live load effect, and γ_{LL} is the rating vehicle load factor.

To meet the required reliability level, the rating vehicle must produce a live load effect (LL) that produces $\beta_T = 2.5$ when RF = 1.0. Thus, setting RF = 1.0 and solving for the required R_n results in:

$$R_n = (1/\phi)(1.25DC + 1.5DW + \gamma_{LL}(LL + IM)) \quad (5)$$

which is the minimum nominal resistance for consideration in reliability rating. Here it should be noted that R_n from Eq. 5 represents a notional, or theoretical resistance, used for evaluation of the reliability level associated with the rating process, and does not necessarily represent the resistance of an actual girder. This is analogous to the standard practice of evaluating components with resistance set just equal to the design limit for reliability assessment of design code specifications, even though actual components are typically over-designed (Nowak 1999).

Considering Eq. 5, if dead load and live load effects are known, R_n can be established. With R_n, known, the mean value $\bar{R}$ of the girder resistance random variable R can be determined using the bias factors λ shown in Table 2 ($\bar{R} = \lambda \times R_n$), and then the reliability index of the limit state in Eq. 3 computed. In this study, however, for which an optimal live load model is to be determined, the total live load effect produced by the rating model ($\gamma_{LL}(LL+IM)$) is unknown. It can be found by setting β_T = 2.5, then determining 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. For convenience, in this study, the quantity $\gamma_{LL}(LL+IM)$ is referred to as the required load effect (RLE); i.e. the total load effect required by the live load rating model such that β = 2.5 when RF=1.0.

In summary, the reliability process is as follows. First, 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 from a selection of typical bridge designs used in previous reliability-based calibration efforts as described above. Next, the mean value of R, needed for reliability analysis, is expressed as the function: $\bar{R} = \lambda$ x R_n, where R_n is given by Eq. 5 and bias factor (λ) given in Table 2 for the type of girder and failure mode considered. Note that R_n, and hence $\bar{R}$, remains a function of the unknown RLE ($\gamma_{LL}(LL+IM)$). Then, reliability index is set to the target level (2.5), and its evaluation is expressed as a function of the random variables (R, D_p, D_s, D_w, DF, IM, and LL) discussed above, considering the limit state function given by Eq. 3. In this calculation, mean girder resistance $\bar{R}$ remains a function of the unknown RLE. In the calculation of β, since reliability index is preset to a known value, the only unknown is the RLE, which is solved for. Thus, the live load effect needed to be produced by the rating live load model (RLE) in order to meet the minimum reliability target can be determined.

A multitude of methods are available to assess the reliability index β_i of the limit state function (Eq. 3), the result of which is used in Eqs. 1 and 2. As optimization generally involves many iterations, the computational cost of each cycle becomes an important factor in the feasibility of the RBDO process. For the particular problem considered here, approximately 195 reliability constraints for moment or shear must be evaluated at every optimization cycle (one for each bridge type and geometry considered, as given above). Additionally, reliability index must be computed twice for each girder to determine whether the governing load effect is generated by vehicles in a single lane or in both lanes. This process thus requires nearly 800 calculations of reliability index for each optimization iteration.

One approach that allows reliability index to be quickly computed is the First Order, Second Moment (FOSM) method, as a closed-form function of the means and standard deviations of random variables. Although its small computational demand is ideal for RBDO, FOSM does not provide exact solutions for limit state functions that are algebraically nonlinear or composed of non-normal random variables. This is problematic in this study because girder resistance R is taken to be lognormal, which will produce a conservative estimate of β if FOSM is used. The degree of conservatism using FOSM with the limit state functions and random variables considered here was investigated by Eamon et al (2014), where it was found that the error in FOSM from the exact solution is consistent at a given level of reliability. That is, regardless of bridge geometry or girder type, the FOSM approach produced a reliability index with a consistent level of conservativeness from the exact value. For the target reliability index used in this study (β_T =2.5), the ratio of the exact value to the FOSM solution was found to be approximately 1.04. Therefore, in this study, the FOSM method is used with the modification suggested by Eamon et al. (2014), where the solution is adjusted by the factor of 1.04 when the target reliability index constraint of 2.5 is imposed in the optimization. It should be emphasized that this adjustment is valid only for the specific limit state functions and random variable parameters used in this study. For other reliability problems, either a more general but costly approach must be used, such as FORM, the First Order Reliability Method (Rackwitz and Fiessler 1978), or a new FOSM adjustment factor developed. For verification, a sample of girder reliability indices were computed with Monte Carlo Simulation (MCS) with $1x10^6$ simulations at the completion of the RBDO. It was found that the indices estimated with the modified FOSM approach described above were within 1% of the "exact" MCS values.

Design Variables

As noted above, design variables within previous RBDO procedures applied to bridges were used to describe geometric and potentially material properties. In this study, however, the optimization concerns a rating load model rather than a structural configuration. As such, design variables must describe critical parameters that define the load model. The existing nominal vehicular load rating model given in the MBE is the governing case of three trucks (Types 3, 3S2, and 3-3; see Figure 1), with a load factor of 1.35. As noted above, to account for local vehicle load requirements, which may higher than the federal standard, some states such as Michigan have increased this rating load. In particular, MDOT specifies 28 vehicles with different load factors for rating, which are meant to model possible legal configurations (MDOT 2005). Of these rating trucks, those that provided the maximum load effects for the spans considered in this study are given in Figure 2. As noted above, use of this existing MDOT rating model, as well as that given by the MBE, produced highly inconsistent girder reliabilities in rating (Eamon and Siavashi 2018).

A simple way that design variables could be used to develop a live load model is to use these parameters to describe a particular rating truck configuration. That is, the number of axles, axle spacing, and axle weights could be taken as design variables in the optimization. Although simple, this approach is somewhat constraining and does not fully utilize the potential of the

RBDO process, as a single rating truck may not provide a good representation of the actual load effects measured across all bridge spans. That is, the load effects that can be generated by a rating truck are not nearly as flexible as load effects that can be generated by other means, such as various mathematical functions not necessarily linked to the physical representation of a single vehicle. This increased flexibility is potentially important because the load effect generated by the rating model must not only account for the effects of single vehicles, but also for load effects caused by multiple following vehicles in one lane, as well as groups of side-by-side vehicles in two lanes, all of which contributed to the development of the live load random variable (LL) statistics shown in Table 2. Thus, the mean maximum live load effect used in the reliability analysis is the result of a complex pattern of traffic loads as a function of bridge span, which may be difficult to well-represent by a single rating vehicle.

Therefore, to allow the optimizer the greatest possibility to reach an ideal rating model with minimal variation in reliability (and thus minimize the objective function given by Eq. 2), design variables are not used to describe a physical representation of a rating vehicle, but rather to directly describe the required live load effect (RLE) caused by a rating vehicle, as a function of bridge span. As defined above, the RLE refers to the total live load effect that must be imposed on the structure in the rating process in order to meet the specified reliability target.

