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Quantifying Bridge Element Vulnerability over Time

Subasish Das[1] and Xiaoqiang Kong[2]

Abstract

The bridge has been a crucial element of the transportation system of the U.S.A. for many years. The National Bridge Inventory (NBI) reported more than 615,000 national bridges in 2018. Maintaining and fixing bridges is a crucial task for transportation agencies to keep the road network connected. Louisiana, which has 12,899 bridges, was selected as the study site for this study. The American Road and Transportation Builders Association (ARTBA) reported in 2019 that 13% of all Louisiana bridges were classified as structurally deficient. This study applies a data mining algorithm, the empirical Bayes geometric mean (EBGM) method, to identify critical patterns of the bridge inventory condition at element level as a measure of vulnerability, using NBI rating data from 2015 to 2018. It finds that severe condition is highly associated with the following elements, regardless of their structural importance: bridge joints, and "bridge rail timber," "bearing other," and "superstructure floor beam reinforced concrete" elements. Poor condition is highly associated with elements like "top flange reinforced concrete," "bearing movable," and "superstructure floor beam reinforced concrete." The quantification scores developed in this study could help transportation agencies and bridge engineers to identify more easily the key element or combination of elements associated with poor or severe condition, so that they can make data-driven decisions in maintaining and repairing the most needed bridge elements.

To provide a safe and adequate highway transportation system and manage bridge inventories efficiently and effectively, the precise assessment of bridge elements and interpretation of the data on their condition is imperative (*1*). By the end of 2018, the U.S. National Bridge Inventory (NBI) was fully maintained by the Assistant Secretary for Research and Technology/Bureau of Transportation Statistics National Transportation Atlas Database, and the Federal Highway Administration (FHWA) reported 615,000 bridges in the U.S.A. The FHWA has invested billions of dollars in federal funding to improve bridge assets (*2*). Before the advent of bridge management systems in the 1990s (*3*), bridge sufficiency rating was the tool most commonly used for prioritizing the allocation of resources for bridge management (*4*). However, some of the parameters, such as bridge condition, led to biases in the ranking (*5*). Therefore, bridge engineers shifted their focus to the condition of the bridge elements to conduct the performance assessment (*6*).

NBI contains information about bridges on all public roads (e.g., Interstate highways, U.S. highways), and publicly accessible bridges on federal and tribal lands. The inventory data describe bridges' location, general condition, and classification, and a breakdown of the condition of each structural element. The collection of bridge asset data, such as the NBI, allows the FHWA and researchers to develop data-driven methods with the purpose of improving national level evaluation, estimation, and recording of bridge condition, and needs such as preservation, improvement, and replacement of bridges. The NBI database could also help bridge engineers as they evaluate individual bridge structures, perform life-cycle analysis, and make decisions on the protection, repair, rehabilitation, and replacement of bridges.

Many studies that have investigated the NBI data (*7*–*9*). It is intuitive for many practitioners to use simple sorting tools to locate critical bridge elements associated with bridges that are in poor or severe condition and use such information to prioritize funding sources. However, there is a potential risk in using sorting tools. The frequency of all kinds of elements varies significantly. An element with high deficient qualities does not necessarily indicate where the funds should go. It could be that only

[1]Texas A&M Transportation Institute, Bryan, TX
[2]Texas A&M University, College Station, TX

Corresponding Author:
Subasish Das, s-das@tti.tamu.edu

a few bridges across the nation used these elements. Other methods have also been proposed to perform bridge assessment better. However, there are no studies using a Bayesian method to identify crucial patterns or elements, to the authors' knowledge. Thus, this study utilized a novel machine learning method—the empirical Bayes geometric mean (EBGM) method—to explore the patterns. This algorithm uses Bayesian theory to calculate the expected frequency of occurrence of each element based on the information presented in the dataset. Comparing the real occurrence count and the expected count in the database could provide a viable and reliable indication of the key patterns and elements that may be associated with those bridges with elements in poor or severe condition. These results could help engineers to identify more easily the real key bridge elements that require special attention.

The State of Louisiana was chosen as the study site, as a state with 12,899 bridges. According to the American Road and Transportation Builders Association (ARTBA) report of 2019: (i) 13% of the 12,899 bridges in Louisiana were classified as structurally deficient, (ii) 2,083 bridges were "posted for load," which restricts the size and weight of vehicles crossing the structure, and (iii) 3,347 bridges needed repair, at an estimated cost of \$7.5 billion (*10, 11*). Furthermore, a recent severe flood in 2016 submerged and damaged many of the bridges. Using four years (2015–2018) of NBI data for the State of Louisiana, this study aims to answer the key research question: How to quantify the vulnerability of bridge elements to being in poor or severe condition over time?

This paper continues with a literature review, including studies concerning the NBI and other relevant bridge inventory studies. The third section is a theoretical framework of the EBGM method. The fourth section provides an explanation of data preparation and descriptive characteristics of key variables. The final section of the paper contains a discussion of the results, conclusions, and recommendations for further research.

Earlier Work and Research Context

Understanding vulnerability measures of bridge elements is a promising research area. Studies have explored the vulnerability or conditional aspects of bridges by: developing methods to control heterogeneity in a probit model of bridge-deck deterioration (*12*), suggesting various machine learning techniques for modeling infrastructure deterioration (*13*), and describing deterministic and stochastic deterioration models for bridge decks in certain states (*14*). To predict long-term bridge performance, Bu et al. (*15*) suggested an advanced integrated methodology for probabilistic bridge-deterioration modeling to construct workable transition probabilities. Similar studies have detailed deterioration research to develop the deterioration of decks over time and obtain the expected service lives of decks on different highways (*16*). Additionally, Qiao et al. (*17*) developed binary probit models to explain trends in bridge component deterioration, especially the probability that the state of a component will drop from one state to another. Bektas et al. (*18*) investigated the use of the recursive partitioning method for developing classification trees. The results were indicative of sufficient predictive accuracy of preliminary decision trees.

