Detect and charge: Machine learning based fully data-driven framework for computing overweight vehicle fee for bridges

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A R T I C L E  I N F O

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Bridge
Machine-learning
National bridge inventory
Weigh-in-motion data

A B S T R A C T

This study develops a fully data-driven framework for computing overweight vehicle fee that combines historical bridge data from National Bridge Inventory (NBI) and weigh-in-motion (WIM) data. In this framework, information regarding vehicle weight distribution on bridges was obtained using Gaussian mixture model (GMM) based interpolation. Using this interpolation approach, the vehicle weight distribution on each bridge could be estimated from WIM data based on their location. Later, these estimated distributions were combined with the NBI for developing a machine learning-based prediction model that inputs bridge characteristics (e.g., age and traffic) and outputs deck condition. The model was employed to calculate the expected bridge service life under two scenarios to compute a bridge life reduction per damaging load. Finally, the bridge life cycle cost was conducted to convert the calculated service life difference into a fee. Integration of this framework with existing geographical information system based online permitiss toolswill allow for detection of bridges on vehicles’ routes and charge them a fee considering their weight and the load capacity of the bridges they will pass over. Therefore, fees will be calculated more accurately and efficiently. Additionally, the proposed framework has the flexibility of being converted into a table for conforming to the conventional permit fee calculation scheme.

1. Introduction

The U.S. population and economy exhibited a significant growth between 2000 and 2014. According to the U.S. Department of Transportation Freight Fact reports \cite{1}, while the population grew by 13% during that time, climbing to an estimated 319 million in 2014, gross domestic product increased by 24.9% in real terms (inflation adjusted), reaching $15,773,516 (millions of chained dollars). This expansion in the economy and population caused a concurrent increase in truck freight transportation which carried 69.6% (by ton) of total goods moved in 2013. Moreover, a total of 13,732 million of tons of goods valued at $11,444 million shipped by trucks in 2013, representing 9.21% and 6.16% increase over the estimates of 2007 by ton and value, respectively \cite{1}.

Well-maintained and functional transportation infrastructures are instrumental to sustain this growth in economy and to provide safer mobility for the increasing truck traffic. Nevertheless, with 20% of roadway miles in poor or mediocre conditions and 9.1% of bridges being structurally deficient or functionally obsolete \cite{2}, state departments of transportation (DOTs) face a major challenge in meeting their infrastructure needs. Therefore, DOTs have become more interested in initiating and supporting research projects that try to address challenges in transportation infrastructure management.

This research addresses one of these challenges under a project supported by Illinois Department of Transportation: quantification of the damage on bridges caused by overweight vehicles. In this research, a fully data-driven framework, “Detect and Charge”, is developed to assess the economic impact of the vehicles that violate federally defined weight limits. Thereby, a permit fee that compensates for the damage imparted on bridges by such vehicles can be established.

In the State of Illinois, the overweight limits for a group of two or more consecutive axles are calculated by the following formula (Eq. (1)):

\[
W = 500 \left( \frac{LN}{N-1} + 12N + 36 \right)
\]

where

W, overall gross weight of any group of two or more consecutive axles, to the nearest 500 lb.
L, distance in feet between the extreme of any group of two or more consecutive axles

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N, number of axles in the group under consideration

This formula, known as the federal bridge (FB) formula, was enacted by Congress in 1975 and updated in 2006. In addition to Illinois, the majority of U.S. states use the FB formula to legislate and enforce legal truck weight limits on interstate highways. Trucks that violate these limits have to buy a permit to travel through the states. A recent study, Comprehensive Truck Size and Weight Limits Study [3], investigated the possibility of modifying the overweight limits determined by the FB. In that study, six different trucks (i.e., scenarios) that would currently be classified as overweight/oversize (OW/OS) trucks were simulated. A comprehensive set of measures including bridge/pavement damage, highway safety, compliance, and modal shift was selected for a holistic evaluation of the potential impacts of allowing these OW/OS trucks to travel on highways. Although several advantages of increasing the limits were noted, the study does not recommend any changes to existing limits.

Although OW/OS limits are set by federal government, each state can develop its own permit fee structures. U.S. Department of Transportation [3] reported that the number of permits increased to approximately 4.2 million from 2.1 million between 2008 and 2012. This increase in OW/OS traffic has motivated DOTs to revise their permit fee structures. Ahmed et al. [3] used an incremental damage approach to assess the damage caused by OW vehicles. Chowdhury et al. [4] developed a finite element model of selected bridges where specific OW vehicles were analyzed. The reduction in fatigue life due to the simulated OW vehicles was computed by analyzing the stresses developed within the bridges. Ghosn et al. [5] compared the overweight vehicles with HS-20 load to quantify their impact on bridge fatigue life. Chowdhury et al. [4] linked the structural analysis results to the fee by exploiting bridge life-cycle cost assessment (BLCCA). Ghosn et al. [5] used unit cost prices from literature to compute the final fee. It should be noted that these studies also present the fee computation for pavements. However, the pavement fee is not included herein; it is out of the scope of this paper.

Because of the high computational cost, a number of representative bridges were selected out of thousands to analyze and develop a fee [4,5]. This approach was criticized in a review written by Transportation Research Board National Academies of Sciences [6] to U.S. Department of Transportation [3] for introducing bias to the decision-making process since it depends on selective bridges.

