CSCE Annual Conference
Growing with youth – Croître avec les jeunes

Laval (Greater Montreal)
June 12 - 15, 2019

DETERIORATION MODELS FOR SUPERSTRUCTURE OF PRESTRESSED CONCRETE BRIDGES IN CALIFORNIA

Sahar, Hasan[1,2] and Emad, Elwakil[1,3]
[1] School of Construction Management, Purdue University, West Lafayette, IN, 47907, USA.

[2] Construction and Project Management Institute, Housing and Building National Research Center (HBRC), Egypt.

[3] eelwakil@purdue.edu

Abstract: About $12.2 billion were estimated for repairs of approximately 17% of California's bridges, at the beginning of 2018. This significant cost refers to the importance of preventive maintenance actions to reduce the deficient bridges. Deterioration models were widely used as a guide for identifying the maintenance priority and consequently reducing the cost of repairs. Prestressed concrete bridges represent about 24% of bridges in California. Thus, detecting damages and rating condition for these bridges is a contribution to the bridges maintenance system. This paper has utilized National Bridge Inventory (NBI) database for California State in order to develop four regression models for predicting the superstructure condition of four structure types (Slab ; Stringer / Multi Beam or Girder; T- Beam; and Box Beam or Girder). The developed models have investigated the significant variables on the superstructure deterioration using regression modeling. This research has come out with significant impact of eight variables with high coefficient of determination (R^2=86%). The developed models have been validated using average validity percentage method (AVP) with a satisfactory result "93%". The developed models will help infrastructure agencies to prioritize the maintenance process for bridges, and support the inspected condition rating with objective opinion instead of subjective expert opinion only.

1. INTRODUCTION

Bridges represent the key component of the infrastructure system, therefore any disability of transportation because of its deterioration results in extensive and costly rehabilitation, as well as social and environmental impacts. Infrastructure agencies should have a maintenance plan to prioritize its actions and allocate available funds appropriately **(**TranSystems Corporation 2011). AASHTO (1993) has considered the deterioration models as one of the minimum requirements for managing the bridges systems. They take into account the inspection variables to track the physical deterioration of their bridge and consequently make the decisions for maintenance (Manafpour 2018, Chang et al. 2017, Saeed et al. 2017, Morcous & Hatami 2011, Morcous et al. 2002). The Federal Highway Administration's National Bridge Inventory (NBI) database is one of the main data sources to be utilized in different techniques. The NBI database assembles reliable information of bridge inventory data and operating variables at the level of individual bridge elements (Deck, Superstructure, and Substructure) (Nieto et al. 2018, Nieto & Cristian 2017, Tolliver and Lu 2012, Veshosky 1994). The NBI have inspected different structure materials for bridges such as concrete, prestressed concrete, steel, and timber. ASCE infrastructure (2018) has reported that at the beginning of 2018, about 6.2% of California's bridges are structurally deficient and approximately 17% of California's bridges are estimated to cost about $12.2 billion for repairs. Prestressed concrete bridges have been built in California State since 1931 up to now, and represent about 24% of its bridge networks

(USDOT, 2017). Detecting damages and rating condition for these bridges contributes to the bridges maintenance system. “Predicting the Deck” condition has been studied more than the other components, although it has been found that the superstructure elements are considered as one of more critical elements to the bridge system deterioration compared to decks (Inkoom & Sobanjo, 2018). Therefore, this study focuses on modeling the superstructure condition for prestressed concrete bridges , through addressing four types of superstructure component; slab, Stringer / Multi Beam or Girder, T- Beam, and Box Beam or Girder.