Fiocco (*2*) conducted a study on FHWA spending and found that FHWA has spent a large portion of federal funding on overcoming issues related to the aging and deterioration of highways and bridges. This research supports the idea that there is a need to develop bridge asset management technology that is both cost-effective and robust to use public funds more efficiently to maintain bridge networks. The bridge management system (BMS) is a computer-based decision support system that can be used to determine the most practical strategy for promoting bridge safety with the lowest possible lifecycle cost (*19*). In many countries, bridge agencies have transitioned to BMS-based bridge asset management. Within the U.S.A., bridge owners have benefited from detailed bridge condition assessment utilizing raw inspection data, performance measures, and deterioration evaluation and forecasting using BMS (*19*).

The American Association of State Highway and Transportation Officials (AASHTO) has published a manual of improvements for changes in the measurement units of bridge decks and slabs and the wearing surface element. Additionally, this manual represents standardization of the number of element states and utilization of expanded elements (*20*). One of the most significant software systems that has been developed to meet the requirements of the BMS is Pontis software. The BMS requires analytical tools that can accurately predict preservation needs based on the level of bridge deterioration and answer hypothetical questions that bridge engineers might have. Hearn et al. (*21*) developed a bridge database using the Pontis BMS to determine NBI ratings for deck, superstructure, substructure, and culvert conditions. Sun et al. (*7*) also utilized NBI data in Pontis to develop a method of estimating the long-term performance of a bridge system based on BMS alternatives. Their findings proved that the use of NBI data for BMS analysis with Pontis was both feasible and practical. The proposed bridge preservation plan would maintain an acceptable system operating condition for a long time under a limited budget.

Researchers have developed models in previous studies, such as the NBI translator, that use element level condition data to predict the corresponding bridge deck, bridge superstructure, and bridge substructure condition ratings. There were concerns about the NBI translator's effectiveness after its development, so Al-Wazeer et al. (*8*) attempted to improve it by developing an alternative prediction method. This method used artificial neural networks (ANNs) to analyze the bridge deck, bridge superstructure, and bridge substructure conditions. The results of that study proved that ANN was more effective in predicting bridge conditions than the NBI translator.

Lee et al. (*22*) developed the backward prediction model, an ANN-based model that creates historical bridge condition ratings based on inadequate bridge inspection records. The researchers found that the model was able to predict the missing historical condition ratings for individual bridge elements based on limited data. In another study, Yanev and Richards (*4*) analyzed the complementary and competitive bridge management strategies at the network and project levels, respectively. They found that the bridge sufficiency rating was the most common tool used for resource allocation and bridge management. Bektas et al. (*23*) conducted a study in which they proposed a new methodology using classification and regression trees (CARTs). The researchers implemented the CART analyses with bridge condition data spanning from 2006 to 2010 that was collected from three state transportation agencies. Their findings indicated that this method was able to make predictions more accurately than previous methods. In a later study, Inkoom et al. (*24*) aimed to investigate issues of the bridge health index (BHI), a practical tool in the Pontis BMS that is used to evaluate bridge conditions and elements at the network and project levels. The researchers identified issues such as the effects of linear versus nonlinear scales when measuring condition state weights for element health index.

Despite previous studies that statistically related NBI and bridge element data, there has been little effort to revert NBI data to bridge element data in recent research. Fiorillo and Nassif (*9*) conducted a study that aimed to use multiple machine learning techniques to address the challenges of mapping bridge element and NBI condition data. The findings of the previous studies show that there is a need for exploration of the NBI data to understand the condition state and vulnerability aspects of the bridge elements. As the dataset contains information such as quantity and length of many bridge elements, conventional statistical models will not be sufficient to extract the more critical bridge elements that require attention for sustainable bridge inspection and maintenance. The current research is focused on eliminating this critical research gap.

EBGM

The EBGM method is a rule mining method (*25*). Rule mining methods can distinguish interesting associations or patterns from datasets with no pre-defined response variable. In a previous study, Das et al. (*26*) identified groups of "vehicle model with major defect" from NHTSA vehicle complaint data using the EBGM method. In another study, Das et al. (*27*) applied EBGM to Louisiana crash data to identify the association patterns of vehicular defects and crashes. This method allows researchers to determine the significance of a certain outcome based on its frequency and its association with other variables. This analysis method gives researchers new areas of focus for further research.

The present study performs analysis using the open-source R package *openEBGM* (*25*, *29*). The parameter used in this method adds Bayesian shrinkage adjustments to a measure known as the relative reporting ratio (RR). This method can be described as a Bayesian approach to RR. This approach decreases large RR toward 1 when N is small because the occurrence of a small N can happen by chance, and therefore should not be considered as a dominant contributor. For larger counts, the shrinkage decreases and becomes very negligible for very large counts. The method demonstrates that the EBGM approach provides more consistent results than the RR measurement (*28*).