This limitation can be overcome using data-driven approaches. Lou et al. [7] used weigh-in-motion (WIM) data to compute the fee for overweight vehicles. Vehicle loadings extracted from WIM data were correlated to the service life of bridges and the fee was computed by employing BLCCA. In Lou et al. [7], it was assumed that bridges on the same highway are exposed to similar traffic characterization. The framework developed in this study, “Detect and Charge”, also exploits a data-driven approach for computing the fee for OW vehicles considering all the bridges in Illinois. Although the results of the framework were specific to bridges in Illinois, the framework can be extended to any state as long as the corresponding data are utilized in the framework as inputs.

2. Detect and charge

In a broad sense, the objective of this study is defined as an economic assessment of overweight vehicle loading on bridges. Many research topics in the area of infrastructure management build on similar objectives where the impact of a variable (e.g., construction material type or traffic) on a type of infrastructures (e.g., buildings, bridges) is quantified economically. In order to perform such quantification, one needs to have an input-output tool that computes the service life of the infrastructure of interest considering the variable of interest along with other significant variables.

Traditionally, in civil engineering, such performance prediction tools are developed using mechanistic approaches, such as finite element analysis, which are generally computationally expensive. Therefore, using such approaches for the aforementioned type of research problems requires subset selection of infrastructures to reduce the number of simulations which, as previously mentioned, may introduce bias to the decision process. Additionally, these approaches have to be built on assumptions that simplify or neglect variables that are too complicated to be represented in mechanistic equations. Alternatively, this study employs a machine-learning algorithm for simulating the performance of bridges over time, based on historical inspection data that captures the actual field behavior of bridges. In other words, this study substitutes mechanistic approaches with the machine-algorithm to provide a computationally efficient approach while producing a realistic bridge performance prediction.

Development of such a prediction model requires addressing some challenges in data preprocessing (e.g., data cleaning and filtering) to ensure the presence of a comprehensive set of inputs (e.g., material properties, applied load, age). For example, estimation of vehicle weight information, which is collected at only limited numbered WIM stations (≈ 20), on thousands of bridges in the network so that the variable of interest (i.e., overweight vehicle loads) can be explicitly incorporated into fee computation. Furthermore, after developing an accurate machine-learning model for predicting bridge service life, one still needs to come up with a way to leverage the developed model to compute the penalty for the vehicles that violate the weight limits (i.e., to develop OW fee).

The developed framework, “Detect and Charge”, outlines the steps that address the aforementioned challenges for the fee development. This framework consists of three main steps: pre-processing, machine-learning model development and post-processing. The pre-processing step includes structuring raw data into an input set for the model development. The inputs can be grouped into two: vehicle weight frequencies and bridge characteristics. The vehicle weight frequencies (VWFs) on each bridge were estimated using the Gaussian Mixture Model (GMM) based interpolation. First, VWFs from limited number of WIM stations are computed. Then, these VWFs are interpolated to each bridge in the network based on their location (i.e., latitude and longitude). The bridge characteristics (including historical performance data) are extracted from the National Bridge Inventory (NBI). Later, a subset selection is performed to determine the most significant variables in NBI for performance prediction. The second step, model development, consists of training Support Vector Machine using selected inputs to predict bridge deck condition. In the third step, post-processing, the trained model is employed to calculate bridge service life under two scenarios: with and without damaging load (DL), which is defined as any load greater than the bridge load carrying capacity. The difference between the service lives from these two scenarios quantifies the reduction in bridge service life due to OW loads. Finally, a bridge life-cycle cost assessment was conducted to convert this service life difference into a fee. The flowchart of the developed framework is illustrated in Fig. 1.

This framework introduces three contributions. The first one is fusing two different data sources (WIM and NBI) to develop a fully data-driven framework for computing the overweight fee. One of the main advantages of using NBI is incorporating realistic field performance of the bridges into fee calculation rather than the outcomes of mechanistic simulations. The second contribution is exploiting GMM to get accurate load information on each bridge over the network based on WIM data. While Chowdhury et al. [4] considered a few vehicles with specific load and axle configuration for the structural analysis, Lou et al. [7] assumed the same traffic characteristics for bridges located on the same highway. The third contribution is represented in the direct consideration of bridge load carrying capacity into the data-driven models for permit fee calculation.

Many DOTs have already had an online permit issuing system that reports routes for OW vehicles based on origins and destinations.
entered. If the framework proposed in this study is combined with the existing online permit system, the bridges on the vehicles’ routes can be detected along with their load carrying capacity and the vehicles can be charged a fee based on the damage they cause to each bridge on the route. This approach would bring two advantages: The first one is overcharging (e.g., the weight of a vehicle can be much less than the load carrying capacity of a bridge) or undercharging (e.g., there might be lower capacity bridges on the route that will be damaged more significantly) would be prevented since the load carrying capacity of the bridges are also part of the fee calculation; and the second is the fact that revenue from the permit fee can be allocated in a smarter way by detecting bridges subject to greater damage. Also, the proposed framework can be converted into a table, thus conforming to the conventional permit fee calculation scheme as presented in this paper.