Prior to the optimization, a preliminary evaluation was done by fitting various expressions to a selection of RLE values corresponding to different span lengths. This goodness of fit should give a reasonable indication of how successful the curve could be used in the optimization, as if the sample of RLEs can be well matched, then variation in reliability index should be able to be well minimized in the RBDO. The curves considered included polynomial, logarithmic, power, compound, logistic, growth, exponential, and sum of sines functions. Using root mean square error as a metric, it was found that a sum of sines function, similar to a Fourier series, could best fit the required rating load effect, and is given as:

$$RLE = \sum_{i=1}^{n} a_i \, sin(b_i x + c_i) \qquad (6)$$

where for n terms, constants a_i, b_i, and c_i represent design variables to be determined in the optimization and x is bridge span length. Because the variation in RLE with respect to moment was found to be substantially different from that of shear, the analysis was conducted separately for shear and moment load effects to maximize the goodness of fit that could be obtained in each case. It was found that for both moment and shear, 3 terms are sufficient for describing required load effects, producing 9 design variables for load effects. Note that Equation 6 is not only significantly more flexible in generating RLE than a single rating truck, but it is also practically less complex in the RBDO. For example, a single 5-axle rating truck would also require up to 9 design variables to describe axle weights and spacing (5 variables for axle weights and 4 for spacing), as well as accompanying expressions needed for conversion of the truck configuration to maximum moment and shear load effects on a given span. Although this study is limited to simple span structures, it was found that the sum of sines function could similarly best fit the variation in RLE required for two-span continuous bridges. However, this would likely require development of a separate optimized load model for best results.

Lower (Y_k^l) and upper (Y_k^u) bounds for the design variables (i.e. constants within Eq. 6) are specified to be from -100000 $\leq Y_k \leq$ 100000. Although not reached in the final results, the limits are important as they influence the generation of design variable values during each iteration of the optimization, as discussed in the section below.

In the optimization, the RLE within Eq. 5 (i.e. the quantity $\gamma_{LL}(LL+IM)$) is taken as a function given by Eq. 6, with design variables a_i, b_i, and c_i (i = 1-3). Following the reliability procedure described above, Eq. 5 in turn determines R_n, which then affects the calculation of girder reliability. Therefore, in one cycle of the RBDO, trial values for design variables a_i-c_i are found, then the RLE, R_n, and finally reliability index for all girders is computed. The objective function (Eq. 2) is then evaluated. Based on the results of Eq. 2, which quantifies the inconsistency in reliability for different girders, the optimizer determines new trial values of the design variables, in an attempt to minimize Eq. 2.

Solution of RBDO Problem

A simple RBDO approach typically requires two iterations; one iteration, the primary 'outer' loop, involves the optimizer, while the 'inner' nested loop concerns the reliability algorithm. In each cycle of the optimization, the objective function (Eq. 2) and reliability constraints (β_{min} = 2.5) are evaluated based on the current design variable (a_i, b_i, c_i) values, and based on these results, design variable values are updated for use in the next iteration. To update these values, each optimization iteration requires multiple evaluations of the objective function, while if an iterative reliability algorithm is used, multiple evaluations of the limit state function are also required. Thus, the double-loop procedure demands high computational effort.

The most common ways to reduce this effort are focused on modifying the interaction of the optimization and reliability algorithms (Kharmanda et al. 2002; Chen et al. 2002; Yang and Gu 2004; Mohsine et al. 2006), or directly increasing the efficiency of the reliability method by using approximate, direct methods in lieu of iterative-intensive approaches (Kirjner-Neto et al. 1998; Grandhi and Wang 1998; Koch and Kodiyalam 1999; Choi and Park 2001; Young and Choi 2004; Zou and Mahadevan 2006; Agarwal et al. 2007). As noted above, in this study, the later approach is used where computational efficiency is improved by using a non-iterative reliability algorithm, modified for accuracy, thus eliminating the inner iterative loop in the RBDO.

As with reliability algorithms, numerous optimization solution procedures are available. One approach is to use a gradient-based solver such as sequential quadratic programming or the modified method of feasible directions (Soler et al. 2012; Vanderplaats 1999). With these methods, gradients of the objective function are taken with respect to the design variables, then this information is used to determine new design variable values for the next iteration cycle. A different approach to optimization is represented by heuristic methods, which often use a form of probabilistic simulation in lieu of computing numerical derivatives. Some of these methods include Simulated Annealing (Kirkpatrick 1984), Insect Colony Optimization (Karaboga and Georgiou 1994), Genetic Algorithm (Koumousis and Georgiou 1994), and Particle Swarm Optimization (Kennedy 2011). In this study, a genetic algorithm (GA) is used, which the authors found to be an effective method in consideration of alternatives used in previous work (Behnam and Eamon 2013; Thompson et al. 2006; Rais-Rohani et al. 2010).

The GA method does not require derivative information, but only direct evaluation of the objective function. At each iteration, new design variable values are determined with directed probabilistic simulation. In general, the process starts with a large set of randomly generated possible solutions (i.e. sets of design variable values), which are refined at each cycle by evaluating how effectively the objective function is satisfied. New potential solutions are generated from the most successful previous solutions until an optimal set is found. To generate new solutions, for each successive iteration, two primary procedures, crossover and mutation, are used. In the crossover procedure, subparts of two randomly selected previous solutions are combined to form a new solution, whereas the mutation procedure applies random changes to randomly selected individual solutions. The purpose of these operators is to retain potentially effective solutions while avoiding convergence to a local rather than global optimum (Man et al. 1996; Tang et al. 1996; Konak et al. 2006; Hao and Xia 2002).

In this study, a possible solution refers to a set of design variable values that represent the values of the constants (a_i, b_i, c_i) given in Eq. 6. The optimization starts by determining 1x10^6 possible solutions with Monte Carlo Simulation (MCS), using uniform distributions bound by the limits Y_k^l and Y_k^u given above. This solution set size remains constant for all iterations. Once this initial set of solutions is generated, the objective function (Eq. 2) is evaluated using all of the potential solutions, and these results are recorded. The next iteration begins by generating a refined set of solutions from several different sources: 1) 80% are obtained by randomly choosing two solutions from the previous set and producing a new solution by taking a weighted average of these two solution values, such that the more effective solution (that with the lowest objective function value) is given proportionally more weight (crossover); 2) the top 10% of most effective solutions are retained from the previous iteration; 3) 9.8% are obtained from MCS, as with the initial set; 4) 0.2% are obtained by randomly choosing a solution from the previous iteration, then randomly choosing one of its design variables and replacing that value with a new, randomly generated value using the MCS process (mutation).