2. BACKGROUND

Tolliver and Lu (2012) has referred to the subjectively record, which may vary from inspector to another. Therefore, the deterioration models are considered as a supportive tool from an empirical standpoint to the physical inspection. Moreover, they assist decision-makers in predicting the condition of facilities and consequently prioritize the allocation of the scarce resources for maintenance (Morcous et al., 2002). The deterioration models have been classified into three categories: Deterministic, Stochastic approaches, and Artificial intelligence models (Inkoom& Sobanjo, 2018; Chang et al., 2017; Saeed et al. 2017, Moomen 2016, Saeed et al. 2016, Bu et al. 2013, Morcous et al. 2002, Veshosky et al. 1994). Chang et al. (2017) and Smith & Saitta (2008) believed that the deterministic approach is still meaningful to investigate the bridge inventory classification according to explanatory variables. Deterministic models incorporate statistical relations for finding a correlation between a set of bridge variables and bridge conditions to establish a relationship between the functional properties of the bridge and the bridge element condition. Regression models are widely applied method for this approach for identifying the related significant factors to the response/predicted variable as well as the relation between them based on the observed data (Inkoom & Sobanjo 2018, Bektas et al., 2012).
Database of NBI has been used in many studies with different approaches for different material structure to develope deterioration models (Nieto et al. 2018, Nieto & Cristian 2017, Saeed et al. 2017, Morcous & Hatami 2011, Veshosky 1994). These studies have used different approaches based on the available data in NBI. Within this context, several explanatory variables have been explored and examined to define their impact on the predicted condition rating. Veshosky et al. (1994), have studied the deterioration rates of prestressed and steel concrete bridge superstructure using regression analysis, in terms of age and average daily traffic, as significant variables in seven selected states to represent diverse environments. The extracted models had coefficients of determination (R^2) adjusted by about less than 50%. Later, Kim & Yoon (2009), have studied the superstructure deterioration for the three material types (Concrete, Prestressed concrete, and steel), and classified for three structural types (Slab, Girder/beam, and truss); located in cold regions. They applied the approach of a combined of regression and Geographical information system. Their study come out with the significant factors; age, followed by the structural characteristics and traffic volumes. They referred to the service of water under the bridge that was critical to the deterioration in cold regions, and recommended the concrete bridges for cold region as more durable. Morcous (2011) has applied another approach using Markov transition probabilities based on NBI condition ratings for developing superstructure deterioration models for steel and prestressed concrete bridges in Nebraska. They classified the bridges in groups based on factors including deck type, wearing surface, deck protection, average daily traffic, average daily truck traffic, and highway district. Saeed et al. (2017), have addressed the predictors for determining the service lives for presstressed concrete superstructure and how their influencing varies across four structure types (slab, stringer, T-BEAM, box-Beam). They used the exponential and polynomial functional forms as part of the modeling process. They revealed that age, number of spans in one unit, and average daily truck traffic do significantly affect the bridge deterioration. Recently, Nieto et al. (2018) have estimated the probability of reaching deficiency for steel bridge superstructures. They applied the data mining techniques, which included the logistic regression, decision trees, neural networks, gradient boosting, and support vector machine using NBI database. The predictors of the developed model included age, average daily traffic, design load, maximum span length, owner, location, and structure length. Furthermore, Nabizadeh et al. (2018) have based on the statistical analysis for NBI records to incorporate the parameters of the type of bridge superstructure, bridge age, maximum span length and average daily traffic as potential risk factors in failure rate of bridge superstructures. The study results showed that maximum span length and average daily traffic could substantially affect the survival of bridge superstructures at various ages.

Based on the above literature review, it has been found that the operational and design variables have been studied more than others; such as Age, Average daily traffic (ADT), Percentage Average daily truck traffic, Structure length, and Max. Span length. While, other variables such as Deck with, Roadway width, Skew degrees, and Structural type have been examined in limited studies. Therefore, this paper has selected both of limited and common variables as potential predictors to examine how they affect together on prestressed bridge superstructure deterioration.

3. METHODOLOGY

This research has mainly focused on developing a model for predicting superstructure condition of prestressed concrete bridges. For achieving that goal, the literature review has come out with the candidate variables, then the regression approach has been used to identify the significant variables affecting the superstructure condition. The proposed methodology for the research is shown in Figure 1. This scheme has illustrated as well, the next processes of statistical analysis for testing significance, and Model validation, up to concluded results.