Theory

This section provides a short preface on the theoretical aspects of EBGM. To obtain a thorough theoretical concept of EBGM, see the study by DuMouchel (*25*). The EBGM approach is appropriate for sampling variation while also documenting the interpretability of associated factors. When considering a contingency table with original cell count N_{ij} that complies with a Poisson distribution with unknown mean μ_{ij}; i and j represent row and column numbers, respectively. To evaluate N_{ij} and rank cells based on their significance, the researchers constitute a statistical measure of expected counts E_{ij}, which can be comprehended as a baseline or null hypothesis frequency. These two counts are then used to predict the hyperparameters of the previous distribution. Next, k is introduced as a grouping or stratification parameter to use the within-group correlation. Cells with much less N_{ij} in comparison with the counts E_{ij} are of specific interest, and they solicit further analysis. E_{ij} can be defined as (*25*):

$$E_{ij} = \sum_{k} \frac{N_{i.k} N_{.jk}}{N_{..k}} \tag{1}$$

where

N_{ijk} = reported frequency of stratified combination k for row i (element type) and column j (quality)

$N_{i.k}$ = reported frequency of stratified combination k for row i (element type)

$N_{.jk}$ = reported frequency of stratified combination k for column j (quality)

$N_{..k}$ = reported frequency of stratified combination k

E_{ij} = expected counts under the assumption that the variables in the rows and columns are independent conditional on the stratification variable.

Consider $\lambda_{ij} = \frac{\mu_{ij}}{E_{ij}}$ as the decision statistics for analyzing unusually large frequencies for each cell in the contingency table. The statistic λ is drawn from a mixture of two gamma densities with (α_1, α_2) and (β_1, β_2) as the shape parameters and rate parameters and θ as proportion constant of the two densities. To evaluate $EBlog2_{ij}$, the posterior expectation of $log_2(\lambda_{ij})$ as the Bayesian version of RR, the following expression can be used (*29*):

$$E[\log_2(\lambda)|N = n] = \{Q_n[\psi(\alpha_1 + n) - \log(\beta_1 + E)] + (1 - Q_n)[\psi(\alpha_2 + n) - \log(\beta_2 + E)]\}/\log(2) \quad (2)$$

where ψ is digamma function, the derivative of $\log[\Gamma(.)]$, N is a draw from a Poisson distribution with unknow mean μ, λ is the ratio of unknown mean μ and baseline frequency E, and Q_n is the posterior probability.

For large values of E and N/E, ψ(n) approaches $\log(n)$, then $EBlog2_{ij}$ or $EB[log_2(\lambda)|N = n]$ approaches $\log(\alpha + N) - \log(\beta + N), or \log(N/E)$ or $\log(RR)$. To make $EBlog2_{ij}$ of the same scale as RR and obtain a value that is easily explainable and comparable, DuMouchel computes $EBGM_{ij}$, the geometric mean of $EBlog2_{ij}$, which is given by the equation $EBGM_{ij} = 2^{EBlog2_{ij}}$ (*25*). In this method, the prior parameters are contingent on the data. In this methodology, the measures $(\alpha_1, \beta_1, \alpha_2, \beta_2, \theta)$ are acquired by increasing the likelihood of these parameters existing simultaneously, or the marginal distribution of N_{ij}.

Methodology

The new element inspection approach includes extensive pertinent experience acquired by state transportation agencies (*23*). The elements are assembled into three categories: national bridge elements, bridge management elements, and agency-developed elements (*20*). The standardized condition states (CS) are: CS1 (good), CS2 (fair), CS3 (poor), and CS4 (severe).

Descriptive Statistics

The research team collected four years (2015–2018) of bridge element data in Louisiana. Table 1 lists the top 30 bridge elements that occur most frequently, that is, with high total quantity. The mean total quantity of "deck reinforced concrete" is 437,711,554 (good = 254,985,479; fair = 171,433,881; poor = 10,513,762; and severe = 778,432), which is 55% of the mean value of the total quantity of all bridge elements in Louisiana. Table 1 presents general information about the collected data and the performance of each element in all bridges across Louisiana. For the majority of bridge elements, the majority are in good condition (except "bridge rail other," which has a higher percentage in fair condition). For four bridge elements, 10% or above are in poor or severe condition: "deck timber," "joint pourable," "top flange reinforced concrete," "bridge rail other," and "joint compression."

The database contains a series of structure numbers with all of the bridge elements associated with each structure number; these bridge elements are designated by an element number (EN). For example, in 2015 structure number 22600000020029 had six elements: (i) slab reinforced concrete (EN = 38, total quantity = 12,250), (ii) substructure abutment reinforced concrete (EN = 215, total quantity = 140), (iii) substructure pile prestressed concrete (EN = 226, total quantity = 56), (iv) substructure pier cap reinforced concrete (EN = 234, total quantity = 210), (v) joint pourable (EN = 301, total quantity = 350), and (vi) bridge rail reinforced concrete (EN = 331, total quantity = 700). The total quantity of elements was 13,706. "Slab reinforced concrete" represented 89% (12,250/13,706) of the total quantity of elements. Another importance measure is the length measure percentage per structure number. Table 2 lists the top 30 bridge elements with a high mean percentage of length (a measure provided for each row in the NBI dataset). For example, the element "culvert prestressed concrete" has the highest mean percentage of a quantity, followed by "culvert reinforced concrete," and "deck other."

The key research approach of this study is to examine the temporal effects on the bridge elements that make some of the elements susceptible to deterioration to poor or severe condition over time. The slope graph is an excellent visualization tool to explore the temporal effect of different elements over time. Figure 1 illustrates the slope graph of the top 20 bridge elements with a high mean of total quantity in good condition. The distribution indicates that the majority of the bridge elements were not in good condition in 2015 and 2016. The ranges of good condition in 2015 were from 0 to 81.12%. In 2016, these values were 0 and 79.68%. These ranges shifted drastically in 2017 and 2018. For example, in 2018, these ranges were from 40.35% to 96.69%. "Bridge rail" had 0% in good condition in 2015 and 2016, however, this might be caused by measurement error in the dataset. "Bridge rail" in good condition then jumped to 92% and above in 2017 and 2018. The minority of "deck timber" elements were in moderate to good condition in 2015 and 2016 (28.2% and 22.67%, respectively), but good condition rose to 75% and above in 2017 and 2018.