The objective function is then evaluated with this new set of potential solutions, and the process repeats during subsequent iterations until the solution converges. Here, convergence implies that additional iterations cannot produce a more optimal solution than that found in previous iterations; i.e. that the objective function cannot be further minimized.

Best Selection Approach

As will be discussed in the Results section, the optimization procedure described above can produce an excellent load model with very low variation in required load effect across the different bridge spans. However, although an RBDO result may represent a theoretically ideal solution, it is accompanied by several notable drawbacks: high computational cost, a somewhat complex problem formulation, and a resulting load model that may bear little resemblance to a realistic vehicle. In this study, an alternative approach is examined where rather than generate an idealized load model by optimization, a set of truck records from the WIM data that produce the least variation from the RLE across all spans and bridge types is formed. Then, an appropriate load factor is chosen for each record in the set such that the RLE is provided for all bridge spans, ensuring that the imposed minimum required reliability requirement of $\beta_{min} = 2.5$ is met. The resulting vehicle that has the least variation in RLE once the load factor is applied is then chosen; i.e. the 'best' available selection. This best selection approach represents a simpler and vastly less computationally costly solution than that obtained from the RBDO. The implementation details and effectiveness of this approach are discussed below.

The first step in this process is to select a set of initial trucks for further consideration. The amount of WIM data available for load model development is typically large. The database used for this study, for example, as noted above, contains 89 million legal and routine permit vehicle records, and full consideration of all vehicles in this set is costly. A much smaller subset of these vehicles can be selected for further consideration by comparing the range of ratios of load effect produced by the vehicle to that required (RLE) across the bridge spans considered. Vehicles are selected based on a range of provided to required load effect ratios. This selection limit can be expressed as:

$$\frac{\left(\frac{VLE}{RLE}\right)_{max}-\left(\frac{VLE}{RLE}\right)_{min}}{\left(\frac{VLE}{RLE}\right)_{min}} < k \qquad (7)$$

where $\left(\frac{VLE}{RLE}\right)_{max}$ and $\left(\frac{VLE}{RLE}\right)_{min}$ are the largest and smallest ratios of the vehicle load effect (VLE) to the required load effect (RLE), respectively, found across the bridge spans considered, and k is the fractional range limit imposed. It was found that a VLE/RLE range of approximately 10% (i.e. $k = 0.10$) provides a reasonable selection of vehicles for further consideration. In this study, using k=0.10 reduced the initial database of 89 million to about 2.2 million.

Although it may appear intuitive to do so, this first step does not simply select the vehicle with the single lowest range of (VLE/RLE); i.e. that which would seemingly produce the lowest discrepancy in reliability across the bridge spans considered. The reason for this is that the appropriate load factors are not yet known for the initial vehicles considered. Any vehicle taken from the WIM data, such as that which initially shows the lowest variation in VLE/RLE ratio, will require a load factor such that its total load effect at least meets the RLE across all bridge spans. However, when this load factor is imposed, it alters the range of (VLE/RLE) ratios, sometimes substantially. This frequently results in a vehicle which initially had the lowest (VLE/RLE) range to no longer having the lowest (VLE/RLE) range after the load factors are applied. This occurs because imposing higher load factors (such as required on lighter vehicles) magnifies the range of (VLE/RLE). This was found to be a nearly linear effect, where imposing a load factor of 2 would generally double the (VLE/RLE) range. This can be seen in Figure 3, which shows two trucks taken from the WIM data used in this study. Before load factors are applied, Truck 2 has the lowest range of (VLE/RLE) from spans of 6-61 m. However, after applying the required load factors to meet the RLE (1.60 for Truck 1 and 15.01 for Truck 2), the (VLE/RLE) range of Truck 1 is lowest. As noted above, setting the selection limit k at 0.10

provided best results as a balance between computational effort and potential for selecting the best solution. Increasing k beyond about 0.1 was found to result in too many unnecessary selections that are highly unlikely to be the optimal solution, needlessly increasing computational effort. Conversely, lowering k much more than about 0.1 was found to eliminate potentially optimal solutions.

After required load factors are applied, the next step is to determine the metric used for best selection. One possible metric would simply be the range of factored vehicle load effect (VLE_f) to RLE: (VLE_f/RLE), where the vehicle with the lowest range would be selected. However, the upper value of this range, $(VLE_f/RLE)_{max}$, may be governed by an outlier, a single, particularly high result generated by a single bridge span. In this case, it may be more desirable to select a vehicle that minimizes the amount of discrepancy among all bridge spans. Various metrics of this nature are available. In this study, coefficient of variation (COV) is used for this purpose. The final step is then to compute the selection metric for all vehicles in the set and select the best result. In this case, COV of (VLE_f/RLE) was computed for all vehicles in the set, and that with the lowest value was taken as the best selection.

In summary, the proposed approach is as follows:

1. Select a target reliability index β_T and compute corresponding required load effects (RLEs) needed to rate each of the bridge girders considered, using the procedure summarized in the "Reliability Analysis" section above. Note that although setting up the problem for the first time may involve effort, once the process is programmed, obtaining the solution (i.e. the RLEs) requires negligible computational time.

2. Compute the vehicle selection ratio given by the left side of Eq. 7 for all vehicle records in the WIM database. Note that the vehicle load effects (VLEs) within Eq. 7 should be

readily available, since VLEs are needed for development of any reliability-based load model, and would have been used to characterize vehicle live load as a random variable prior to the reliability analysis (for example, see Eamon et al. 2016). Since Eq. 7 is very simple algebraically, it requires relatively small computational effort, even when many millions of vehicles are considered

3. For the set of trial vehicles that have selection ratios less than k = 0.1 (i.e. that satisfy Eq. 7), for each vehicle, determine the load effect factor γ_F necessary for the VLE to match the RLE of each considered girder. This is simply the RLE divided by the VLE: γ_F = RLE/VLE. Then, apply the governing load effect factor γ_{GF} among all girders for that vehicle to its VLE to produce the factored VLE: $VLE_f = VLE \times \gamma_{GF}$.

4. For each vehicle in the set of trial vehicles found in step 3, compute the COV of the (VLE_f/RLE) ratios for each bridge girder considered. The result with lowest COV represents the final, Best Selection vehicle to be chosen for the rating model. Note that the actual live load factor required for MBE-based load rating (γ_{LL}) using this vehicle can be easily recovered by setting the total imposed load effect (VLE_f) equal to the denominator of Eq. 4, and solving: $\gamma_{LL} = (VLE_f / (LL + IM))$, where in this case LL represents the unfactored Best Selection vehicle load effect. Since VLE_f and LL vary with span, the maximum γ_{LL} across all spans is chosen in practice.

This process is summarized in Figure 4.

