Integrated Structural Health Monitoring System and Multi-Regression Models for Determining Load Ratings for Complex Steel Bridges

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ABSTRACT

This paper presents a multi-regression-based framework to efficiently and accurately determine load ratings of complex steel bridges. To validate the efficiency and accuracy of the proposed framework, the framework was applied to an in-service steel bridge located in Iowa. A network of strain sensors was placed on critical regions of the bridge to capture its behaviors resulting from actual ambient five-axle trucks. To approximate the trucks, relevant Weigh-In-Motion (WIM) data were secured from two weigh stations nearest the bridge. As part of the load rating calculation process, strain sensors were tested for significance and compared to the WIM data to explore which trucks significantly affect the sensors. Four different regression methods were used with the significant WIM data that were condensed to match the size of conventional rating data obtained from a series of structural analyses of the bridge based upon the AASHTO Manual. The four different truck data sets obtained from the regression methods were then each combined with the conventional data to create the corresponding regression models to predict load ratings. The predicted data were compared to the conventional data to determine the best fit regression model. Using the best fit model, a sensitivity analysis was performed to test which truck characteristic parameters affect the predicted ratings the most. Findings indicated that the framework can build the best fit regression model capable of accurately and rapidly predicting load ratings given unknown truck data. It was also found that each axle weight and the largest axle spacing have a great influence on the predicted ratings, implying that these variables may be holistically considered to ensure structural safety of steel bridges subjected to unknown trucks.

Key Words: Complex steel bridge, Load rating, Multi-regression analysis, Weigh-In-Motion data, Sensitivity analysis

INTRODUCTION

The rapid and accurate determination of live-load carrying capacity of steel bridges is a key part in assuring proper bridge repair, rehabilitation, and countermeasure, resulting in public safety in our society. In particular, it is essential to estimate real-time structural integrity of a bridge to be able to adequately and timely repair bridge damage that may occur over time due to increasing heavy traffic volumes. According to the AASHTO Manuals (1, 2), live-load carrying capacities of bridges are normally determined in terms of load ratings through field testing coupled with known vehicular loadings. However, concern has risen about the determination of load ratings at a random point in time with unknown live-loads. Consequently, some statistical studies to estimate live-load capacity of existing steel bridges (3) and to simulate arbitrary truck patterns and/or characteristics using Weigh-In-Motion (WIM) data (4) have been done, but these have not reached the extent of real-time structural integrity assessment of steel bridges. In addition to these studies, numerous past efforts (5-8) have focused on establishing different algorithms to diagnose particular types of damage for in-use steel bridges under unknown live-loads.

When determining load ratings using field tests, the field data is significantly limited due to the limited time and cost associated with field testing; thus, the resulting ratings are limited. To overcome this issue, a load rating protocol has been recently proposed by Seo et al. (9) via strain-based Structural Health Monitoring (SHM) system to monitor ambient unknown truck-induced bridge response and Multiple Simulation and Calibration (MSC) analyses with actual data to calculate load ratings of a bridge according to the AASHTO Manuals (1, 2). It was found that determining ambient unknown truck characteristics related to actual data was a critical part in accurately determining its load ratings of the bridge. Due to the high expense and time demands associated with field testing, the integration of joint SHM-MSC into the proposed protocol has been considered relatively effective in the real-time structural integrity assessment of the bridge over time. However, considering the significant number of MSCs with continuously increasing measures resulting from ambient trucks in time is a challenge given the complexity of interaction between bridge responses and ambient trucks. Therefore, there is a pressing need to establish a framework enabling computationally cost-effective analyses to accurately predict load ratings of steel bridges subjected to ambient trucks.

The goal of this study is to develop a framework in conjunction with multi-regression analyses that enables to estimate the live-load carrying capacity of in-service steel bridges under multiple ambient trucks in use on highways. This paper consists of three additional sections, for a total of four sections. The second section describes the framework in real-time bridge structural integrity assessment through the use of multiple regression models with actual strain measures and WIM data. The third section is an application of the framework and provides a detailed load rating computation procedure for a complex steel bridge in use on US Highway 30 in Iowa. Critical regions of the bridge were instrumented with a suite of strain sensors to monitor its behaviors over time. The monitored strains and WIM data obtained from two weigh stations adjacent to the bridge were used to examine the influence of WIM trucks on its strain responses at each critical region. Conventional rating data were obtained by performing a series of structural analyses of the bridge under the influential WIM trucks in accordance with the AASHTO Manuals. Four different regression models were generated based on the conventional data, and ratings yielded from each model were compared to the conventional data to identify the best fit regression model capable of accurately estimating the load ratings at low computational costs. The closing section presents a summary and conclusions.