Table 1. Top 30 Bridge Elements (Sorted by Total Quantity)

Element no. (EN)	Description	Total quantity	Good (%)	Fair (%)	Poor (%)	Severe (%)
12	*Deck reinforced concrete*	437,711,554	58.3	39.2	2.4	0.2
515	Steel protective coating	114,505,963	47.0	43.1	8.1	1.9
38	*Slab reinforced concrete*	86,135,360	62.0	33.8	4.1	0.2
109	Superstructure girder/beam prestressed concrete	42,995,213	79.2	15.6	4.4	0.8
331	Bridge rail reinforced concrete	22,519,204	76.9	18.6	4.0	0.5
510	Wearing surfaces	12,871,006	80.7	12.4	6.0	1.0
107	Superstructure girder/beam steel	10,526,638	76.3	19.2	4.2	0.3
234	Substructure pier cap reinforced concrete	8,622,688	73.2	21.4	5.4	0.0
31	Deck timber	6,297,017	45.8	41.0	11.6	1.6
301	Joint pourable	5,311,970	41.9	29.5	23.7	4.9
111	Superstructure girder/beam timber	5,016,906	74.1	23.2	1.8	0.9
110	Superstructure girder/beam reinforced concrete	4,434,831	69.6	24.7	5.4	0.3
113	Superstructure stringer steel	3,782,303	85.8	11.6	2.4	0.2
16	Top flange reinforced concrete	3,330,771	44.6	38.6	16.8	0.0
330	Bridge rail steel	3,096,897	87.7	10.2	1.6	0.5
13	*Deck prestressed concrete*	2,397,551	95.5	4.2	0.2	0.0
215	Substructure abutment reinforced concrete	2,328,065	83.9	14.6	1.4	0.1
241	*Culvert reinforced concrete*	2,119,697	70.0	27.5	2.4	0.1
333	Bridge rail other	1,581,168	6.9	74.9	17.5	0.7
304	Joint open	1,515,708	90.3	2.3	4.1	3.2
30	Corrugated or orthotropic deck steel	1,425,674	92.9	3.8	3.2	0.1
28	Open grid deck steel	1,408,895	80.2	13.0	4.3	2.4
302	Joint compression	1,366,639	41.8	26.6	5.5	26.1
104	Superstructure closed web/box girder prestressed concrete	1,244,621	54.0	43.8	2.2	0.0
152	Superstructure floor beam steel	1,150,357	80.8	14.1	4.5	0.7
310	Bearing elastomeric	1,081,133	91.9	4.4	3.7	0.0
216	Substructure abutment timber	832,348	57.7	29.4	9.7	3.2
15	Top flange prestressed concrete	816,821	89.3	10.2	0.5	0.0
305	Joint assembly without seal	711,441	81.6	13.0	4.0	1.4
235	Substructure pier cap timber	690,202	75.0	20.4	3.0	1.6

The good condition percentages in 2017 and 2018 are not significantly different for any bridge element. A majority of the bridge elements show a low percentage in good condition in 2016 when compared with the respective condition in 2015. The "superstructure girder/beam prestressed concrete" element showed 96% and above in good condition in 2017 and 2018. The percentages of this element in good condition were significantly lower in 2015 and 2016.

Results

This study utilized the open-source R package *openEBGM* with regard to the EBGM data mining approach created by DuMouchel (*25*). This method contains information about the importance of frequency, considering a given combination of effect and response in the contingency table. This method works with very large but sparse tables as well. The final database has 260,011 records and 1,293 unique combinations of "Variable 1-Variable 2-Strata." Year is considered as the stratum to show the temporal impact of the bridge element. Variable 1 describes the bridge element, and Variable 2 specifies the prevalent condition of the bridge element. N indicates the count of the "Variable 1-Variable 2-Strata" combination. If "Variable 2" changes, N also changes. If a bridge element had a good condition score of 60%, a fair condition score of 20%, and the rest in poor condition, then "Variable 2" would be considered "good" condition because good condition indicates a higher percentage compared with fair or poor condition. The consideration of year as stratum will not affect the proportional reporting ratio (PRR) calculations, but this stratification will affect the measures of E and RR calculations. Because of the form of the large contingency tables, conventional statistical procedures are insufficient to determine significant rules from this dataset. Table 3 notes the variable applied for the final analysis.

Users can evaluate the hyperparameters by exploring the parameter space of the likelihood function using either the full data set of Ns and Es or the compacted set (compact the dataset to reduce the amount of computation needed to estimate the hyperparameters). Starting points must be chosen to begin the exploration. This study used the expectation/conditional maximization

Table 2. Top 30 Bridge Elements with a High Mean Percentage of the Quantity

EN	Description	Mean length percentage (%)
245	*Culvert prestressed concrete*	*92.4*
241	*Culvert reinforced concrete*	*78.2*
60	*Deck other*	*75.7*
38	*Slab reinforced concrete*	*70.9*
12	*Deck reinforced concrete*	*68.7*
65	*Slab other*	*67.2*
240	*Culvert steel*	*64.1*
13	*Deck prestressed concrete*	*60.7*
54	*Slab timber*	*59.8*
243	*Culvert other*	*58.2*
16	Top flange reinforced concrete	52.0
31	Deck timber	46.2
15	Top flange prestressed concrete	43.5
141	Superstructure arch steel	41.7
30	Corrugated or orthotropic deck steel	34.0
510	Wearing surfaces	33.9
111	Superstructure girder/beam timber	31.0
117	Superstructure stringer timber	24.3
116	Superstructure stringer reinforced concrete	24.0
112	Superstructure girder/beam other	20.5
515	Steel protective coating	19.6
521	Concrete protective coating	18.8
28	Open grid deck steel	18.0
109	Superstructure girder/beam prestressed concrete	12.9
106	Superstructure closed web/box girder other	12.1
110	Superstructure girder/beam reinforced concrete	10.8
105	Superstructure closed web/box girder reinforced concrete	9.6
113	Superstructure stringer steel	7.5
155	Superstructure floor beam reinforced concrete	7.2
218	Substructure abutment other	6.7

Note: EN = element number.