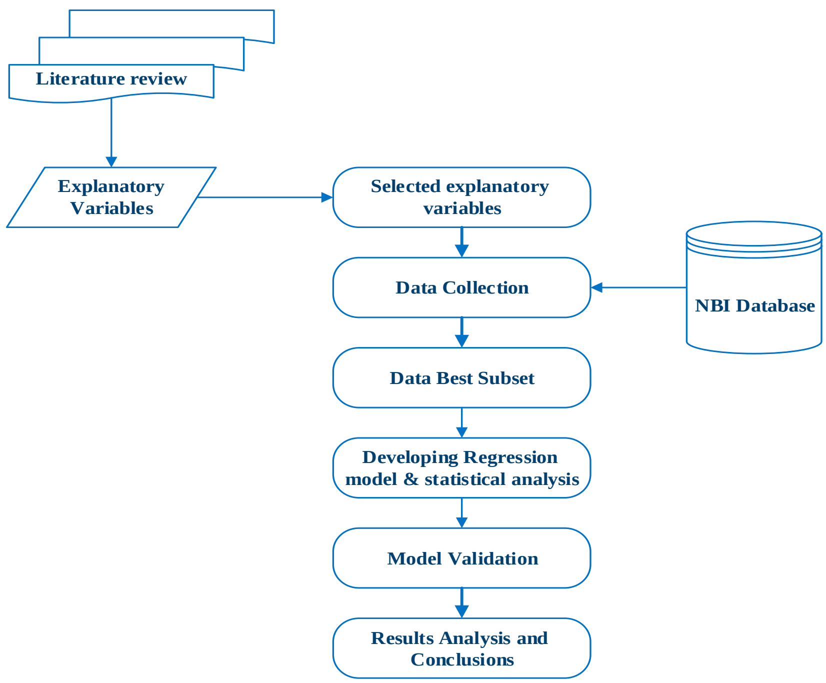

Figure 1. Research Methodology

4. DATA COLLECTION:

The collected data based on the inspection and inventory data NBI of 2017 for prestressed concrete bridges in California State. At the beginning, the observations related to bridge reconstruction or rehabilitation were excluded in this study to avoid the conflict of reconstruction impacts. The collected data was mainly for urban roads, with length of maximum span (between 20 - 30m), and Aged from 30 to 39 years. These filtration and classification processes have narrowed the sample size to contain 30 bridges. The included structure types were four types: slab; Stringer / Multi Beam or Girder; T- Beam; and Box Beam or Girder. Where both of Stringer / Multi Beam or Girder, and Box Beam or Girder represent the majority bridges; about 93% of sample size.

The dependent variable of the model was the superstructure condition rating. According to (FHWA 1995) ranges from zero to nine, where nine for the best condition and zero is the worst rating .While the independent variables have included quantitative and qualitative variables. Quantitative variables composed of estimated age, average daily traffic (ADT), percentage average daily truck traffic, structure length, deck width, roadway width, skew degrees, and max span length. While qualitative/category variable was the structure type. The description of these variables even integer or dummy variables were listed in Table1.

Table 1. List of Variables Used in This Study with description

Variables in Study	Code	Description*
Estimated AGE(years)	AGE	years since initial Construction of bridge up to 2017
Average Daily Traffic (Vehicle/Day)	ADT	Average Daily Traffic (Vehicle/Day)
Degree of skew (Degrees)	DS	The angle between the centerline of a pier and a line normal to the roadway centerline.
Max. Span Length(m)	ML	Length of Maximum Span.
Structure Length(m)	SL	The length of roadway, which is supported on the bridge structure; from back to back of the abutments.
Roadway width(m)	RW	It is the most restrictive minimum distance between curbs or rails on the structure roadway.
Deck Width (m)	DW	Deck width, out-to-out
Percent Average Daily Truck Traffic (%)	PT	Percent Average Daily Truck Traffic.
Structure Type (Integer)	ST	(Slab ; Stringer / Multi Beam or Girder; T- Beam, and Box Beam or Girder)
*The Description from NBI coding guide (FHWA 1995).		