Results

Following the RBDO approach, because variation in girder reliability (as a function of spacing and span) with respect to moment was found to be substantially different from that of shear, the analysis was conducted separately for shear and moment load effects to maximize the goodness of fit that could be obtained in each case. These results are calculated considering the database of 195 hypothetical girder bridge designs of prestressed concrete I and box-shapes, composite steel, and reinforced concrete, as discussed in the Reliability Analysis section above. This results in two rating vehicles (models) from the procedures considered (RBDO and Best Selection), one each for moment and shear effects, as compared to three existing AASHTO rating trucks and 28 existing MDOT rating trucks for both moment and shear. For the RBDO, the optimal results were obtained with approximately 500 iterations. For each load effect result (moment and shear), the Best Selection approach was completed in approximately 17 minutes on a modern desktop computer (with an Intel i7 2.7 GHz processor and 32 GB of RAM), while the traditional RBDO process described requires approximately 14 hours of computational effort, an increase in computational effort of nearly 50 times. Note that further reductions in computational effort are likely possible with the use of more sophisticated algorithms and procedures. For example, replacing the GA optimizer with a gradient-based solver may allow for greater efficiency. However, such choices have possible drawbacks as well, such as finding local rather than global minimums and potential convergence difficulties.

The final set of values obtained for the parameters of Eq. 6 are shown in Table 3, while the trucks obtained from the Best Selection Approach are given in Figure 5. In Figure 6, the ratio of the factored vehicle load effect to the required load effect (VLE_f/RLE) for rating moment effect is given. In the figure, results are shown for the RBDO solution, the Best Selection Truck, and the MDOT and AASHTO rating trucks, once required load factors are applied such that all truck models meet the minimum RLE (i.e. $VLE_f/RLE \geq 1.0$). These load factors are 2.02, 1.35, and 1.93 for the Best Selection and governing MDOT and AASHTO Trucks, respectively. For each model, the governing bridge (i.e. that which produced least reliability, governing the required minimum load factor) case was a side-by-side box beam bridge 6 m long; note that the values given in the Figure represents the governing case of all bridge girder types considered (steel, prestressed concrete, steel, side by side and spaced box beams) for a particular span. As shown, most consistency as well as closeness to the RLE, and thus target reliability index, can be obtained with the RBDO-developed model. This is particularly so when compared to the MDOT rating trucks, which result in significant conservatism in rating for the shorter spans, where the highest (VLE_f/RLE) ratio reached approximately 1.85 at the 18 m span. Although not as severe, the AASHTO trucks also showed significant discrepancy at the lower spans, with a (VLE_f/RLE) ratio of about 1.20 at the 18 m span. Figure 6 also shows that the single Best Selection Truck is nearly as good as the RBDO model, producing discrepancies much less than existing MDOT and AASHTO models. Results from all rating models shown in Figure 6 are quantified in Table 4, where the minimum (β_{min}) and maximum (β_{max}) reliability indices corresponding to the largest discrepancies shown in Figure 6 are given, as well as the coefficient of variation of reliability index (V_β) from all girders considered across all bridge types and span is given. To fairly compare results, a best possible outcome is also given, provided that the same rating load model would be used for all bridge types, as is expected in rating practice. This is given as the "Exact (using RLE)" result. For this case, the results presented in the table correspond to a (VLE_f/RLE) ratio of 1.0 for all spans on Figure 6. Notice that this best possible outcome does not produce identical reliability values across all cases, however, as the range of reliability index for the "Exact" case actually varies from 2.5 – 3.95, as shown in Table 4. This occurs because there are multiple bridge types analyzed when each span is considered, and because different uncertainties in resistance and load distribution are associated with these different bridge types, a different reliability index in rating will be achieved if the same load model is used to rate these different types of structures (Eamon and Siavashi 2018). In the results shown, as noted above, it is assumed that the same rating truck will be used for all bridge types of a given span; i.e. the rating agency would not use one type of rating truck for steel girders, and a different rating truck for concrete girders, etc. Because the same rating model is used for all bridge types, only one of these types will produce the largest RLE, and the others, with lower RLE, will be rated somewhat more conservatively. It is this governing RLE case that is shown on Figure 6 as a function of span. Thus, a variation in reliability index, as shown in Table 4, results even for the "Exact" case, which practically cannot be improved further.

As shown in Table 4, the RBDO model produces results nearly identical to the Exact model, with only a slightly higher average reliability index among all cases (β_{ave} , Exact = 2.83; β_{ave} , RBDO = 2.84). The Best Selection Truck produces results nearly as good, with only a slightly higher β_{max} and β_{ave} than the Exact result (β_{max}; 3.96 vs 3.95 and β_{ave}; 2.88 vs 2.83). More notably, the COV of reliability indices for all bridge cases is identical (to 2 decimal places) among the Exact, RBDO, and Best Selection results, of 0.13. When the existing MDOT trucks are considered (with the required load factor (LF) applied), it can be seen that the maximum, average, as well as COV of reliability index are markedly greater than the ideal solution. In comparison, as shown in Table 4, the AASHTO Trucks produced surprisingly good results for moment effect overall, while although worse than the RBDO and Best Selection solutions, results were relatively close, with the AASHTO model (once the required minimum load factor of 1.93 was applied) producing β_{max} and β_{ave} only 5-7% higher than the ideal solution, and COV increasing from 0.13 to 0.15. The relative accuracy of this model did not hold for shear results, however, as discussed below. In comparison, the MDOT model (with required load factors) produced a much worse solution, with β_{max} , β_{ave}, and COV significantly higher than the alternative models.

Shear results are given in Figure 7 and Table 5. The same bridge that governs for moment did so for shear as well (6 m, side by side box beam), with minimum required load factors of 1.79, 1.40, and 2.40 for the Best Selection, MDOT, and AASHTO Trucks, respectively. In the figure, some interesting results are shown, where although for moment, the most conservatively rated span for the AASHTO and MDOT models is 18 m (prestressed concrete box beams with 3.6 m girder spacing) and a 24 m span of the same bridge type for the Best Selection truck, for shear, the most conservatively rated span is 30 m for all models. Moreover, discrepancies with the MDOT model decreased, where the maximum load ratio (VLE_f/RLE) dropped from about 1.85 for moment to 1.56 for shear, but discrepancies for the AASHTO model increased, with maximum load ratios changing from about 1.20 to 1.35. Similarly, results for the Best Selection Truck worsened (where the maximum load ratio increased from about 1.03 to 1.10), whereas the RBDO solution for shear produced nearly the same accuracy as for moment, with discrepancies within 1%. Note that although the Best Selection result worsened for shear, it remains a substantially better solution compared to the AASHTO and MDOT shear models.