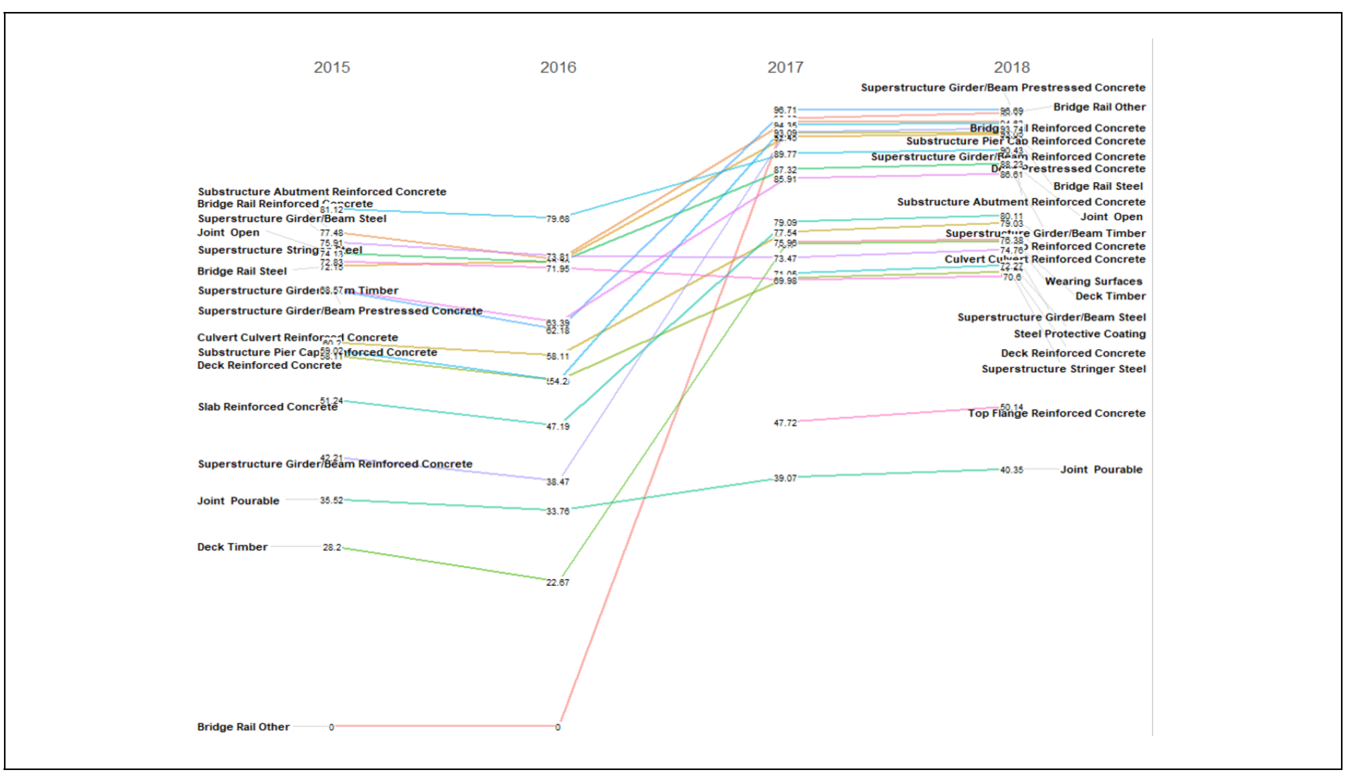

Figure 1. Slope graph of top 20 bridge elements with high mean of total quantity in good condition.

Table 3. Variable Used for Empirical Bayes Geometric Mean

Variable 1 (Var 1)	Variable 2 (Var 2)	Strata
Bridge element name	Condition	Year

(ECM) algorithm for the optimization. This approach uses a single starting point to find a local maximum likelihood estimate for θ by finding roots of the score functions to minimize the negative log-likelihood function. The convergence was preliminarily done by quasi-Newton unconstrained optimization technique. This approach uses function values and gradients to build up a picture of the surface to be optimized. As this paper is more applied in nature, additional details on the optimization are not elaborated. Readers can consult Meng and Rubin (*30*) for additional details on the convergence criterion for each parameter. Figure 2 shows the tracking of the log-likelihood and hyperparameter estimates at each iteration that will provide an illustration of the behavior of the algorithm.