5. MODEL DEVELOPMENT

5.1. Best subset and Regression model

About 80% of the collected data (24 bridges ≅80%) were selected and included for model building process and the remaining data are excluded for later validation processes. Minitab 18 as statistical software has been used for developing the regression model and statistical analysis. Best subset analysis identifies the best fit regression model that can be conducted with the specified number of variables with regard to the highest R^2 values. Consequently, many iterations have been done to get the highest R^2 and these trials included additional factors based on literature review in addition to that listed in Table 1. These include, frequency of inspection, service type on the bridge, service under the bridge, and surface type, but these earlier iterations have come out with low R^2 ($R^2 < 70\%$). Based on the analysis of data in hand, the final list of significant variables have been prepared for developing regression models.

5.2. Model building and statistical analysis:

As a result of best subset analysis the regression models were conducted for further analysis. The regression equations for the developed models were listed in Table 2, where the models were classified according to the included four structure types.

Table 2. Developed Regression model for Predicting Superstructure condition for Prestressed Bridges

Structure Type	Regression Model for predicting superstructure condition rating	Points
slab	7.51 - 0.0733 AGE - 0.000003 ADT+ 0.00457 DS - 0.0275 ML- 0.00392 SL + 0.1249 RW- 0.0984 DW+ 0.0048 PT	1
Stringer / Multi Beam or Girder	11.17 - 0.0733 AGE - 0.000003 ADT+ 0.00457 DS - 0.0275 ML- 0.00392 SL + 0.1249 RW- 0.0984 DW+ 0.0048 PT	10
T- Beam	11.20 -0.0733 AGE - 0.000003 ADT+ 0.00457 DS - 0.0275 ML- 0.00392 SL + 0.1249 RW- 0.0984 DW+ 0.0048 PT	1
Box Beam or Girder	10.87 -0.0733 AGE - 0.000003 ADT+ 0.00457 DS - 0.0275 ML- 0.00392 SL + 0.1249 RW- 0.0984 DW+ 0.0048 PT	12

According to the Minitab output for the developed model, The ***R^2*** is **86.13%**, which indicates that the predictors explain 86.13% of the variance in "response variable- superstructure condition rating". The P-value is asked for testing the significance results for the developed models. ***P-value*** (statistical significance) for the developed model is **0.001(**P-value<0.05), meaning that that the estimated model is sound and significant at α-level of 0.05 and 0.01, and the null hypothesis is rejected. This means that none of the regression coefficients is zero.

5.3. Residual analysis

Figure 2 shows the normal probability and frequency plots for the residuals of the developed models. The normal probability plot shows that error terms are nearly normal. Where a small shift from normality do not cause serious problems (Kutner et al., 2005). Consequently, the results could be satisfied and could be interpreted by the possibility of outliers. In addition to Figure 3, it shows the residuals vs. the order of data plot for the model under consideration, where points around the regression line should be independent for each value of predictors. The results show the residuals are at inner bands of X values, except for some points of outliers such as two points 7&13 that lies on the outer negative and positive bands respectively.

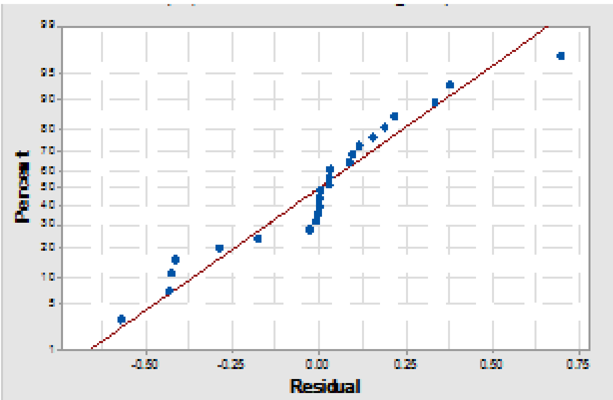

Figure 2. Normal probability of residual plots for super structure condition model