3. Data preprocessing

3.1. Bridge condition prediction database using NBI

The NBI [8], published and maintained by the Federal Highway Administration (FHWA), provides researchers with an extensive database that includes information about material, structure characteristics, traffic, and condition of bridge components. Over the past decades, there have been a number of studies that have developed bridge condition prediction models utilizing NBI data to compute the service life of bridges [9–11]. The proposed framework in this study also uses the NBI to obtain information about bridge characteristics and combines it with WIM (because NBI does not include information about applied loads). Because the deck of bridge typically deteriorates more rapidly than the entire bridge superstructure and substructure [9,12], prediction models in this study were developed only for bridge decks.

3.1.1. Data filtering and cleaning for NBI

Data filtering and cleaning starts with identifying and extracting the variables that were preliminarily considered important for this study, thereby resulting in loss of entries (i.e., a row) because an insignificant variable was avoided. For example, there is a variable in NBI called traffic safety feature (item 36) that represents information about existing traffic safety features on a bridge, such as approach guardrail, bridge railings, and so on. This variable was omitted from NBI data before data filtering and cleaning. Consequently, an entry (i.e., a row) that has a blank cell for this variable, but has information for other variables (e.g., deck condition, traffic), remained after the data cleaning process.

The preliminarily selected variables are given below along with their item code in NBI. The Appendix presents the definition of the preliminarily selected variables.

State Code (item 1), Highway Agency District (item 2), Inventory Route (item 5), Structure Number (item 8), Location (item 9), Latitude (item 16), Longitude (item 17), Owner (item 22), Functional Class of Inventory Route (item 26), Year Built (item 27), Lanes On and Under the Structure (item 28), Average Daily Traffic (item 29), Year of Average Daily Traffic (item 30), Design Load (item 31), Type of Service (item 42), Structure Type Main (item 43), Structure Type Approach Spans (item 44), Length of Maximum Span (item 48), Structure Length (item 49), Deck (item 58), Superstructure (item 59), Substructure (item 60), Operating Rating (item 64), Inventory Rating (item 66), Structural Evaluation (item 67), Deck Geometry (item 68), Bridge Posting (item 70), Approach Roadway Alignment (item 72), Inspection Date (item 90), Designated Inspection Frequency (item 91), Bridge Improvement Cost (item 94), Year Reconstructed (item 106), Wearing surface/protection system (item 108), Average Daily Truck Traffic (item 109).

The following data filtering criteria were applied on the selected variables:

![Fig. 1. The flowchart of “Detect and Charge”](image-url)
• Rows having a blank cell or cells that were deemed non-applicable were omitted. Non-applicable entries were removed from variables where they generally represent missing data, such as deck condition or average daily traffic rather than an observation.
• Duplicate rows within each year and between years were detected and removed.
• Rows with the same built and reconstruction year, which can be defined as “imaginary bridges” (i.e., there was a plan to build the bridge, but the bridge was not constructed) were removed from the NBI data [13].
• Bridges owned by state agencies were considered in the analysis because their maintenance and evaluation processes are more reliable [12]. Culverts were detected and omitted from the NBI data.
• Unrecorded major maintenance activities are one of the main problems in the NBI. They manifest a sudden increase in a bridge age versus deck condition curve in which no reconstruction or major maintenance activity is reported. Detection and removal of the entries that were contaminated by unrecorded major activities are explained below.

3.1.2. Outlier detection and removal

Machine-learning algorithms develop a regression (or classification) model by solving an optimization problem [14], which minimizes the total error of the developed model. In the presence of outliers, this optimization process may result in overfitting because the error from outliers may dominate the minimization. Therefore, it is a crucial yet challenging task to detect and remove outliers from data to significantly improve the accuracy and reliability of the model.

In the NBI, the main source of outliers is unrecorded maintenance and repair activities that may result in classifying bridge components as in an unrealistically good condition. Detection of these outliers starts with the calculation of bridge age, which is the minimum of two numbers: inspection year minus year built and inspection year minus reconstruction year (i.e., min (inspection year - year built, inspection year - reconstruction year)). For example, say that 2014 data are to be analyzed (i.e., 2014 is the inspection year); the bridge being analyzed was constructed in 1970. In this case, the age of the bridge is 44 years (2014 minus 1970). However, it is reported in the database that the bridge was reconstructed (major rehabilitation) in 2000. Therefore, the bridge age drops to 14 years, min (44, 14).

After the age of the bridge was calculated for each entry, the criteria shown in Table 1 (originally developed by [13] and extended in this study) were applied to filter out the outliers.

3.1.3. Building up the database for model development

After the NBI data was cleaned and filtered, it was reorganized to serve as a database for data-driven model development. This process is demonstrated in Fig. 2. As shown, each entry in the NBI was transferred to the database as a row, along with the calculated bridge age explained in the previous section and other variables. In this database, the variable “deck” is a dependent or target variable, the other variables (material, age, and so on) are independent or explanatory variables.