As shown in Table 5, the range of shear reliability index for the exact solution has increased somewhat from that of moment, with β_{max} and β_{ave} increasing from 3.95 to 4.20 and 2.83 to 2.90, respectively. The variance of all results has decreased, however, from 0.13 to 0.10, with both the RBDO and Best Selection models producing nearly identical solutions, although a slight increase in occurs β_{ave} with the Best Selection Truck, from 2.88 for moment to 3.00 for shear. As with moment results, COV for shear results for the Best Selection Truck (0.10) matched that of the RBDO and exact solutions. For shear, the AASHTO model considerably worsened when compared to moment results, producing a substantially higher β_{max}, β_{ave}, as well as COV as compared to the exact solution, with values of 4.97, 3.33, and 0.14, respectively. In this case, AASHTO results are similar to those found from the MDOT model, which again produced worst results overall.

It should be noted that the reliability index and RLE results are not based on nor are significantly impacted by any single maximum WIM data vehicle load effect. In fact, removing any single, or numerous single vehicles, including the best selection vehicle, from the WIM data will have no practical impact on the computed live load random variable (*LL*) parameters shown in Table 2. Rather, these values are based on a load projection using hundreds to thousands of vehicle load effects, the governing of which are from multiple vehicles together (in following and side-by-side configurations; see Eamon and Siavashi 2018 and Eamon et al. 2016). That is, the Best Selection vehicle does not represent a governing, nor even typical, load effect. Rather, its configuration best-replicates the pattern of projected load effects across the different spans considered.

Although results were shown for the specific traffic data described above (i.e. Michigan legal and routine permit vehicles), to verify the applicability of the Best Selection method, this approach and the RBDO procedure were repeated on a set of 78 million vehicles collected from Michigan that meet the Federal Bridge Formula (FHWA 2015). Significantly more restrictive than the originally considered Michigan database of legal and extended permit vehicles, this new set of vehicles would meet the legal requirements common to many states. Application of Eq. 7 (with k = 0.10) reduced this set of vehicles to approximately 740,000 for further consideration.

Comparing the results of both vehicle databases, nearly identical results were found using the Best Selection approach in terms of closeness to the ideal RBDO solution.

Although this Best Selection approach was found to be effective, several limitations should be noted. First, as potential solutions are found within the collected vehicle database, a reasonably large pool of vehicles must be available. Although 2.2 million vehicles were used in this study (i.e. after the application of Eq. 7) , it was found that nearly as good results (with a difference of a few percent) could be obtained using only approximately 1/6th of this vehicle pool, or about 350,000 vehicles. However, as the size of the database decreases, correspondingly worse solutions will result. Second, the data set used in the Best Selection process should be representative of the entire pool for which the load model is to be developed. That is, conducting the best selection on data from a single WIM site rather than a series of sites throughout the state may be problematic, as results may be locally biased, potentially missing the most effective solutions. Third, there is inherent uncertainty as to how close the Best Selection result will be to the ideal solution. Fortunately, error is readily quantifiable by comparing results to the required load effects (RLE); unacceptably large errors may indicate the need to implement the more costly RBDO method.

Finally, further note that the RLE values can be readily determined using the relatively simple reliability analysis described in the corresponding section above. Direct use of the RLE would not only allow for an exact reliability-based rating assessment for each structure, but would avoid any additional computational effort associated with further load model development. Although theoretically ideal, this approach may be problematic in practice. In particular, existing rating and posting procedures used by most state DOTs are based on a framework that uses representative vehicles. This includes the use of specialized rating software that requires vehicle configurations as inputs, the desire for compatibility with the vehicle-based format of existing rating standards, as well as the desire to minimize the need to use different loads, vehicles, and/or factors for different spans and bridge types. Thus, the direct use of RLE values may be difficult to implement in current practice, and hence the alternative vehicle-based alternatives considered here, which were recently proposed to MDOT and are currently under consideration.

Summary and Conclusion

The potential effectiveness of using RBDO and an alternative method to develop a reliability-based load rating model considering state-specific traffic was studied.

It was found that the RBDO procedure could develop a load model more effective than the existing rating models suggested by AASHTO as well as the significantly more complex, state-specific DOT model. In particular, a modest improvement was achieved over the AASHTO model for moment effects, while a significant improvement was made for shear, as well as a significant improvement for both moment and shear effects from the DOT model. However, for the RBDO process to be feasible, it was found that reduction of computational effort as much as possible was essential. This was effectively done using a slightly modified, non-iterative reliability approach to allow use of a single-loop RBDO procedure. The RBDO solution produced final results nearly identical to a theoretically ideal solution.

In comparison, a Best Selection Approach was studied, where it was proposed to select a vehicle directly from the WIM data that minimizes discrepancies in load effects. It was found that this method produced nearly identical results as the RBDO solution for moment rating and only slightly worse results for shear rating. It was further found that more complicated rating models are not necessarily most effective. The most simple vehicle model studied, that developed from the Best Selection Approach, uses only a single rating vehicle for moment effects and another vehicle for shear effects, while it produced significantly more consistent results overall when compared to the multiple-vehicle AASHTO and MDOT alternative models.

Given that the Best Selection Approach represents a large reduction in problem complexity and computational cost as the RBDO solution, as well as provides a realistic (actual) load rating vehicle, it is recommended for future consideration for state-specific load rating model development.

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Table 1. Michigan Legal and Routine Permit 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
Permit (Construction)*	Length ≤ 26 m Any axle ≤ 107 kN GVW ≤ 667 kN 2 ≤ Number of axles ≤ 11 Vehicle Length ≤ 26 m

*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*	λ	
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	*LL*	1.07-2.08[2]	0.16-0.27[3]
Vehicle Live Load, Shear	*LL*	1.0-1.64[2]	0.16-0.30[3]
Live Load Impact Factor	*IM*	1.13;1.10[4]	0.09;0.055[4]
Vehicle Load Distribution Factor	*DF*	0.72-0.99	0.11-0.18
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 as the ratio of mean load effect to the nominal Michigan legal rating truck load effect; varies as a function of span.
3. Includes uncertainties from data projection, site, WIM data, impact factor, and load distribution; varies as a function of span.
4. Bias factor is given as a multiple of static LL, such that the total vehicular load effect is LL*$bias_{IM}$. First values refer to single lane load effects; second values refer to two-lane load effects.

Table 3. Coefficients for Sum of Sines Model.

Load Effect	Parameter								
	a_1	b_1	c_1	a_2	b_2	c_2	a_3	b_3	c_3
Moment	8556	0.015	-0.621	4879	0.022	2.07	295	0.053	1.91
Shear	244	0.002	.021	113	0.002	6.30	4.59	0.062	-1.67

Table 4. Comparison of Moment Design Load Models.

Design Load	Load Factor	β_{min}	β_{max}	$\beta_{average}$	COV
Exact (using RLE)	-	2.50	3.95	2.83	0.13
RBDO Load Model	-	2.50	3.95	2.84	0.13
Best Selection Truck	2.02	2.50	3.96	2.88	0.13
MDOT Trucks (current LF)	varies[1]	2.13	5.52	3.74	0.20
MDOT Trucks (required LF)	1.35	2.50	5.74	4.09	0.18
AASHTO Trucks (current LF)	1.80	2.25	3.85	2.84	0.15
AASHTO Trucks (required LF)	1.93	2.50	4.14	3.05	0.15

1. See Figure 2 for load factors.

Table 5. Comparison of Shear Design Load Models.