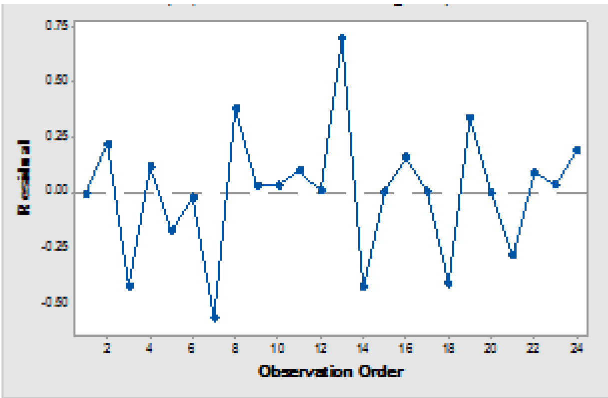

Figure 3. Residual vs. order of data plot for superstructure condition model

6. MODEL IMPLEMENTATION AND VALIDATION

To demonstrate the applicability and validity of the developed models in this paper, the validation processes were implemented using approximately 20% of collected data (6 bridges ≅ 20%) that have been picked randomly and excluded earlier from model building. The validation data have included two types (two models), which represented 93% of collected data.

Validation processes are comparing the predicted results of the models with actual data (observed conditions in NBI) for checking its capability for predicting the condition rating. Fares et al.(2012), and Zayed& Halpin (2005) have used two terms for model validation : 1)The Average Invalidity and Validity Percent for the prediction error (AIP , AVP%) in Equations (1&2) which shows the validation as a percentage ; and 2) the Root Mean Square Error (RMSE) in Equation (3). If the value is closer to zero, the model is sound; and a value closer to one shows that the model is not appropriate.

[1] $\text{AIP} = \frac{\sum_{i=1}^{n} |1-(E_i/C_i|}{n}$

[2] $\text{AVP}= 1 - AIP$

[3] $\text{RMSE}= \sqrt{\sum_{i=1}^{n} (\mathrm{C}_i - \mathrm{E}_i)^2 / n}$

Where, E_i: Predicted value for case i; C_i: Actual value; and N: Number of bridges for validation.

Table 3. Validation summary results

No.	Structure Type	Actual	Predicted	AIP	RMSE

		SUPER. COND.	SUPER COND.		
1	Box Beam or Girder	7	7.68	0.097	0.462
2	Stringer / Multi Beam or Girder	8	7.45	0.067	0.293
3	Box Beam or Girder	8	7.75	0.031	0.062
4	Stringer / Multi Beam or Girder	7	8.15	0.165	1.340
5	Stringer / Multi Beam or Girder	8	7.96	0.004	0.001
6	Stringer / Multi Beam or Girder	8	7.57	0.052	0.179
				AIP =6.98%	0.624
				AVP =93.02%	

Table 3 summarizes the estimated values for these terms for model validation based on the randomly selected data for validation (6 bridges =20% of collected data). Where it shows that, the *AVP*=93%, and *RMSE*=0.624<1; as satisfied values to prove that the proposed models were able to forecast the superstructure condition. Figure 4 represented the actual and predicted superstructure condition in a scatter diagram where most of actual and predicted points are close, except for point 4.