The first steps are to populate actual counts of the combinations, expected counts, and RR under the row/column independence assumption, and calculate PRR. The PRR measure compares the proportion of bridge elements under a particular temporal and vulnerability (good to severe condition) condition with the same proportion for all bridge elements in the database. It is important to note that PRR calculations ignore stratification, but E and RR calculations are affected. To approximate the hyperparameters of the previous distribution, the original counts (N) and expected counts (E) were used. Large contingency tables with many cells will result in computational complexities for the optimization procedures necessary for estimation. Minimizing the negative log-likelihood function is the most common practice for hyperparameter estimation. The optimized hyperparameters produced for this study are $(\alpha_1, \beta_1, \alpha_2, \beta_2, \theta)$ = (0.4297678, 0.2856132, 10.7010612, 10.8022525, 0.4994921). The ECM algorithm was used to perform the optimization. If the generated rule was found at a usually high rate, it would be indicated by a score with a value larger than one. The top 20 combination groups with Variable 2—or consequently as "severe" condition—are listed in Table 4. EBGM scores are indicative of the tuned estimation for RR. For example, the "joint compression → severe condition" rule has an EB score of 15.84. With this score, it is known that the presence of this rule occurred 15.84 times more frequently in the data than expected with the assumption of no association between condition and bridge element. The 5% and 95% quantiles of the posterior distributions were used for a two-sided 90% credibility interval for λ_{ij} (given N_{ij}). It was found that, in Louisiana, the joint elements of bridge assets are most related to "severe" condition.

Table 4 presents multiple bridge elements that are more highly associated with "severe" bridge condition than expected, based on the E value in the table. These elements are: joint compression, joint open, bridge rail timber, joint strip seal, bearing other, joint pourable, and superstructure floor beam reinforced concrete, all of which have EBGM scores higher than 3. In other words, these elements are three times more frequently present in the bridge elements with severe condition than expected if there were no association between the element and the

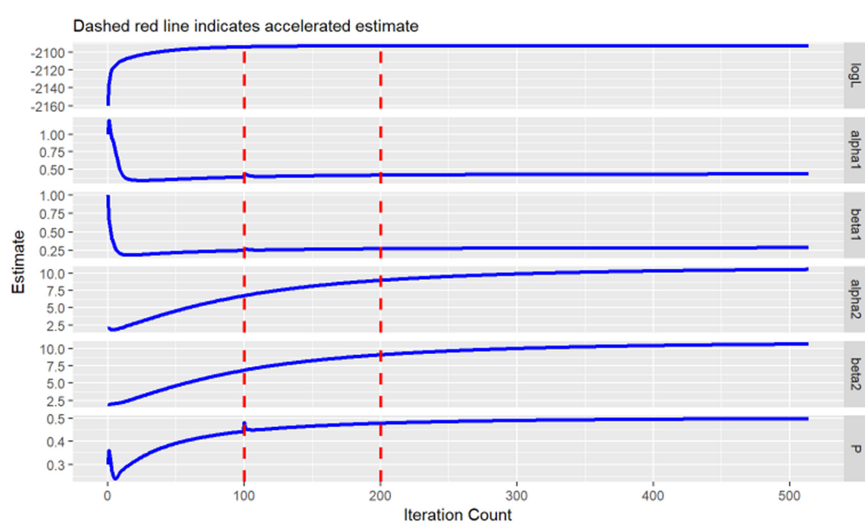

Figure 2. Log-likelihood and other hyperparameters as components of convergence assessment.

Table 4. Top 20 Rules with High Empirical Bayes Geometric Mean (EBGM) Values (Consequently Severe)

Var 1 (bridge element)	Var 2 (condition)	N	E	RR	PRR	EBGM	Q05	Q95
Joint compression	Severe	913	57.33	15.92	19.50	15.84	15.00	16.73
Joint open	Severe	231	46.31	4.99	5.09	4.96	4.44	5.52
Bridge rail timber	Severe	101	20.17	5.01	4.97	4.93	4.18	5.80
Joint strip seal	Severe	134	27.31	4.91	5.00	4.85	4.20	5.58
Bearing other	Severe	10	1.84	5.45	7.21	4.64	2.62	7.65
Joint pourable	Severe	1575	351.65	4.48	6.33	4.47	4.29	4.66
Superstructure floor beam reinforced concrete	Severe	2	0.16	12.82	12.10	3.11	0.81	11.42
Steel protective coating	Severe	305	180.92	1.69	2.32	1.66	1.51	1.83
Bearing movable (roller, sliding, etc.)	Severe	75	49.55	1.51	1.50	1.44	1.19	1.74
Substructure abutment timber	Severe	246	172.63	1.43	1.42	1.40	1.27	1.56
Joint assembly without seal	Severe	46	31.16	1.48	1.42	1.37	1.09	1.74
Joint assembly with seal (modular)	Severe	9	5.59	1.61	1.57	1.27	0.81	2.11
Superstructure truss steel	Severe	5	3.68	1.36	1.31	1.10	0.65	1.89
Bearing fixed	Severe	44	41.88	1.05	1.05	1.03	0.82	1.29
Culvert steel	Severe	32	32.14	1.00	0.98	0.98	0.75	1.27
Open grid deck steel	Severe	7	7.17	0.98	0.97	0.95	0.60	1.45
Substructure column timber	Severe	24	25.97	0.92	1.22	0.93	0.69	1.23
Bridge rail other	Severe	48	53.72	0.89	0.63	0.90	0.72	1.12
Concrete protective coating	Severe	2	2.69	0.74	0.98	0.83	0.35	1.50
Deck timber	Severe	47	62.84	0.75	0.72	0.77	0.61	0.96

Note: E = expected count; N = original count; PRR = proportional reporting ratio; RR = relative reporting ratio; Q05 = 5th percentile; Q95 = 95th percentile.
*Sorted by EBGM scores.

severe condition. Moreover, for the bridges with "severe" condition, it is not likely to be caused by one specific element. It is also important for bridge professionals to identify multiple elements with high EBGM scores, which might work in combination resulting in the bridge elements being in "severe" condition. In Table 4, Q05 is the 5th percentile and Q95 is the 95th percentile. These two quantile measures form the lower and upper bounds of 90% credibility intervals for the empirical Bayes scores. If 1 is present for the Q05–Q95 for an EBGM score, it cannot be said with high confidence that the Var1-Var2 combination for that particular rule is truly reported more than expected.