Design Load	Load Factor	β_{min}	β_{max}	$\beta_{average}$	COV
Exact (using RLE)	-	2.50	4.20	2.90	0.10
RBDO Load Model	-	2.50	4.25	2.91	0.10
Best Selection Truck	1.79	2.50	4.20	3.00	0.10
MDOT Trucks (current LF)	varies[1]	2.10	4.67	3.22	0.14
MDOT Trucks (required LF)	1.40	2.50	5.05	3.55	0.14
AASHTO Legal Trucks (current LF)	1.80	1.70	3.85	2.67	0.13
AASHTO Legal Trucks (required LF)	2.40	2.50	4.97	3.33	0.14

1. See Figure 2 for load factors.

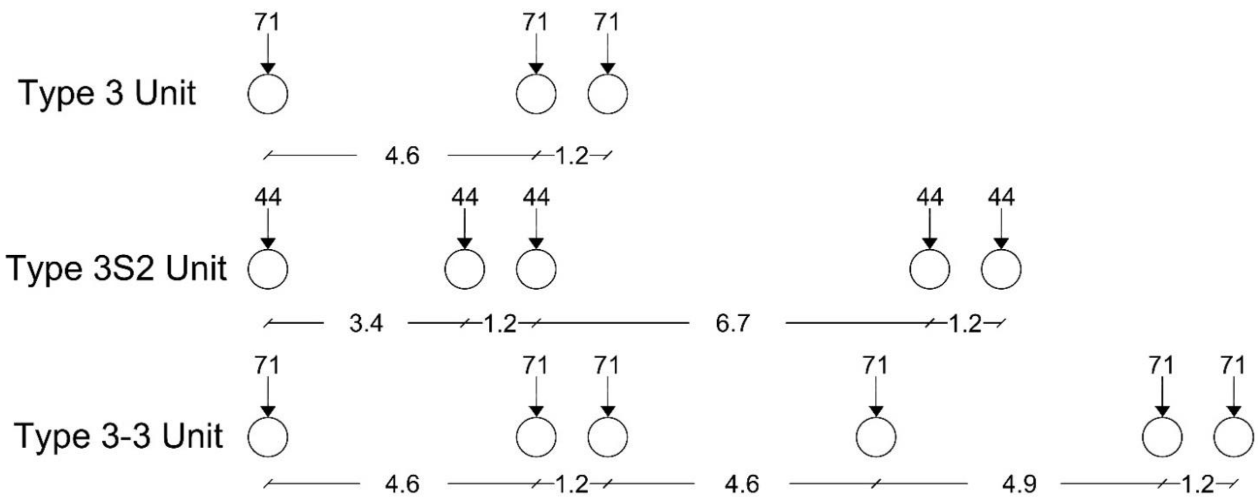

Figure 1. AASHTO Rating Trucks (kN, m).

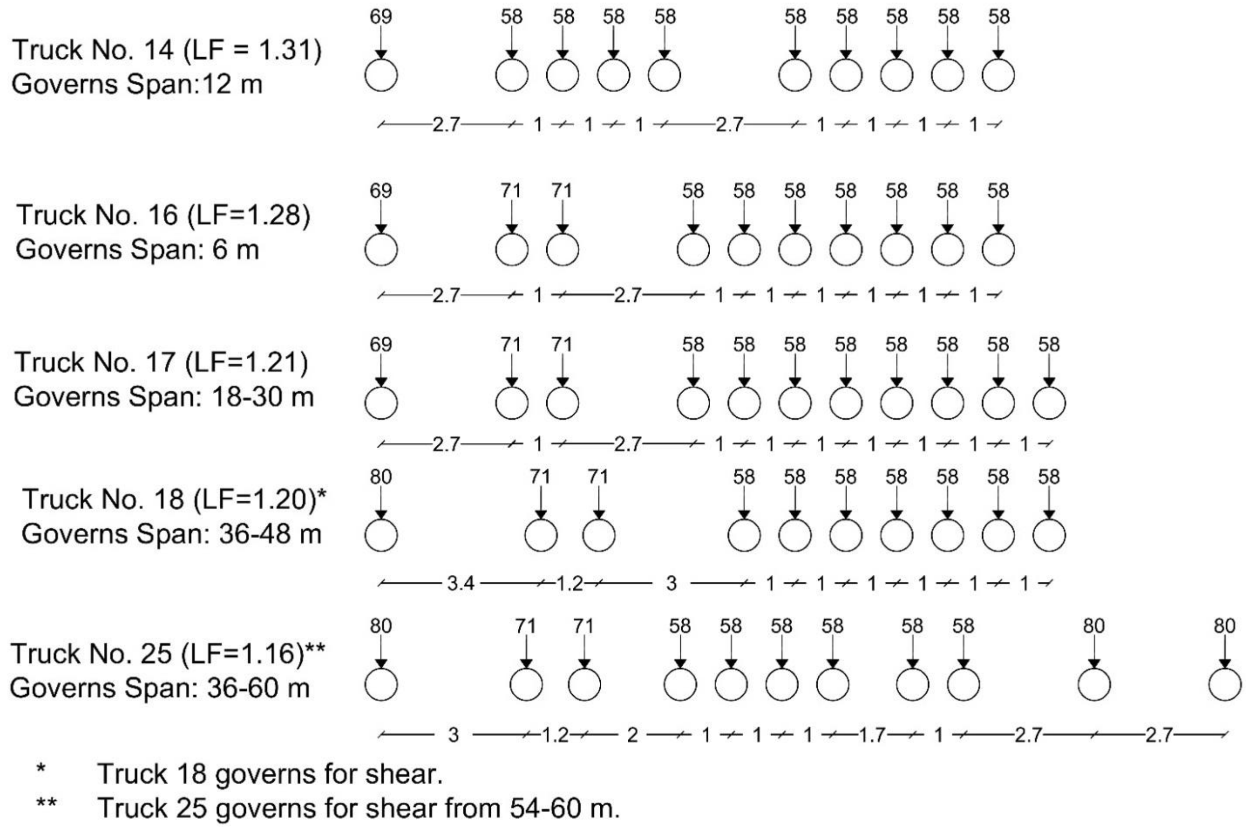

Figure 2. Governing MDOT Rating Trucks (kN, m).