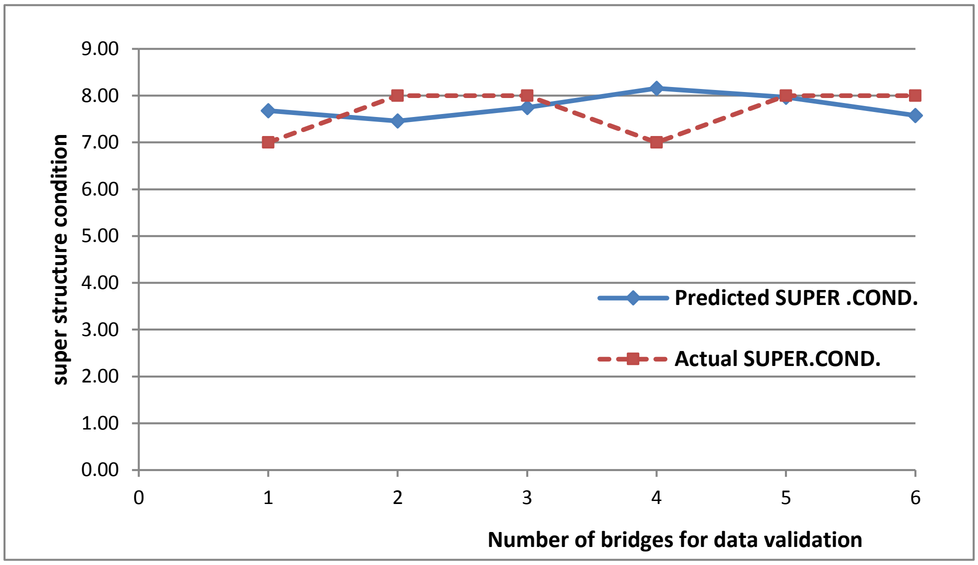

Figure 4. Actual and predicted superstructure condition for developed models

7. RESULTS

Based on the developed regression models; the following findings have been revealed for all four models:

i. The early best subset processes revealed that some candidate factors were not significant such as frequency of inspections, service under the bridge, service on the bridge, and surface type. Further research with different classification of collected data is recommended to examine these factors on the superstructure condition.

ii. The developed regression models shown in Table 2 have indicated the same impact of the eight explanatory variables on the superstructure condition for all of four superstructure types. Therefore, in order to generalize this result, it is recommended to apply this methodology for collected data with unlimited superstructure types for prestressed bridges.

iii. Increasing age and ADT are associated with poorer condition. This correlation agreed with the findings of Nabizadeh et al. (2018) and Saeed et al. (2017). Where they found the same effect for both of these variables in case of a prestressed concrete box-beam single superstructure.

iv. Max span length, structure length, deck width have a negative correlation with superstructure condition, which give attention that those bridges with high related values for mentioned variables should be inspected in nearly frequencies.

8. CONCLUSIONS AND RECOMMENDATIONS

Four regression models have been developed using regression analysis and best subset to find the variables that have the most significant impact on superstructure condition based on NBI database for California State. The developed models have reflected the impact of eight significant variables on the superstructure deterioration with high Coefficient of determination (R^2=86%). Two models that represented the majority of collected data have been validated with satisfactory results "93%" using average validity percentage method. The developed models are limited by specific structure types (Slab; Stringer / Multi Beam or Girder; T- Beam, and Box Beam or Girder. It is concluded that there are variables correlated negatively with the superstructure condition such as age, average daily traffic, max span length, structure length, and deck width. Others correlated positively with degree of skew, roadway width, and percent average daily truck traffic. Regarding the positive impact of degree of skew and percent average daily truck traffic, it needs more research where these results contradicted with the previous studies. The predicted condition rating helps engineers and infrastructure agencies to support the inspected condition rating objectively instead of subjective expert opinion only. It also helps them for prioritizing the maintenance. Further research is recommended to include more of structure types with different range of age. The model could be improved if some factors that were not available for currently collected data are studied in further researches, such as bridge maintenance records and weather variables. Furthermore, regarding the other two structure types (Slab , and T- Beam) , it is recommended for further validation to be generalized.

ACKNOWLEDGEMENT

The authors would like to acknowledge the support of the FHWA for providing bridge inspection data.

9. REFERENCES

American Association of State Highway and Transportation Officials (AASHTO). 1993. Guidelines for bridge management systems. American Association of State Highway and Transportation Officials.

American Society of Civil Engineers (ASCE). 2018. California's surface transportation report card an analysis of roads, bridges, and transit. Available at: www.infrastructurereportcard.org/california

Bektas, B. A., Carriquiry, A., & Smadi, O. 2012. Using classification trees for predicting national bridge inventory condition ratings. Journal of Infrastructure Systems, 19(4), 425–433. doi:10.1061/(asce)is.1943-555x.0000143.