PROPOSED FRAMEWORK

The proposed framework for creating a regression model to determine the live-load carrying capacity of in-service steel bridges is described herein. The relevant flow chart consisting of eight steps taken in this study can be seen in FIGURE 1. Each step is detailed as follows:

Step 1 is to collect field data containing strain data resulting from unknown ambient trucks and WIM truck data obtained from weigh stations in close proximity to a target complex steel bridge. The strain data are obtained from a network of strain sensors located on critical sections of the selected bridge. The sensors measure strain time history responses of the bridge when an ambient truck passes over it; thus, a single strain set for the sensor network can be collected. The WIM data measure different truck characteristics, such as axle weights and spacings. These datasets are employed in combination as the basis for the bridge rating evaluation.

Step 2 is to determine which strain sensor locations are significantly affected by unknown ambient trucks. This is done using two methods. Sensor location method 1 uses logical ranges from the strain data from unknown trucks. A parameter is set on the range values to determine whether the value is large enough to be considered significant or not. If the value fits in the parameter, this sensor location is considered significant. Sensor location method 2 uses a linear regression for the strain data. The regression model is built from this method to compare all of the sensor locations to determine which locations appear more significant. The P-values are examined to help evaluate this process. These methods are compared and sensor locations that are significant in both methods are deemed highly significant.

Step 3 is to identify those WIM trucks that are more likely to cross the bridge. Strain quantities of the significant sensors found in Step 2 are analyzed to assist in better understanding particular features (e.g., axle weights, etc.) for the WIM trucks assembled in Step 1. A tolerance interval is created based on particular truck features. This interval helps to investigate the total number of and the features of WIM trucks that almost certainly pass over the bridge and that significantly affect the sensor locations.

Step 4 is to compute a suite of load ratings based upon the WIM truck pool identified from Step 3. An analytical base model is initially created using commercially available finite element modeling software and then is calibrated with real-time strain data obtained in Step 1. It is noted that each single truck from the pool is applied as input loads to the base model when calibrating the model with field strain responses. During the calibration process, it is initially essential to determine how many calibration models are required to reliably estimate load ratings of the target bridge by appropriately treating the uncertainty in unknown trucks having different axle weights and spacings. Hence, it is assumed that the number of calibration models matching the annual average daily truck traffic number (ADTT) of the bridge is used in the calibration process, leading to a comparable number of bridge models necessary for its load rating calculations. This process is repeated to generate the number of calibration models that matches the ADTT of bridge. Finally, the calibration models subjected to the AASHTO HS-20 trucks are simulated to determine load ratings of the bridge with respect to the AASTHO Manuals (1, 2).

Step 5 is to create WIM-based regression rating models. Four regression rating methods are implemented to do so. Each method uses the WIM trucks and the ratings predetermined in Step 4. The first method selects every n^{th} truck from the WIM truck dataset collected in Step 1; n^{th} is determined by matching the size of the predetermined ratings for each strain set. The second method randomly selects n^{th} trucks from the WIM dataset. The information on n^{th} trucks combined with the rating values for each strain set is used to create this model. The third method uses intervals on specific truck characteristics such as axle spacings based upon the results from the two sensor location methods proposed in Step 2. The third regression model is then derived for each strain set. The fourth rating regression method combines ratings for all strain sets collected during certain monitoring periods. The cumulative ratings are used with the WIM trucks to create the fourth model. All resulting regression models are employed to independently predict ratings from the WIM characteristics.

Step 6 is to compare the regression-based ratings with the conventional ratings. The regression ratings are compared to the conventional ratings in the form of a cumulative distribution function (CDF) through a statistical approach. The use of CDFs is useful to determine how well the predicted values match the conventional ratings by examining the difference between the graphs at different percentiles. The regression models can also be statistically looked at to investigate how well each model is able to accurately predict rating values. The regression model with the smallest difference obtained through both CDF and statistical approach is considered the best fit linear regression model.

Step 7 is to conduct a sensitivity analysis using the best fit regression model. This model was analyzed to determine how each truck parameter affects the predicted ratings. Multiple parametric plots were created from the model to show graphically how each parameter affects the data. A main effect table is also created and examined to determine statistically the most significant parameters on the data. The graphical and statistical information help to draw conclusions specifically about which truck parameters largely affect the load ratings.

Step 8 is to make recommendations based upon the findings. Recommendations reflecting certain significant truck parameters affecting the target bridge are made for the modification of current truck design guidelines to ensure structural safety of steel bridges subjected to ambient trucks.