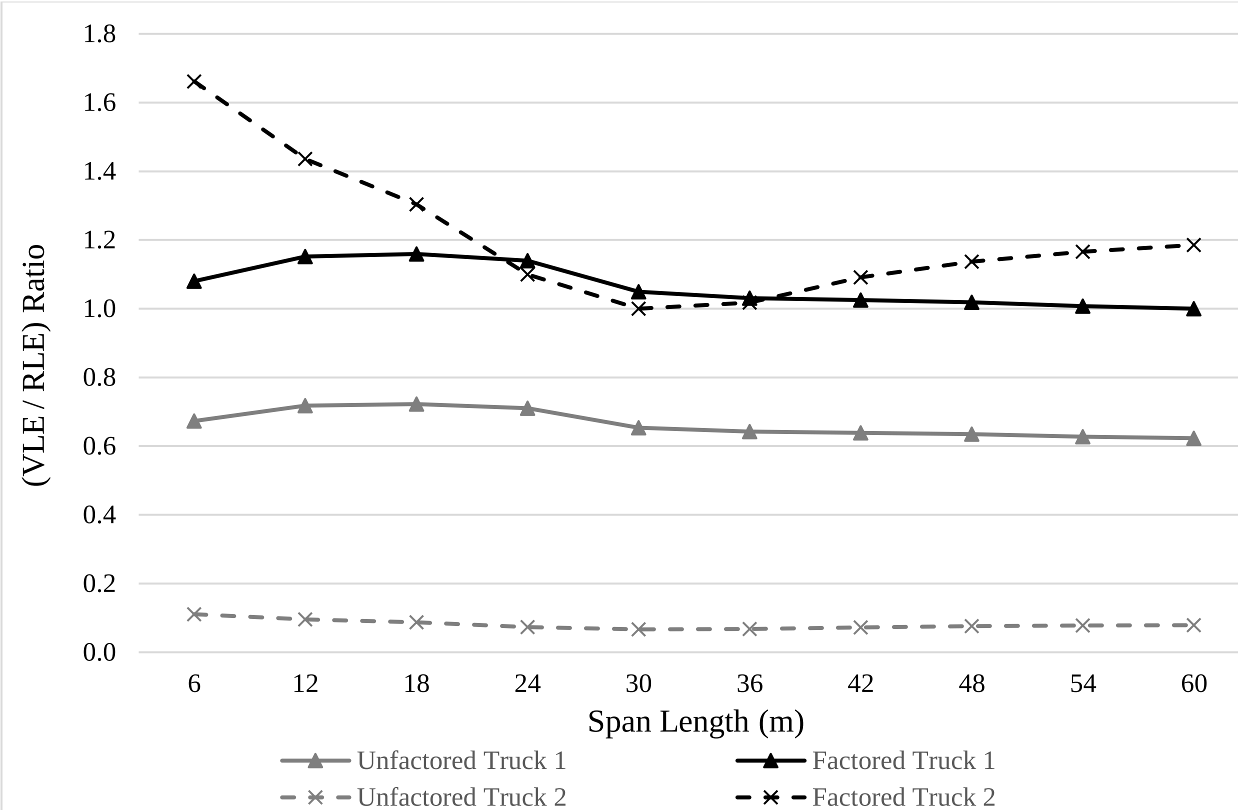

Figure 3. Example Comparison of Load Effect Ratios Using Best Selection Method.

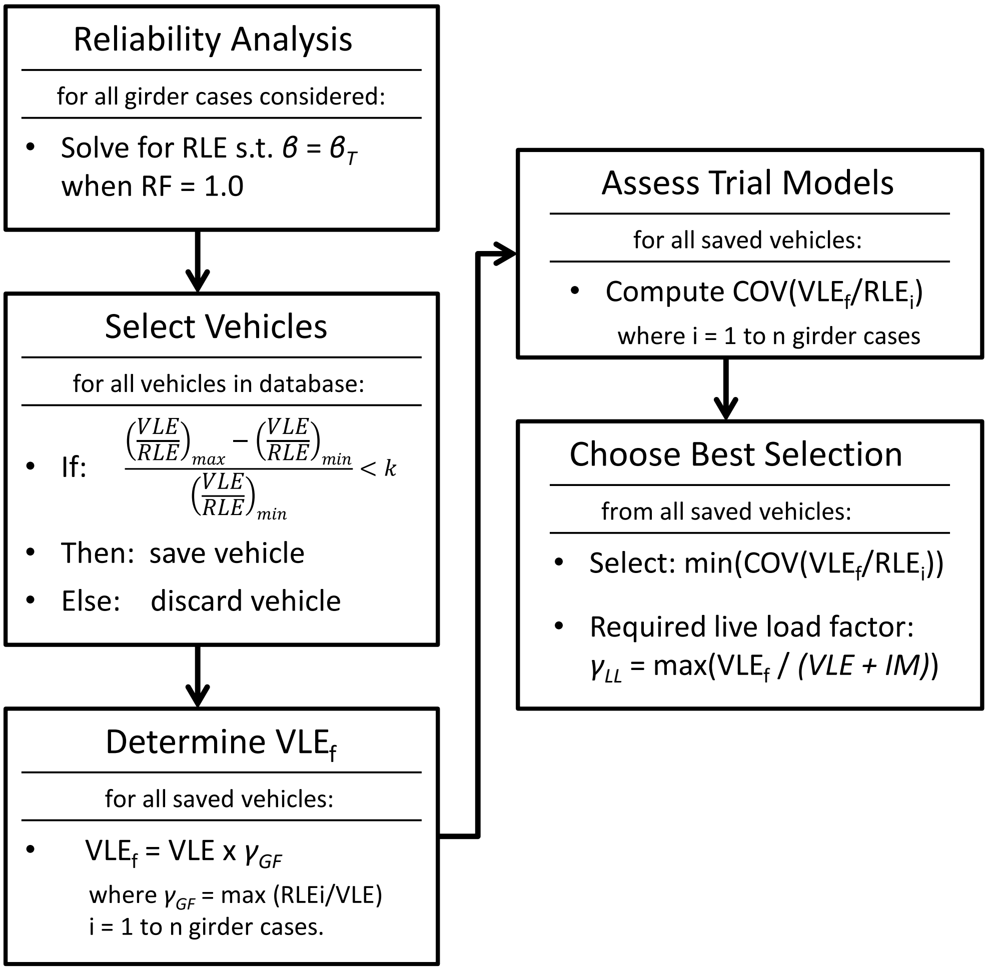

Figure 4. Best Selection Method Flowchart.

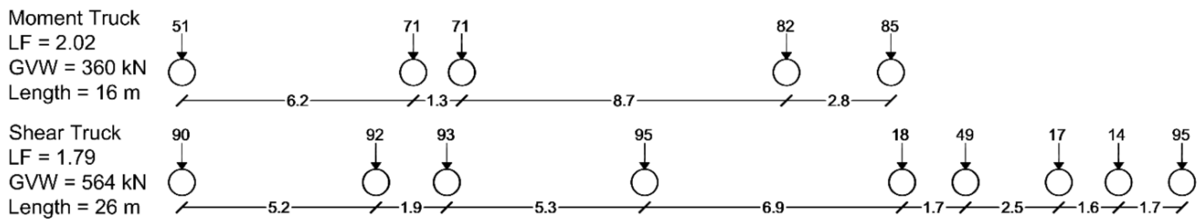

Figure 5. Best Selection Approach Trucks (kN, m).