Table 5 presents the top 20 rules with high EBGM value for the sub dataset of bridge elements with poor condition. The combination group "top flange reinforced concrete → poor condition" rule has an EBGM score of 5.01. This score indicates that the presence of this rule occurred in the data 5.01 times more frequently than expected under the assumption of no association between bridge element and condition. "Joint pourable" with poor condition occurs in the database 6,245 times with an EBGM score of 4.91. The "bearing movable," "deck other," "superstructure floor beam reinforced concrete," and "joint strip seal elements" have EBGM value higher than 3. These elements or a combination of them require more attention from bridge engineers.

Tables 4 and 5 list the top 20 rules for bridge elements with poor or severe condition separately. The judgment as to whether bridge elements are in a poor or severe condition is unavoidably subjective. It is also possible that a bridge element in poor condition may deteriorate into severe condition soon. Thus, to take a closer look at poor or severe condition types, another table is prepared using the top 20 rules (see Table 6) to explore the pattern for bridge elements with poor or severe condition. The rule with the highest EBGM score is "joint strip seal → poor or severe condition." The EBGM score of this rule indicates that the presence of this rule occurred in the data 12.27 times more frequently than expected under the assumption of no association between bridge element and condition. The frequencies of these rules are lower than the rules listed in Tables 4 and 5. There are several elements that have EBGM scores higher than 3. These elements are: "joint open," "bearing movable," "substructure abutment timber," "substructure column steel," "bridge rail other," and "superstructure truss steel." Both "substructure abutment timber" and "substructure column steel" have lower EBGM scores in Tables 4 and 5. These elements may also require attention. If we consider only the bridge elements with condition poor or worse, these elements are highly associated with these undesirable conditions.

Figure 3 illustrates the top EBGM scores by "Variable 1-Variable 2" combination (only Variable 1 is shown for easy visualization) rules by using the dataset with the severe, poor, or poor-severe condition of the bridge elements. The "error bars" using the lowest and highest

Table 5. Top 20 Rules with High Empirical Bayes Geometric Mean (EBGM) Values (Consequently Poor)

Var 1 (bridge element)	Var 2 (condition)	N	E	RR	PRR	EBGM	Q05	Q95
Top flange reinforced concrete	Poor	84	16.45	5.11	3.74	5.01	4.17	5.98
Joint pourable	Poor	6245	1270.39	4.92	7.9	4.91	4.81	5.02
Bearing movable (roller, sliding, etc.)	Poor	813	177.19	4.59	4.87	4.58	4.32	4.85
Deck other	Poor	2	0.08	23.83	17.44	3.9	0.87	13.93
Superstructure floor beam reinforced concrete	Poor	4	0.60	6.69	6.98	3.81	1.13	9.23
Joint strip seal	Poor	315	95.89	3.29	3.35	3.27	2.98	3.59
Slab timber	Poor	4	0.81	4.94	5.81	2.85	0.97	7.29
Bridge rail other	Poor	876	325.84	2.69	3.49	2.69	2.54	2.84
Superstructure truss steel	Poor	33	13.61	2.42	2.51	2.29	1.62	3.1
Bearing other	Poor	10	3.51	2.85	2.08	2.27	1.16	4.13
Joint assembly with seal (modular)	Poor	46	20.36	2.26	2.32	2.16	1.63	2.79
Substructure abutment masonry	Poor	3	0.75	3.99	2.91	1.98	0.78	5.97
Deck timber	Poor	363	230.68	1.57	1.63	1.56	1.43	1.69
Joint open	Poor	229	167.65	1.37	1.4	1.35	1.21	1.5
Wearing surfaces	Poor	239	179.36	1.33	0.97	1.31	1.18	1.46
Substructure column timber	Poor	62	49.68	1.25	0.91	1.2	0.99	1.46
Steel protective coating	Poor	385	346.02	1.11	0.81	1.11	1.02	1.21
Substructure abutment timber	Poor	647	619.84	1.04	1.06	1.04	0.98	1.11
Superstructure floor beam steel	Poor	65	64.47	1.01	1.03	1	0.82	1.21
Joint compression	Poor	200	206.89	0.97	0.98	0.97	0.86	1.08

Note: E = expected count; N = original count; PRR = proportional reporting ratio; RR = relative reporting ratio; Q05 = 5th percentile; Q95 = 95th percentile.
*Sorted by EBGM scores.

Table 6. Top 20 Rules with High Empirical Bayes Geometric Mean (EBGM) Values (Consequently Poor or Severe Condition)