Chang, M., Maguire, M., & Sun, Y. 2017. Framework for mitigating human bias in selection of explanatory variables for bridge deterioration modeling. Journal of Infrastructure Systems, 23(3), 04017002.

Fares, H., Shahata, K., Elwakil, E., Eweda, A., Zayed, T., Abdelrahman, M., & Basha, I. 2012. Modelling the performance of pavement marking in cold weather conditions. Structure and Infrastructure Engineering, 8(11), 1067-1079.

Federal Highway Administration (FHWA). 1995. Recording and coding guide for the structure inventory and appraisal of the nation's bridges. Washington, DC: USDOT.

Inkoom, S., & Sobanjo, J. 2018. Availability function as bridge element's importance weight in computing overall bridge health index. Structure and Infrastructure Engineering, 14(12), 1598-1610.

Kim, Y. J., & Yoon, D. K. 2009. Identifying critical sources of bridge deterioration in cold regions through the constructed bridges in North Dakota. Journal of Bridge Engineering, 15(5), 542-552.

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. 2005. Applied linear statistical models. 5th ed. USA:McGraw-Hill.

Manafpour, A., Guler, I., Radlińska, A., Rajabipour, F., & Warn, G. 2018. Stochastic analysis and time-based modeling of concrete bridge deck deterioration. Journal of Bridge Engineering, 23(9), 04018066.

Moomen, M. 2016. Deterioration Modeling Of Highway Bridge Components Using Deterministic And Stochastic Methods. M.S. thesis, Purdue, Univ., West Lafayette, IN.

Morcous, G. 2011. Developing deterioration models for Nebraska bridges.

Morcous, G., Rivard, H., & Hanna, A. M. 2002. Modeling bridge deterioration using case-based reasoning. Journal of Infrastructure Systems, 8(3), 86-95.

Nabizadeh, A., Tabatabai, H., & Tabatabai, M. 2018. Survival analysis of bridge superstructures in Wisconsin. Applied Sciences, 8(11), 2079.

Nieto, C. (2017). A Data-Driven approach to support bridge asset management (Doctoral dissertation, Oklahoma State University).

Nieto, C., Shan, Y., & Lewis, P. 2018. Characterization of steel bridge superstructure deterioration through data mining techniques. Journal of Performance of Constructed Facilities, 32(5), 04018062.

Saeed, T. U., Moomen, M., Ahmed, A., Murillo-Hoyos, J., Volovski, M., & Labi, S. 2017. Performance evaluation and life prediction of highway concrete bridge superstructure across design types. Journal of Performance of Constructed Facilities, 31(5), 04017052.

Saeed, T. U., Qiao, Y., Moomen, M., Ahmed, A., and Labi, S. 2016. Discrete-Outcome modeling of bridge component deterioration: accounting for the effects of maintenance and observation-specific correlation using random effects. Proc., 8th Int. Conf., on Bridge Maintenance, Safety and Management, CRC Press/A.A. Balkema, Leiden, Netherlands, 380

Smith, I. F., & Saitta, S. 2008. Improving Knowledge Of Structural System Behavior Through Multiple Models. Journal of structural engineering, 134(4), 553-561.

Tolliver, D., & Lu, P. 2012. Analysis of bridge deterioration rates: A case study of the northern plains region. In Journal of the Transportation Research Forum (Vol. 50, No. 2).

TranSystems Corporation . 2011. asset management guide for local agency bridges in michigan. Michigan Transportation Asset Management Council, Available at: (https://www.fhwa.dot.gov/bridge/management/).

U.S. Department of Transportation (USDOT). 2017. Federal Highway Administration National Bridge Inventory. Retrieved in November 10, 2017. https://www.fhwa.dot.gov/bridge/nbi/ascii2017.cfm.

Veshosky, D., Beidleman, C. R., Buetow, G. W., & Demir, M. 1994. Comparative analysis of bridge superstructure deterioration. Journal of Structural Engineering, 120(7), 2123-2136.

Zayed, T. M., & Halpin, D. W. 2005. Pile construction productivity assessment. Journal of Construction Engineering and Management, 131(6), 705-714.