FIGURE 1 Flow chart of the proposed framework

APPLICATION OF PROPOSED FRAMEWORK TO STEEL BRIDGE

A sample application of the framework is detailed in the following subsections: field data, sensor location significance testing, WIM truck identification, analytical rating calculation, WIM-based regression rating models, rating comparison, sensitivity analysis, and recommendations.

Field Data

For this study, a three span continuous steel girder bridge with a skew of 20° on US Highway 30 located in Iowa was selected (8-9). The first, second, and third span lengths of the bridge are 29.7m, 38.1m, and 29.7m, respectively. This bridge has a reinforced concrete deck with 9.1m width. The superstructure is considered a more complex structural system relative to normal girder bridges. It has two steel plate girders, multiple floor beams, and two steel stringers which have much smaller size of the girders. Although this bridge consists of two travel lanes, only ambient five-axle trucks crossing on the south lane of the bridge were reviewed in this study. FIGURE 2(a) shows a three-dimensional view of the bridge, while FIGURE 2(b) shows a cross section of the bridge where networks of sensors are located. Photos of a side view and bottom view of the bridge can be seen in FIGURE 3. Detailed information on this bridge can be found elsewhere (8).

Data that included WIM data and strain time history data were obtained from the previous study (9). The WIM data was obtained from two weigh stations nearest the bridge. The WIM data contains approximately 223,000 trucks. Within that total approximately 175,000 five-axle trucks that are compatible with the monitored ambient five-axle trucks on the bridge were used for this study. The WIM data includes gross vehicle weight (GVW), class and speed, number of axles, axle weight, and axle spacing. The data also collected in the previous study (9) includes strain time history data sets measured when individual ambient trucks passed over it. The total number of strain sets is five. The strain sets were obtained from a network of 48 sensors located on critical sections of the bridge; 40 of these sensors were located on the steel plate girders, steel stringers, and floor beams and 8 were located on the deck bottom surface. Further profiles for each strain set can be found elsewhere (8).

(a)

(b)

FIGURE 2 US 30 bridge: (a) 3D schematic showing overall dimension of bridge and (b) cross section to show sensor locations (9).

(a)

(b)

FIGURE 3 Photo views: (a) side view and (b) bottom view (8).

Strain Location Significance Testing

To characterize ambient trucks that are most likely to cross the bridge, the sensors located throughout the bridge must be analyzed. To determine the most significant sensor locations, five different strain sets were run on the bridge to collect approximately 2,600 data points at each sensor location. Two methods were used to determine significant sensor locations. Each is detailed in the following subsections.

Sensor Location Method 1: Logical Values

The first method that was used to calculate the significance of each sensor analyzed logical values. The five strain sets of data were condensed using the range of each sensor per each set. Once the data was condensed, a logical value function was run in MATLAB (10). This function takes true values (any positive integer) and outputs a 1, and takes false values (0 or negative values) and outputs a 0. Since all range values were positive every value came back as a 1. To receive both true and false values a parameter was set. The median of the range values was computed to be 38.53 for the steel plate girders and 10.03 for deck bottom sensors. Every value above that was considered true (1), while every value below was considered false (0). This way the values larger than the median were returned as 1s. The values that were 1s were considered to be significant sensor locations on the bridge.

After the significant values were determined, the actual range value was put back into all of the sensors that had a 1. These values were then combined with each sensor. For example, representative girder sensors and deck bottom sensors are listed in TABLE 1. This data was then analyzed and all the sensors with values other than 0 in all five strain sets were reviewed.

TABLE 1 Representative girder sensors and deck bottom sensors

Sensor Location	Strain 1	Strain 2	Strain 3	Strain 4	Strain 5
Section B-North Girder-Bottom Flange	48.206	49.31	38.53	0	38.53
Section B-North Stringer-Bottom Flange	0	0	0	0	0
Section B-South Stringer-Bottom Flange	0	0	0	0	0
Section B-South Girder-Bottom Flange	121.82	112.46	98.33	83.84	98.33
Section C-South Girder-Bottom Flange	39	0	0	0	0
Deck Bottom Line 1	58.02	73.9	71.08	71.86	80.99
Deck Bottom Line 2	16.99	16.8	16.07	12.01	14.91