### Table 1

<table>
<thead>
<tr>
<th>Conditional rating</th>
<th>Earliest possible age</th>
<th>Latest possible age</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>0</td>
<td>30</td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>60</td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>70</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>80</td>
</tr>
<tr>
<td>3</td>
<td>30</td>
<td>90</td>
</tr>
<tr>
<td>2</td>
<td>40</td>
<td>100</td>
</tr>
</tbody>
</table>

### 3.2. Estimation of vehicle weight frequency within bridge network

Knowledge about the load applied on each bridge is key to quantifying the effects of overweight vehicles on bridges. WIM data is the only source available to provide information about traffic along with loads. However, vehicles are weighed at the WIM stations, which are few compared with the number of existing bridges. Therefore, simplifications, such as assuming that every point on a highway has the same traffic and load distribution as the WIM station on the highway, had to be made [7]. This study overcomes this limitation and introduces a new approach that calculates the applied load on each bridge by estimating vehicle weight distribution on the bridges.

The first step in estimating the applied load on each bridge was to calculate vehicle weight frequency (VWF) for each WIM station. To calculate the frequency of vehicle gross weight, daily truck traffic was categorized into five groups (Categories A through E) based on gross weights and a weight frequency histogram was created (Fig. 3a). Vehicles heavier than 100 kips are counted proportionally to their weight. For instance, if a vehicle carries 110 kips, it is counted as 1.1 vehicle (110/100). It should be noted that the higher number of categories (i.e., six or seven categories instead of five) were tried and resulted in more accurate approximation for the vehicle weight distribution. However, only very few data points exist in the heaviest category that compromised the performance of GMM based regression. Therefore, the number of categories was limited to five.

The histogram was then normalized by a total number of vehicles to compute the frequency of each weight category (Fig. 3b). Afterwards, GMM was used to interpolate vehicle weight frequencies that were computed from limited number of WIM stations on the entire bridge network. GMM based interpolation starts with computing Euclidean distance matrix, given in Eq. (2). Hereinafter, while scalars are donated by italic letters, matrices and vectors are donated by underlined bold and bold letters, respectively.

$$
D = \begin{bmatrix}
0 & d_{12}^2 & d_{13}^2 & \cdots & d_{1n}^2 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
d_{m1}^2 & d_{m2}^2 & 0 & \cdots & d_{mn}^2
\end{bmatrix}
$$

(2)

where

$$
D_{ij} = \|x_i - x_j\|
$$

$x_i$ coordinates of a WIM station

$n$, Number of WIM stations

Afterwards, Gaussian kernel is applied on each element of the distance matrix, which results in Gram matrix (Eq. (3)). In this equation, the variable $h$, the scale parameter, determines the width of the kernel. In order to increase interpolation accuracy, its optimum value should be computed. Hence, a set of candidate values of the scale parameter is generated; and for each candidate value, a new Gram matrix is computed. Later, a model matrix (i.e., design matrix or regressor matrix) is built by stacking each generated Gram matrices side by side (Eq. (4)).

$$
G^k_y = \exp\left(\frac{d_{ij}^2}{h^2_k}\right)
$$

(3)

where

$$
h_k, k_{th} \text{ value for scale parameter}
$$

$$
M = \begin{bmatrix}G^1 & G^2 & \cdots & G^k\end{bmatrix}
$$

(4)

Using the design matrix, a regression equation that inputs the distance between WIM stations and output frequency value of each vehicle
category can be defined as in Eq. (5). After developing such a regression model, vehicle frequency value for each category can be estimated at any arbitrary point (i.e., bridge for this study) by incorporating its coordinates for distance calculation.

\[
M_w = \mathbf{Y} - \mathbf{w}
\]

where

\[\mathbf{Y}, \text{ a vector that stores the frequency values for a category (Fig. 3) from each WIM stations.}\]
\[\mathbf{w}, \text{ Regression coefficients}\]

As one may expect, the number of variables (i.e., number of columns of matrix \(M\) which equals to number of WIM stations times number of candidates for scale parameter) is much greater than number of data points (i.e., number of WIM stations), which may cause overfitting and lead to low testing accuracy. Therefore, the regression equation given in Eq. (5) should be regularized to find optimum values for the candidate scale parameters to avoid overfitting. Because Eq. (5) has a linear algebraic form, the regularization techniques used for linear regression models can also be applied to avoid overfitting. In this study, the elastic net [15] was used for regularization that combines \(L_1\) and \(L_2\) penalties of least absolute shrinkage and selection operator [16] and ridge regression, respectively. The equation for the elastic net is given below.

\[
\frac{1}{N} (\mathbf{Y} - M_w)(\mathbf{Y} - M_w) + \lambda \left( \frac{1 - \alpha}{2} ||w||_2^2 + \alpha ||w||_1 \right)
\]

The first part of this equation is the mean squared error of the model, where predicted and actual values are shown by \(M_w\) and \(\hat{Y}\), respectively. The second and third parts present the ridge and lasso regularization, respectively. The lambda (\(\lambda\)), which is calculated using cross-validation, is the trade-off parameter between error and variance. The alpha (\(\alpha\)) is a weight coefficient between these two different regularization methods and is a user input. In this study, this equation was solved using a package known as “glmnet” [17] in the programming language of R.