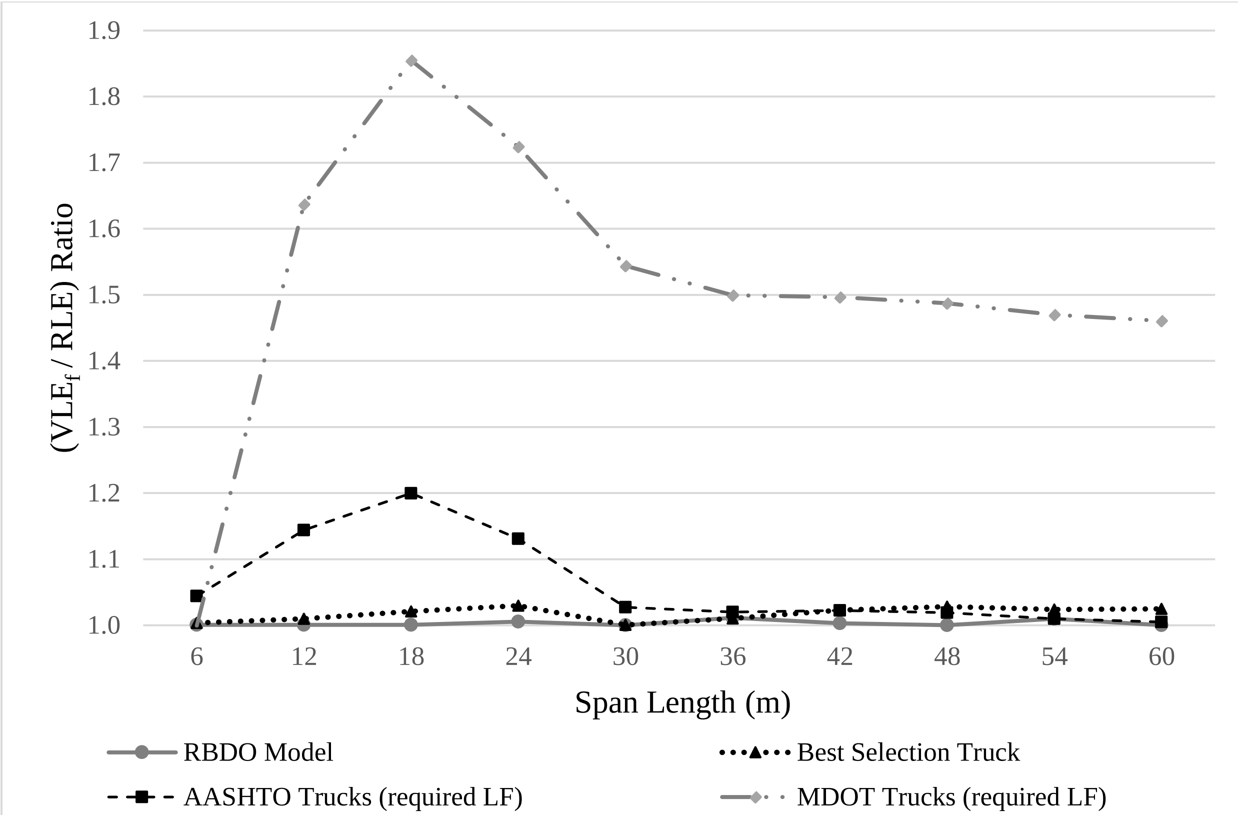

Figure 6. Vehicle to Required Load Effect Ratios for Moment.

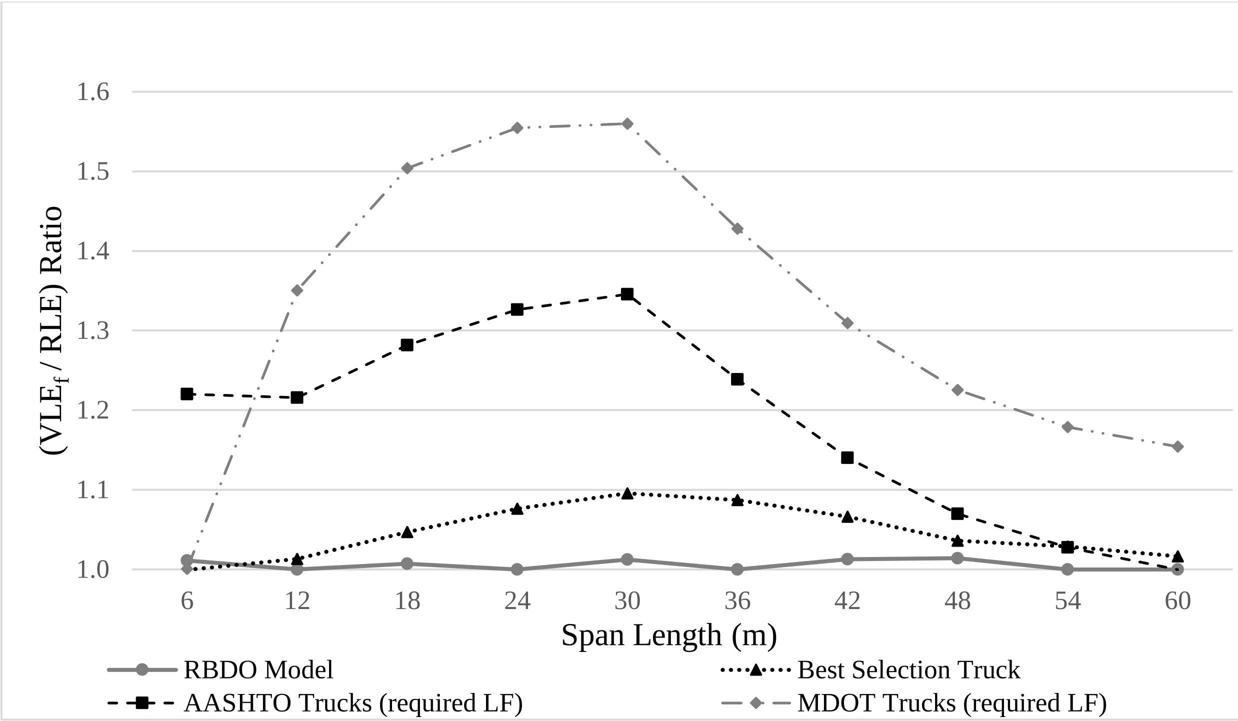

Figure 7.Vehicle to Required Load Effect Ratios for Shear.