Sensor Location Method 2: Linear Regression

The second method that was used to analyze the sensors used dummy variables to create a linear regression model. The strain data was used for this method, unlike sensor location method 1 that used the range from the field data of each sensor. First, dummy variables were created for each of the sensor locations. Dummy variables are numerical variables used to represent different sensors within each strain set. The dummy variable function in MATLAB was used and created 1s and 0s from the five strain data sets to compare the different sensors, similar to the logical value method (10). This method however, automatically creates a 1 for each time one particular sensor is present, so each value in the data set can be compared to each other. A regression model was then created to compare the sensor locations via dummy variables. It was found that the P-value for each sensor showed a good measure of how significant each location was. A P-value comparison was made and for any P-value less than 0.01 the sensor was considered highly significant, all values greater than 0.01 were insignificant and were assigned a zero. These values were then aligned with the sensor location code to determine which sensors were highly significant. The data outcome for significant sensors did not appear as accurate as the logical values approach even though the majority of the sensor locations appeared highly significant according to their P-value. This result could be due to the fact that the entire sensor data set for each strain was used, compared to only the ranges in the first method. TABLE 2 shows the data obtained and the significant sensors present for the representative girder sensors and deck bottom sensors from strain set 1.

TABLE 2 Representative girder sensors and deck bottom sensors

Sensor Location Name	Sensor Significance
Section B-North Girder-Bottom Flange	0
Section B-North Stringer-Bottom Flange	0
Section B- South Stringer-Bottom Flange	0
Section B-South Girder-Bottom Flange	4.74E-05
Section C-South Girder-Bottom Flange	2.54E-27
Deck Bottom Line 1	2.04E-14
Deck Bottom Line 2	7.18E-23

Significant Sensor Locations

These two methods were compared to identify those sensors significant for both methods. It was found that a total of 10 sensor locations are significant for both methods. These sensors includes Section B-

South Girder-Bottom Flange, Section C-South Girder-Cut-back Region, Section D-South Girder-Bottom Flange, Section E-North Girder-Cut-back Region, Section E-North Girder-Cut-back Region, Section E-Floor Beam (South Stringer)-Bottom Flange, Section E-South Girder-Bottom Flange, Section F-South Girder-Bottom Flange, Deck Bottom Line 1 and Deck Bottom Line 2.

WIM Truck Identification

The five-axle truck characteristics from the WIM data were compared to truck characteristics that were approximated by exploring strain sets obtained at the significant sensors. An example of a five-axle truck configuration along with the labeled axel spacing and weight can be seen in FIGURE 4. The significant sensors from each set were graphed separately on a 0.0085 second time interval. It was found by comparing the two sensor location methods that each deck bottom strain sensor carried the most significance and their peaks were prominent in identifying truck axle spacings, especially deck bottom line 1 (see FIGURE 2a). The significant girder sensors did not carry prominent truck axle spacing and other characteristics such as axle weights due to their location under the bridge and not directly applied by the ambient trucks. FIGURE 5 shows a graph of deck bottom sensors for lines 1 and 2 for strain set 1. Each peak is considered to be one axle of the truck that is passing over the sensor; in this case it is a five-axle truck crossing the sensors, since there are five major peaks. The distance between each peak was measured to obtain the distance between each axle on a five-axle truck, also known as the axle spacing. FIGURE 6 shows the eight significant sensors from strain set 1 that were significant in both significant sensor testing methods. This figure shows the peaks in the strain data from the most highly affected sensor locations. It appears some peaks from different locations are higher than others. This may be due to one sensor location being affected moderately more than the others.

FIGURE 4 Five-axle truck configuration

FIGURE 5 Representative strain time history data for significant deck bottom sensors

FIGURE 6 Representative strain time history data for significant girder sensors

The axle spacing from FIGURE 5 was then used to create a tolerance interval to apply to the WIM data to explore which trucks were most likely to cross the bridge given the axle spacing from the strain deck bottom data (11). Tolerance intervals are used to examine a specified portion of a data sample (11). In this case the intervals were used to discover the truck characteristics that correlate the best with the strain data. The tolerance intervals were calculated for each spacing using equation 1, which follows (11).

$$K_2 = \sqrt{\frac{v(1 + \frac{1}{N})Z_{(1-p)/2}^2}{X_{1-\gamma, v}^2}} \quad (1)$$

where

N = the sample size

$X_{1-\gamma, v}^2$ = critical value of chi-square distribution

v is the degrees of freedom (N-1)

γ is the probability of the data that is included in the tolerance limit

$Z_{(1-p)/2}$ = critical value of the normal distribution

p is the proportion that the data will fall within the two sided tolerance limit

This equation used the mean and variance of the strain data for five-axle trucks. After this equation was used on each spacing, a maximum and minimum value was created for each spacing. The interval was compared with the corresponding axle spacings from the WIM data. The WIM data axle spacings that appeared in every tolerance interval were retained for analysis. As a result of this analysis, 6,933 WIM five-axle truck data remained from strain set 1; 1,114 for strain set 2; 5,365 for strain set 3; 758 from strain set 4; and 31,832 from strain set 5. TABLE 3 shows statistics from these sets.