A total of 22 WIM stations were used as base points to predict the applied load on each bridge. Latitude and longitude of the WIM stations, which imported from Illinois Department of Transportation [18] were used to compute the distance between base points. Ten different values for the scale parameter, which change between the minimum and maximum covariance of the distance matrix (Eq. (2)), were generated. This resulted in 220 (22 \times 10) variables for the regression (i.e., the column numbers of Eq. (4)). The errors for estimating VWF for each category are given in Fig. 4a through e. In these plots, the vertical bars show the error standard deviation on each cross-validation to determine the best lambda, and the red dots show the mean of these errors. The number of variables used at each cross-validation step is given at the top of the plots. For example, for category A (Fig. 4a), the number of variables was reduced to 45 from 220 for the highest validation accuracy. The plots show that vehicle categories can be estimated with good accuracy, with mean square errors changing from 0.000534 to 0.00337.

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There are two main advantages for the GMM based interpolation...
over traditional interpolation techniques. First, calculated scale parameters enable the resultant model to capture the local effects in the area. Second, the rank-deficient problem caused by having similar rows in the matrix (e.g., two close base points) is inherently eliminated using the non-linear kernel functions.

4. Development of deck condition predictor

4.1. Explanatory variable analysis

The total error of the data-driven models can be decomposed into two measures: bias and variance [19]. Bias is simply the error of the model on training data. Variance, on the other hand, refers to the likelihood that the coefficients of a model are inaccurately estimated. The summation of these two measures gives the total error of the model. As shown in Fig. 5, when the complexity of a model increases (i.e., adding more explanatory variables), bias decreases; but the
variance increases. Therefore, the tradeoff between bias and variance should be optimized to find the optimum set of variables [25]. Therefore, additional explanatory variable analysis should be conducted to eliminate insignificant explanatory variables in order to avoid the high variance problem.

Explanatory variable analysis was conducted by combining three rationales: knowledge-based evaluation, statistical analyzes, and trial and error. Knowledge-based evaluation was explained under "Data filtering and cleaning for NBI". The number of variables in NBI was reduced to 38 from 123 by selecting variables that were considered important for predicting bridge condition. The strength-related variables were omitted since they were incorporated into the framework while calculating the fee (See "Computing the fee using deck condition predictor"). In the trial-and-error stage, various combinations of variables were generated. Later, SVM with linear kernel was trained for each combination on training dataset (90% of the dataset) and evaluated on remaining testing dataset. The combination that produced the highest testing accuracy was bridge age, daily truck traffic, latitude, longitude, and expected applied load. While the first four variables can be directly imported from the NBI, the expected applied load variable must be computed based on the estimated vehicle weight categories using GMM based interpolation. Table 2 demonstrates the selected variables along with their illustrative values. The sample calculation for expected applied load is given below.

\[
\frac{1}{2} |w|^2 + C \sum_{i=1}^{N} \xi_i
\]

where

- \( w \) and \( b \), model parameters
- \( C \), tuning parameter for margin and training error
- \( \xi_i \), slack variable for defining soft margin
- \( N \), the number of data points

SVM is capable of separating the data without error if the data are linearly separable. However, for most real-life problems, including predicting bridge condition, the relationship between independent and dependent variables is highly non-linear. For linearly inseparable data, SVM uses the kernel trick, which maps the training data into a higher dimension space where the data become more linearly separable (Fig. 7). Several kernel functions are used in SVM. The most common ones are radial-based kernel, polynomial kernel, Gaussian kernel, and exponential kernels. The selection of the kernel function is crucial to build an accurate model [21]. Through 5-fold cross-validation, the radial-based kernel was selected for this study (Eq. (7)).

\[
e^{-\gamma(x-x')^2}
\]

where

- \( \gamma \), scaling parameter
- \( x \) and \( x' \), data samples

4.3. Model results

The deck conditions in the NBI come from manual inspections, which are highly subjective. For example, an inspector can grade a recently constructed bridge either 8 or 9, both corresponding to perfect condition (i.e., a deck without any distress). Therefore, to reduce possible errors in the model caused by the subjectivity, all condition levels were mapped to three categories based on their definitions given in Federal Highway Administration [8]: good (9 and 8), medium (5–7), and poor (0–4). The mapping, however, resulted in an imbalance data problem. Fig. 8 shows the resulting imbalanced dataset. As shown in the Fig. 8, while only 6% (5387 data points) of the dataset represents decks that are in poor condition, that number jumps to 63% (56,638 data points) of the dataset. The deck conditions in the NBI come from manual inspections, which are highly subjective. For example, an inspector can grade a recently constructed bridge either 8 or 9, both corresponding to perfect condition (i.e., a deck without any distress). Therefore, to reduce possible errors in the model caused by the subjectivity, all condition levels were mapped to three categories based on their definitions given in Federal Highway Administration [8]: good (9 and 8), medium (5–7), and poor (0–4). The mapping, however, resulted in an imbalance data problem. Fig. 8 shows the resulting imbalanced dataset. As shown in the Fig. 8, while only 6% (5387 data points) of the dataset represents decks that are in poor condition, that number jumps to 63% (56,638 data points) of the dataset.