Var 1 (bridge element)	Var 2 (condition)	N	E	RR	PRR	EBGM	Q05	Q95
Joint strip seal	P-S	18	1.18	15.31	16.85	12.27	8.2	17.81
Joint open	P-S	22	2.05	10.75	12.19	9.4	6.54	13.19
Bearing movable (roller, sliding, etc.)	P-S	15	2.17	6.9	7.5	6.07	3.89	9.11
Substructure abutment timber	P-S	38	7.58	5.02	6.1	4.82	3.67	6.25
Substructure column steel	P-S	2	0.06	36.22	34	4.34	0.91	15.21
Bridge rail other	P-S	15	3.45	4.34	4.96	3.97	2.51	5.99
Superstructure truss steel	P-S	2	0.17	12.02	12.41	3.02	0.81	11.12
Steel protective coating	P-S	13	5.41	2.4	2.31	1.96	1.13	3.35
Joint compression	P-S	6	2.52	2.38	2.44	1.6	0.85	3.5
Substructure column timber	P-S	2	0.78	2.57	2.39	1.32	0.61	4
Culvert steel	P-S	3	1.40	2.14	2.16	1.3	0.66	3.25
Joint pourable	P-S	20	15.46	1.29	1.34	1.17	0.85	1.61
Bridge rail steel	P-S	10	7.92	1.26	1.26	1.11	0.73	1.66
Joint assembly without seal	P-S	2	1.41	1.42	1.44	1.04	0.51	2.27
Bearing fixed	P-S	2	1.82	1.1	1.11	0.96	0.46	1.84
Substructure pile reinforced concrete	P-S	4	4.77	0.84	0.85	0.88	0.48	1.44
Superstructure girder/beam steel	P-S	2	2.56	0.78	0.78	0.84	0.36	1.53
Substructure pile timber	P-S	5	7.72	0.65	0.64	0.76	0.41	1.22
Substructure pile prestressed concrete	P-S	1	8.68	0.12	0.11	0.12	0.02	0.6
Substructure abutment reinforced concrete	P-S	2	17.87	0.11	0.1	0.11	0.03	0.32

Note: E = expected count; N = original count; P-S = poor or severe condition; PRR = proportional reporting ratio; RR = relative reporting ratio; Q05 = 5th percentile; Q95 = 95th percentile.
*Sorted by EBGM scores.

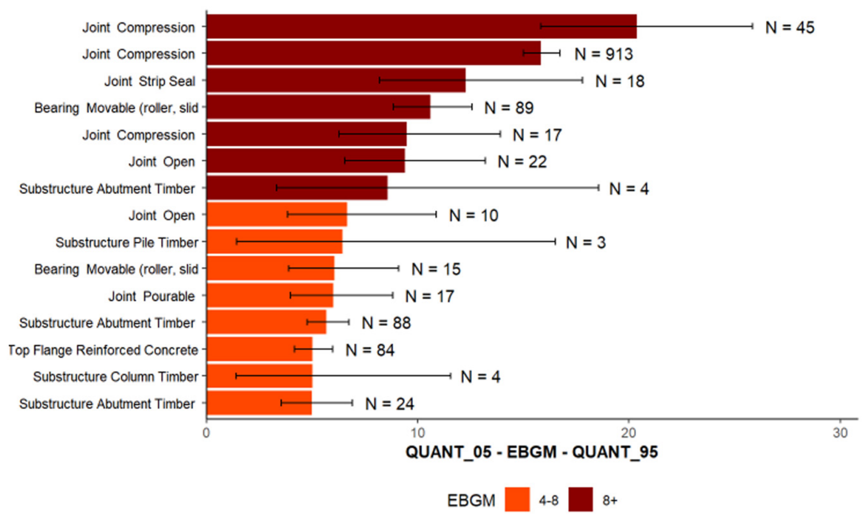

Figure 3. Top 15 rules from the dataset with severe, poor, or poor-severe condition of the bridge elements.

quantiles and the sample size for each rule are also plotted. The majority of the bridge elements with top EBGM scores are the "joint compression" elements. The "bearing movable" and "substructure abutment timber" elements are also on the top EBGM list.

Conclusion

The recent ARTBA report indicated that 13% of 12,899 bridges in Louisiana are classified as structurally deficient (*11*). Limited research has been conducted to evaluate the condition of bridge elements in Louisiana, and there is an urgent need for an in-depth study focusing on this issue. This study used four years of Louisiana bridge inventory data to determine the key patterns of bridge deterioration. In recent years, many transportation engineering studies have applied different data analysis methods such as correspondence analysis, cluster analysis, cluster correspondence analysis, Bayesian network, and EBGM to identify the hidden trends (*31–37*). The EBGM scoring method, an advanced categorical data analysis approach which is used in this study, identified some key groups that require further attention. This study shows the uniqueness of EBGM in determining the significant associations between the factors. The findings of this study are the following:

- The majority of the bridge elements did not have a high percentage in good condition before 2017. The rate of good condition changed negatively from 2016 to 2017.
- The EBGM scoring indicates that bridge joints, "bridge rail timber," "bearing other," and "superstructure floor beam reinforced concrete" are bridge elements highly associated with severe condition.
- The EBGM scoring indicates that bridge joints, "top flange reinforced concrete," "bearing movable," and "superstructure floor beam reinforced concrete" elements are highly associated with poor condition.
- The study also shows the bridge joints, "bearing movable," "substructure abutment timber," "substructure column steel," "bridge rail other," and "superstructure truss steel" are bridge elements highly associated with condition of poor or worse.
- The quantification scores (EBGM scores) could help authorities in making data-driven decisions when managing bridge maintenance and repair.
- The identified patterns that are strongly associated with severe and poor conditions should have more weight in the bridge asset management systems when assessing the bridge condition or allocating possible budget for future bridge element maintenance. There are several considerations to utilize these findings. One is to increase the weight of individual identified elements for the bridge. Meanwhile, more weight should be considered if a combination of these identified elements is found in the bridge.

The current study is not without limitations. The current analysis is limited to four years of bridge element data in one state. Consideration of a longer time period would help in understanding the historical trends by year. The current analysis is also limited to bridge inventory data. Fusion of data from other sources, like crash data and traffic volume data, could help researchers better understand the associations between bridge element conditions and other surrogate measures.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S. Das; data collection: S. Das; analysis and interpretation of results: S. Das, X. Kong; draft manuscript preparation: S. Das, X. Kong. Al authors reviewed the results and approved the final version of the manuscript.

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ORCID iDs

Subasish Das https://orcid.org/0000-0002-1671-2753
Xiaoqiang Kong https://orcid.org/0000-0002-8120-0754

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