TABLE 3 Statistics for the identified WIM trucks

Strain Sets	Statistics	WIM Truck Characteristics								
		x1	x2	x3	x4	x5	x6	x7	x8	x9
Strain 1	Mean	44.57	6.09	55.31	1.48	55.42	10.43	56.9	3.45	56.92
	STD	4.13	0.21	13.32	0.02	13.42	0.16	20.14	0.05	20.37
Strain 2	Mean	42.45	5.59	56.82	1.48	56.84	14.26	49.46	1.46	50.56
	STD	5.18	1.14	11.9	0.02	12.06	1.32	15.99	0.29	15.38
Strain 3	Mean	46.1	6.76	56.84	1.47	56.24	10.95	50.25	1.40	51.06
	STD	3.87	0.15	15.56	0.02	15.41	0.20	19.84	0.05	19.98
Strain 4	Mean	48.49	4.96	42.76	1.43	43.48	4.73	42.66	1.82	44.24
	STD	23.51	1.27	32.77	0.16	33.24	1.59	35.39	1.04	35.37
Strain 5	Mean	45.19	5.97	55.34	1.48	54.86	12.41	49.31	1.45	49.67
	STD	4.20	0.52	14.81	0.02	14.76	0.54	18.56	0.32	18.61

Note that the units of axle weights (x1, x3, x5, x7, and x9) and axle spacings (x2, x4, x6, and x8) are kN and m, respectively.

Analytical Rating Calculation

To generate a regression model to predict the bridge ratings, there must be calculated conventional rating resulting from the identified WIM trucks. An analytical model was created using commercially available finite element modeling software, WinGen (12). The model can be seen in FIGURE 7. One truck at a time crossed the bridge at a transverse location that was applied to the model and the corresponding structural responses at the significant sensors were measured and calibrated with each strain set. The calibration process was made using multiple iterations, including the least square regression analysis to reduce

statistical errors between the model and the strain set. Included in the errors were the percent error, percent scale error, and correlation coefficient. The process was terminated when the errors were minimized by modifying values for the structural property parameters, such as flexural stiffnesses of girders, within their plausible ranges (9). The statistical errors representing the model accuracy for all five strain sets is listed in TABLE 4. The majority of the strain sets had good statistical correlation with the field data, excluding the strain 4. The discrepancy of errors between the strain 4 and the other sets can be attributed to the fact that the strain 4 set was the response suite resulting from a ambient five-axle dump truck, but the majority of trucks in the WIM pool are five-axle semi-trucks. Note that the models for the other sets were refined against the five-axle semi-truck-induced responses. This finding indicates that selecting WIM trucks closely matching the characteristics of actual trucks crossing the bridge is vital to minimize the statistical errors between analytical and field response. More detailed information for the model calibration with the strain sets can be found elsewhere (9).

TABLE 4. Model accuracy for random truck selection (9)

Strain Sets	Statistical Errors					
	Percent Error		Percent Scale Error		Correlation Coefficient	
	Mean	STD	Mean	STD	Mean	STD
Strain 1	9.78%	3.86%	7.02%	0.95%	0.96	0.01
Strain 2	9.11%	4.00%	6.37%	1.16%	0.96	0.01
Strain 3	8.77%	3.66%	6.30%	0.93%	0.96	0.01
Strain 4	21.02%	9.37%	6.53%	2.30%	0.91	0.03
Strain 5	12.99%	4.55%	13.00%	1.92%	0.95	0.02

This process is repeated to generate 500 calibration models where it is assumed that the number is close to the number of the five-axle trucks daily crossing the bridge. Further information on this process can be found elsewhere (9, 13). The 500 calibrated models subjected to the AASHTO standard HS-20 Trucks were then used in a rating factor equation used to calculate the load ratings for each strain set. This equation is shown below in Equation 2 (1, 2).

$$RF = \left(\frac{C - \gamma_{DL} \cdot DL}{\gamma_{LL} \cdot LL \cdot (1 + I)} \right) \quad (2)$$

where

- C = bridge capacity
- DL = dead load effect
- LL = live load effect
- γ_{DL} = dead load factor
- γ_{LL} = live load factor
- I = dynamic impact factor

The bridge capacity was calculated according to the AASHTO Load Factor Rating method, and the models were used to calculate the dead and live load effect for each strain set. For the dead and live load factors, both factors are 1.30 for operating load ratings, while the dead load factor is 1.30 and the live

load factor is 2.17 for inventory load ratings. Note that the operating load ratings are computed for this study.