### Table 2

<table>
<thead>
<tr>
<th>Age</th>
<th>Load</th>
<th>ADTT</th>
<th>Lat.</th>
<th>Long.</th>
</tr>
</thead>
<tbody>
<tr>
<td>49.75</td>
<td>0.882</td>
<td>555.0</td>
<td>41.66167</td>
<td>−88.48167</td>
</tr>
<tr>
<td>5.00</td>
<td>0.454</td>
<td>3349</td>
<td>40.62105</td>
<td>−89.44697</td>
</tr>
<tr>
<td>7.83</td>
<td>0.682</td>
<td>9336</td>
<td>41.83875</td>
<td>−87.66576</td>
</tr>
<tr>
<td>40.50</td>
<td>0.885</td>
<td>162</td>
<td>37.37081</td>
<td>−88.488</td>
</tr>
<tr>
<td>28.58</td>
<td>0.845</td>
<td>288</td>
<td>39.85262</td>
<td>−88.8826</td>
</tr>
<tr>
<td>36.25</td>
<td>0.662</td>
<td>2890</td>
<td>37.144</td>
<td>−88.68341</td>
</tr>
<tr>
<td>39.00</td>
<td>0.723</td>
<td>792</td>
<td>41.83833</td>
<td>−90.16667</td>
</tr>
</tbody>
</table>

4.2. Support vector machines

Development of a model that uses the aforementioned selected explanatory variables as inputs to predict deck conditions requires a robust prediction engine. This study utilizes one of the very well-known machine-learning algorithms, support vector machine (SVM). SVM is a supervised machine-learning algorithm developed by Cortes and Vapnik [20]. SVM constructs a hyperplane by solving a constrained optimization problem given in Eq. (7). The constraints (Eq. (8)) ensure that the resultant hyperplane will have the highest margin, which is the distance between the hyperplane and the closest data point.

Fig. 6 presents an example of estimated VWF on a bridge with a latitude and longitude of 41.305° and −90.3766°, respectively. The expected applied load is calculated by multiplying the frequencies by load categories. For this example, the expected applied load would be as 61.1 kips (0.087 ⋅ 20 + 0.236 ⋅ 40 + 0.253 ⋅ 60 + 0.343 ⋅ 80 + 0.073 ⋅ 100).

Fig. 7. Mapping the data into higher dimension using kernel functions.
testing data are given in Table 3 based on commonly used measures. The performance evaluations of trained SVM model on unseen splitting were repeated 10 times to remove the effect of random se-
training (80%) and testing datasets (20%). The under-sampling and random under-sampling. This dataset was later randomly split into of points.

The size of the dataset was reduced to 16,160 from 89,666 after
random under-sampling. This dataset was later randomly split into training (80%) and testing datasets (20%). The under-sampling and splitting were repeated 10 times to remove the effect of random selection. The performance evaluations of trained SVM model on unseen testing data are given in Table 3 based on commonly used measures [23,26]. As shown in Table 3, the value of the overall accuracy is comparable. This demonstrates the homogeneity of the developed model to all classes.

5. Postprocessing: computing the fee using deck condition predictor

The previous section presented the development of a machine-learning model for predicting bridge condition given a set of inputs. This section further explains how this predictor is used to compute the fee by integrating an additional variable into the framework: inventory rating of the bridges.

5.1. Inventory rating

As mentioned before, this study combines WIM data with NBI data to account for bridge load capacity in computing the fee for overweight vehicles. Accomplishing this goal requires identification of the variables in the NBI that represent bridge load capacity. Two variables were identified: operation rating and inventory rating.

The NBI defines operation rating as a “capacity rating [that] will result in the absolute maximum permissible load level.” By definition, bridges are not supposed to be used by vehicles that carry weight higher than the bridges’ operation rating. Therefore, this variable was not considered representative of bridge load capacity because it is a conservatively calculated failure limit. The second variable, inventory rating, is defined in the NBI as follows: “This capacity rating will result in a load level which can safely utilize an existing structure for an indefinite period of time”. Moreover, Hearn [24] states that inventory rating considers the current condition of the bridge. Therefore, by definition, the inventory rating represents a realistic and current bridge load capacity and sets a weight limit for gross vehicle weight. Vehicles that carry weight more than this limit are the ones that damage the bridges and shorten their service life. This statement, of course, considers load-related deterioration only and overlooks other detrimental (e.g. environmental) impacts on bridge performance.

5.2. Estimating service life under two scenarios: with and without damaging loads

The development of scenarios using inventory rating is explained as follows. First, predicted VWF for each bridge is normalized by its in-
ventory rating. For example, Fig. 9a demonstrates the normalized version of a histogram presented in Fig. 6. The inventory rating for this particular bridge is 73.4 kips. As a result of the normalization, the x-axis becomes the damage ratio from the vehicle weight. Then, damaging vehicle categories (or damaging load) are identified as the ones with ratio(s) > 1. Based on the definition of inventory rating, loads greater than the bridge inventory rating cause load-related damage to the bridge and actually shorten the bridge service life. For example, in Fig. 9a, the vehicle categories D and E were identified as damaging loads.