FIGURE 7 US 30 Bridge Model

WIM Based-Rating Regression Models

To create a regression model based on two combined sets of WIM and conventional rating data, the data sets must have the same number observations. To obtain two data sets of the same number of observations the WIM truck data must be condensed to create a data set containing 500 trucks which matches the total number of the rating data. The current truck data of 175,392 trucks was sorted into ascending order according to GVW. The rating data was also sorted into ascending order. For this study, four different regression rating methods were used to create corresponding regression models. The first method used to create a truck data set matching the rating data, used every 351st truck characteristic from the 175,392 WIM five-axle truck data. This data set along with the rating data was then used to create a regression model. This model consists of the four axle spacings and five axle weights to predict 500 ratings. This model generated via the operating load rating resulting from strain set 1 can be seen in Equation 3. As stated previously, each variable in this equation is a truck parameter as shown in FIGURE 2, and an equation per a strain set is created through this method.

$$\begin{aligned}
 y = & 1.310 + 8.560 \times 10^{-6}(x1) - 0.002(x2) + 0.002(x3) - 0.076(x4) \\
 & - 1.434 \times 10^{-5}(x5) - 0.002(x6) + 1.899 \times 10^{-4}(x7) - 0.003(x8) \\
 & + 0.001(x9)
 \end{aligned} \tag{3}$$

The second method also used the original five-axle truck data of 175,392. However, to condense the data set for this method, the truck data were extracted randomly. This method can reduce computational costs relative to the first method. The randomly extracted data were then used to create a regression model with the rating data per a strain set. As an example, the equation from this method for strain set 1 can be seen in Equation 4 as follows.

$$\begin{aligned}
 y = & 1.161 + 6.503 \times 10^{-6}(x1) - 5.397 \times 10^{-4}(x2) + 5.713 \times 10^{-6}(x3) \\
 & + 0.003(x4) + 1.317 \times 10^{-6}(x5) - 7.303 \times 10^{-6}(x6) + 2.713 \times 10^{-6}(x7) \\
 & + 7.236 \times 10^{-4}(x8) + 2.555 \times 10^{-6}(x9)
 \end{aligned} \tag{4}$$

The third method utilized the truck data obtained through the tolerance intervals for the truck identification in Step 3. As an example, 6,933 truck data extracted for the tolerance intervals of strain set 1, and from the dataset 500 trucks were randomly selected to be used to create a regression model. A

regression model was created the same as the other two methods using the conventional rating data. These equivalent processes were taken for the other strain sets. Note that the different strain data used different intervals due to the different number of trucks and its characteristics. The equation built from the first interval using data from strain set 1 is shown in Equation 5.

$$y = 1.192 + 3.031 \times 10^{-4}(x_1) - 1.867 \times 10^{-4}(x_2) - 0.001(x_3) \\ + 0.137(x_4) + 0.011(x_5) - 0.024(x_6) + 3.712 \times 10^{-4}(x_7) + 0.059(x_8) \\ - 4.593 \times 10^{-4}(x_9) \quad (5)$$

The fourth method used the combined data from the third method with all of the rating data resulting from all five strain sets to create a regression model. This model was used to predict all rating data points covering all strain sets that were cumulatively collected for the bridge. The resulting equation can be found in Equation 6.

$$y = 1.483 + 1.751 \times 10^{-4}(x_1) + 0.007(x_2) + 8.857 \times 10^{-4}(x_3) \\ + 0.021(x_4) - 4.792 \times 10^{-4}(x_5) - 0.019(x_6) - 2.609 \times 10^{-4}(x_7) - 0.003(x_8) \\ - 1.727(x_9) \quad (6)$$

Regression Model Comparison

The ratings predicted from each regression method were compared to the conventional rating data in a graphical and statistical manner. As stated previously, the graphical comparison was made via a CDF. FIGURE 8 illustrates multiple CDFs of each strain set, comparing the predicted ratings from the first three methods and the conventional rating data from that strain set. For example, FIGURE 8a compares the first three methods for strain set 1 along with the conventional rating data from strain set 1. Examining this graph, it appears that the regression rating methods 1 and 2 accurately predict the rating data, while there is a significant difference in the CDFs between the method 3 and conventional method. FIGURES 8b-e show the CDFs for strain sets 2-5, appearing that the resulting trends are consistent with that for the strain set 1. On the other hand, regression rating method 4 was independently graphed in Figure 9 due to the fact that the resulting CDF contained 2,500 rating data points resulting from all the strain sets and is compared against that for the combined conventional data. It shows that the rating data is predicted fairly well, but not as well as the regression rating methods 1 and 2.

In addition to the graphical evaluation of CDFs, the statistical evaluation to identify the method that best predicts the rating data was made. TABLE 5 compares statistics from each strain set within each method. The statistical information in terms of Mean Square Error (MSE) and R-Squared values were analyzed for this evaluation. For a well-fitting linear regression model, the MSE should be close to 0, which is seen in the methods 1 and 2 in this table. Similarly, the R-squared values of both the methods are closest to 1 for most strain sets when compared to the other methods. It is worth to note that the R-Square value is closest to 1, meaning that the ratings are being predicted most accurately. The differences in the rating values between each method and the conventional method at 5th, 50th, and 95th percentiles were also found to assist in the best-fit rating model determination. The method 2 appears to have the smallest rating differences at these percentiles relative to the other methods. Comparing each value in the table, it can be concluded that the method 2 is the best fit regression model.

(a)

(b)

(c)

(d)

(e)

FIGURE 8 Comparison between CDFs resulting from the regression rating methods 1, 2, and 3 and the conventional method for each strain set: (a) strain set 1; (b) strain set 2; (c) strain set 3; (d) strain set 4; and (e) strain set 5.

FIGURE 9 Comparison between CDFs from the regression rating method 4 and the conventional method for all strain sets.

TABLE 5 Statistics from each strain set within each method

Method	Strain Set	MSE	R-Squared	Rating Difference		
				5th Percentile	50th Percentile	95th Percentile
1	1	6.44E-04	0.787	0.010	0	0.010
	2	9.27E-04	0.773	0.010	0	0.020
	3	6.89E-04	0.829	0.010	0	0.010
	4	0.002	0.821	0.010	0	0.020
	5	6.17E-04	0.923	0	0	0.020
2	1	6.15E-04	0.797	0.010	0	0.020
	2	8.84E-04	0.784	0.007	0	0.020
	3	6.88E-04	0.829	0.010	0	0.010
	4	0.002	0.816	0.010	0	0.020
	5	6.10E-04	0.924	0.005	0	0.020
3	1	0.003	0.018	0.080	0	0.081
	2	0.004	0.025	0.080	0.080	0.094
	3	0.004	0.012	0.100	0	0.100
	4	0.009	0.012	0.130	0	0.100
	5	0.008	0.034	0.120	0	0.130
4	all	0.006	0.351	0.068	0	0.070

Sensitivity Analysis

Since the best fit regression model with a small MSE, and an R-Squared value closest to 1 compared to the other methods was found to be regression rating method 2, this model was used to create parametric plots for each strain set to do sensitivity analysis of the effect of each truck parameter on the predicted ratings. As shown in FIGURE 10, each plot from the five strain sets indicates how each truck characteristic parameter individually affects the predicted rating. The length of the line shows a confidence interval of how much the parameter affects the predicted rating, and the circle in the middle of the line represents the mean value. It appears that the axle weights, including x_1 , x_3 , x_7 , and x_9 and axle spacing variable, x_6 , have a more substantial effect on the predicted rating data. To quantify the differences in terms of range and slope obtained from each plot, these values are also listed in TABLE 6. The bolded rows are parameters that have a significant impact on the predicted ratings. As expected, the majority of the axle weight parameters having positive slopes, x_1 , x_3 , x_7 , and x_9 , and a single parameter for the axle spacings having a negative slope, x_6 , were significant. As the weights in x_1 , x_3 , x_7 , and x_9 increase independently, the load ratings of the bridge intensely decrease. Oppositely, as the spacing in x_6 largely increases, the decrease in the load ratings occurs. This is attributed to the fact that the five-axle semi-trucks with x_6 having large values can longitudinally and largely distribute the major weights to all the axles for the semi-trail part, x_3 , x_5 , x_7 and x_9 .

(a)

(b)

(c)

(d)

(e)

FIGURE 10 Effect of each truck characteristic parameter on load ratings: (a) strain set 1; (b) strain set 2; (c) strain set 3; (d) strain set 4; and (e) strain set 5.