A hypothetical scenario is created where damaging vehicles are converted into non-damaging loads, taking into account the fact that the amount of goods (i.e., amount of load) carried over a bridge should stay the same. Additionally, because the number of trucks is desired to be minimized, damaging vehicles are converted to the non-damaging category with the highest capacity. Finally, the service life is computed using the deck condition predictor under two scenarios. Calculating the service life starts with estimating the bridge condition by setting the bridge age as zero (0) and keeping the other variables the same. Then, the bridge age is increased by one (1) until the deck condition becomes 4 or lower, which is assumed to be the failure limit for decks [9]. The entire procedure is explained with an example in the following paragraph.

For the bridge used as an example in this section, the daily truck number (i.e. daily truck traffic) is given as 250 for the year 2015. Moreover, the number of trucks in categories D and E is calculated as 104 using VWF, as shown in Fig. 9a. Additionally, the expected load for this bridge is computed as 61.1 kips (Section “Explanatory variable analysis”). The 104 trucks (categories D and E) for the hypothetical scenario are converted to Category C (non-damaging category with the highest capacity), keeping the amount of load the same. This results in a new truck distribution (Fig. 9b). This new distribution has the expected load of 51.32 kips. Moreover, the new truck number is calculated as 298 (250 + 61.1/51.32), keeping the total amount of load the same. Feeding this new set of inputs (from hypothetical case) along with the original set of inputs (real scenario) into the prediction engine, the service life for these two scenarios is calculated at 45 and 40 years, respectively. Consequently, the expected bridge service life is reduced by five years as a result of damaging vehicles. Quantification of this reduction regarding cost is presented in the next section.

5.3. Bridge life-cycle cost assessment

The bridge life-cycle cost assessment used in this study was adapted from Lou et al. [7]. The First Net Present Value (NPV) was calculated using Eq. (10).
\[ NPV = \sum_{t=0}^{T} \frac{C_t}{(1 + r)^t} \]  

(10)

where

- \( T \), lifetime of the project, which was assumed to be 75 years
- \( C_t \), The agency cost at the time \( t \) of construction activity; the cost for new construction \( (t = 0) \) and deck replacement were adapted as $162.4/ft^2 and $112.5/ft^2 (these values are computed based on the data provided by IDOT)
- \( r \), discount rate, which was assumed to be as 3.00%

\( r \) was later converted to equivalent annual uniform cost (EUAC) using Eq. (11).

\[ EUAC = NPV \left( \frac{r(1 + r)^T}{(1 + r)^T - 1} \right) \]  

(11)

Following this formula, EUAC can be calculated based on any given bridge service life. For the aforementioned example (five years), the difference in EUAC would be $0.21/ft^2 for 45 and 40 years of expected bridge service life. The damaging load, which is estimated based on daily traffic, was calculated as 9.78 kips. Therefore, the EUAC per damaging truck for this bridge would be $5.66E−7/Δkip ∗ ft^2 (0.21/ (9.78 ∗ 365 ∗ 104)). It should be noted that the load is multiplied by 365 to convert daily load to yearly to make the units consistent with EUAC. Since the same bridge has the deck area of 7300 ft^2, the resultant cost would be computed as $0.41E−3/Δkip, where Δkip is the difference between the applied load and the inventory rating of the bridge.

6. Implementation of detect and charge

The previous section presented the developed framework called “Detect and Charge (DC)” for computing the overweight fee for bridges. The framework was explained using a bridge from the NBI database as an example. Following the same steps, DC can be applied on any bridge in the network.

The ideal implementation of DC requires that bridge information be obtained. The implementation is demonstrated in Fig. 10. First, the bridges on a route, based on origin and destination, are detected and their service lives are computed using the developed SVM-based deck predictor. The average computational time for computing the bridge service life for each bridge is determined as 0.41 s. Then, information about the detected bridges are fetched from NBI and their service lives are computed. Later, the inputs are extracted and fed to the DC to compute EUAC for each bridge. Finally, the EUACs are multiplied by the deck area of the bridges that are also obtained from NBI. Given that many DOTs already have a GIS-based online tool for issuing permits, integration of the developed framework would be relatively straightforward. Thereby, each overweight vehicle will be assessed a permit fee in a fairer and more accurate way.

The developed framework, however, can also be converted into a table to conform to conventional permit fee calculation schemes by averaging the cost over all bridges based on the data from the most recent year. Table 4 shows the mean and standard deviation for reduction in service life and its corresponding costs when DC is applied all the bridges in the state of Illinois. The average cost was found to be $3.93E−6/Δkip ∗ ft^2. The average deck area for state-owned bridges is reported by IDOT as 10,679 ft^2. Additionally, bridges per mile should be estimated. To avoid double counting the parallel structures, they were divided by two and subtracted, resulting in a modified number of bridges of 6919 (7847–1856 ∗ 0.5). Based on the aforementioned inputs, the average per-mile cost of damage is calculated as $0.0182/ mi ∗ Δkip (3.93E−6 + 10,679 + 6919/15,969), where Δkip should be calculated by subtracting the average inventory rating of state-owned bridges extracted from NBI (80.38 kips) from the gross weight of an overweight vehicle.