TABLE 6 Range and slope for the best-fit regression model

Strain Set	Truck Parameters	Range	Slope
1	x1	0.061	0.070
	x2	0.007	-0.001
	x3	0.085	0.057
	x4	0.002	0.004
	x5	0.018	0.013
	x6	0.028	-0.001
	x7	0.047	0.027
	x8	0.007	0.001
	x9	0.047	0.026
2	x1	0.074	0.081
	x2	0.011	-0.002
	x3	0.108	0.072
	x4	0.007	0.017
	x5	0.021	0.014
	x6	0.011	-0.0003
	x7	0.036	0.02
	x8	0.012	0.002
	x9	0.064	0.034
3	x1	0.087	0.095
	x2	0.002	-0.0002
	x3	0.091	0.061
	x4	0.010	-0.024
	x5	0.030	0.023

	x6	0.023	0.001
	x7	0.051	0.030
	x8	0.007	0.001
	x9	0.057	0.023
4	x1	0.099	0.108
	x2	0.003	0.0003
	x3	0.036	0.024
	x4	0.015	-0.038
	x5	0.134	0.094
	x6	0.095	0.003
	x7	0.043	0.025
	x8	0.009	0.001
	x9	0.133	0.072
5	x1	0.066	0.071
	x2	0.001	0.0001
	x3	0.044	0.030
	x4	0.015	0.038
	x5	0.111	0.078
	x6	0.026	-0.001
	x7	0.079	0.046
	x8	0.008	-0.001
	x9	0.115	0.062

Recommendations

Analyzing the sensitivity results, it can be inferred that the majority of axle weight parameters and the middle axle spacing parameter with the small spacing can adversely affect the live-load carrying capacity of the bridge that was studied. From these results it can be recommended that the bridge owner may consider the significant parameters to make a decision regarding legal five-axle trucks permitted to cross the bridge under unknown ambient trucks so as to ensure its structural safety over time.

SUMMARY AND CONCLUSIONS

This study proposed a multi-regression-based framework to identify the best-fit regression load rating model enabling the most efficient and accurate real-time structural capacity evaluation for complex steel bridges subjected to ambient trucks. To demonstrate its efficiency and accuracy, this framework was applied to a steel bridge located in Iowa. Key findings from this application are provided as follows:

Using two different statistical methods, including logical value and linear regression methods, the most significant strain sensors were found. Examining the sensors in every strain set resulting from a single passage of an unknown ambient five-axle truck in both methods showed that eight girder sensors such as sensors placed at the bottom flanges among 40 sensors and two deck bottom sensors directly loaded by the truck wheels among eight sensors were identified as the most significant sensors.

Using the significant sensor data, it was found that the Weigh-In-Motion (WIM) axle spacing data correlates well with the distance between peaks in the strain time history data of the deck bottom sensors. The identified axle spacing was then used to create a tolerance interval to apply to the WIM data to explore which trucks were most likely to cross the bridge. One at a time randomly selected from the identified truck pool was applied to the finite element model created with as-built bridge sectional and material properties to compute conventional load ratings according to the AASHTO Manuals. Using the WIM data, four regression models were created to predict the conventional load ratings. The four

regression models were then compared graphically and statistically using a Cumulative Distribution Function (CDF). It was found from the graphical evaluation that the methods 1, 2 and 4 matched well with the conventional rating data compared to method 3. It was also found by analyzing the data from the CDFs in a more statistical manner that the method 2 was the best-fit regression model capable of predict the ratings the most accurately. Using the best-fit regression model, the sensitivity analysis was conducted to explore how much each truck characteristic parameter affects the predicted ratings. It was found as expected that the majority of the axle weight parameters and the middle axle spacing for the WIM five-axle trucks were significant. This highlights the importance of treating variability in these parameters when selecting appropriate WIM trucks specific to the ambient truck induced bridge and calculating its load ratings.

As a final point, the proposed framework can help identify WIM trucks which closely match characteristics of actual trucks that are likely to cross a bridge and determine its load ratings in an efficient manner. However, there are some limitations in the use of framework: 1) the use of framework is restricted to steel girder bridge types and five-axle semi-trucks; 2) the use of WIM truck database obtained from weigh stations nearest a selected bridge is required to successfully conduct this study; and 3) the use of linear regression models that are solely valid when statistically identifying critical sensor locations and determining bridge ratings is recommended. In the future, the framework can be incorporated with fragility curve derivation algorithms to assess ambient truck-induced vulnerability of bridges. The fragility curves can be used to determine a conditional probability that a bridge exceeds a prescribed performance state when subjected to a varying range of truck weights, configurations, speeds, positions, and bridge conditions. Such future research is needed to shed more light on the reliability analysis of deteriorating bridges over time under ambient traffic loads. **In addition, another future work is to integrate an actual long-term data obtained from the bridge to the framework enabling the training process to establish the correlations between truck characteristics and bridge responses over time so as to predict time-dependent load ratings related to structural deterioration.**

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