7. Summary and conclusion

This paper develops a data-driven framework to compute fees for overweight vehicles passing bridges. The framework explicitly considers the applied load by the vehicles and the load carrying capacity of the bridges. This provides the ability to compute fees in a fair and accurate way. The load information was estimated using KST on each
bridge within the network based on the traffic data provided by WIM stations. The load information was combined with NBI data and incorporated into SVM to develop a predictor for bridge deck condition. The predictor was used in two scenarios (with and without damaging vehicles) to assess the damage caused by the vehicles that carry loads more than the inventory rating of the bridges.

When developed framework is coupled with an online GIS-based system, currently used by DOTs to issue permits, the bridges can be detected on the route of OW vehicles along with required inputs. This allows to calculate a fee specific to vehicle weight and bridges passed by the vehicle. This would be an ideal implementation; however, the proposed framework has been converted into a table format to conform to the conventional and current way of charging OW vehicles.

The primary limitation of this study is that the oversize vehicles could not be considered because there is no data set available on vehicles' heights and widths. Furthermore, moment capacity of the bridges could not be incorporated into the developed framework since NBI includes on-load carrying capacity. This limitation will be addressed in future studies by coupling machine-learning models with mechanistic approaches (e.g., finite element analysis). Additionally, a robust, unsupervised machine-learning based algorithm will be developed to efficiently detect and eliminate outliers (i.e., bridge data with unrealistic information) from NBI.

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Appendix

- State Code (item 1): This variable indicates the name of the state in which the bridge is located.
- Highway Agency District (item 2): This variable indicates the code of the highway district (state or federal) in which the bridge is located.
- Inventory Route (item 5): This variable presents five pieces of information: (i) if the inventory route is carried on or under the structure; (ii) type of the route (e.g., interstate highway, state highway); (iii) designated level of service of the route (e.g., bypass, mainline); (iv) route number; (v) directional suffix (e.g., north, east).
- Structure Number (item 8): This variable is the ID of the bridge assigned by agencies.
- Location (item 9): This variable contains a narrative description of the bridge location.
- Latitude (item 16): This variable is the latitude of the bridge.
- Longitude (item 17): This variable is the longitude of the bridge.

- Owner (item 22): This variable indicates the type of the agency that is primarily responsible for maintenance and rehabilitation of the bridge (e.g., state highway agency, county highway agency).
- Functional Class of Inventory Route (item 26): This variable indicates the functionality of the inventory route (e.g., principal arterial, major collector).
- Year Built (item 27): This variable shows which year the bridge was built.
- Lanes On and Under the Structure (item 28): This variable indicates the number of lanes under the bridge.
- Average Daily Traffic (item 29): This variable represents the average daily traffic volume for the inventory route identified in Item 5.
- Year of Average Daily Traffic (item 30): This variable indicates the year represented by item 29.
- Design Load (item 31): This variable indicates the live load for which the structure was designed.
- Type of Service (item 42): This variable indicates the type of service on and under the bridge.
- Structure Type Main (item 43): This variable presents two information about the bridge: (i) kind of material and/or design (e.g., concrete, steel), (ii) type of design and/or construction (e.g., slab, tee beam, suspension).
- Structure Type Approach Spans (item 44): This variable indicates the type of structure for the approach spans to a major bridge or for the spans where the structural material is different.
- Length of Maximum Span (item 48): This variable indicates the length of the maximum bridge span.
- Structure Length (item 49): This variable represents the length of the structure to the nearest tenth of a meter.
- Deck (item 58): This variable describes the overall condition rating of the deck.
- Substructure (item 59): This variable describes the physical condition of all structural members.
- Type of Service (item 60): This variable describes the physical condition of piers, abutments, piles, fenders, footings, or other components.
- Operating Rating (item 64): This capacity rating will result in the absolute maximum permissible load level to which the structure may be subjected for the vehicle type used in the rating.
- Inventory Rating (item 66): This capacity rating will result in a load level which can safely utilize an existing structure for an indefinite period of time.
- Structural Evaluation (item 67): This variable is used to evaluate a bridge in relation to the level of service which it provides on the highway system of which it is a part.
- Deck Geometry (item 68): This variable indicates overall rating for deck geometry and includes two evaluations: (a) the curb-to-curb or face-to-face of rail bridge width (b) the minimum vertical clearance over the bridge roadway.
- Bridge Posting (item 70): This variable evaluates the load capacity of a bridge in comparison to the State legal load Approach Roadway Alignment (item 72): This item identifies those bridges which do not function properly or adequately due to the alignment of the approaches.
- Inspection Date (item 90): This variable records the month and year that the last routine inspection of the structure was performed.
- Designated Inspection Frequency (item 91): This variable represents the number of months between designated inspections of the structure.
- Bridge Improvement Cost (item 94): This variable represents the estimated cost of the proposed bridge or major structure improvements in thousands of dollars.
- Year Reconstructed (item 106): This variable records the year of most recent reconstruction of the structure.

### Table 4: Cost quantification results.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSL (^{\text{a}}) (years)</td>
<td>12.26</td>
<td>8.43</td>
<td>47</td>
<td>1</td>
</tr>
<tr>
<td>EUAC (($/\text{kip} + f^2))</td>
<td>3.93E−6</td>
<td>2.29E−5</td>
<td>6.56E−04</td>
<td>5.49E−09</td>
</tr>
</tbody>
</table>

\(^{\text{a}}\) RSL stands for reduction in service life due to damaging loads.
References


