Statistical Forecasting of Bridge Deterioration Conditions

M. Ilbeigi, Ph.D., M.ASCE[1]; and M. Ebrahimi Meimand, S.M.ASCE[2]

Abstract: The United States has more than 615,000 bridges. US national bridge inspection standards developed by the Federal Highway Administration (FHWA) require routine inspections of these bridges every 24 months regardless of bridge characteristics such as age, average daily traffic (ADT), and current deterioration condition of a bridge. Previous studies reported that this routine inspection process is considerably costly and inefficient. If the future condition of a bridge can be predicted accurately, costly routine inspections with uniform intervals can be avoided. The objective of this study is to create a forecasting model that predicts future bridge deterioration conditions based on the bridge characteristics. Historical data of more than 28,000 bridges in the state of Ohio from 1992 to 2017 were used to create an ordinal regression model to statistically examine effects of bridge characteristics on variations in bridge condition and predict future bridge conditions. The outcomes of this study indicate that bridge characteristics such as age, ADT, deck area, structural material, deck material, structure system, maximum length of span, and current condition of the bridge are statistically significant variables that explain variations in bridge deterioration. The results of the forecasting process show that the created ordinal regression model can statistically predict future bridge conditions precisely. This study will help bridge owners and transportation agencies accurately model and predict bridge deterioration and assign inspection and maintenance resources efficiently. The efficient inspection process, customized based on predicted deterioration condition, can result in investing the millions of dollars currently funding unnecessary inspections into much-needed infrastructure development projects. **DOI: 10.1061/(ASCE)CF.1943-5509.0001347.**

Author keywords: Bridge deterioration condition; Bridge characteristics; Forecasting; Ordinal regression; National Bridge Inspection Standard.

Introduction

Following the Silver Bridge collapse in 1967, the Federal Highway Administration (FHWA) introduced the National Bridge Inspection Standard (NBIS) in 1971. The NBIS requires routine inspections to monitor bridge deterioration. Based on the NBIS procedure, whenever a bridge is inspected, a rating condition from 1 to 9 is assigned to the bridge. Table 1 describes the bridge condition ratings by the NBIS. Detailed information about the inspection procedures and criteria is available in the *Bridge Inspector's Reference Manual* (BIRM) by the FHWA (2012).

The typical inspection interval is 24 months but can be extended to 48 months for short-span bridges in good condition with low average daily traffic (ADT) (FHWA 1988). For certain bridges with existing damage, a shorter inspection interval may be requested by owners. However, the majority of bridges in the US are inspected based on the 24-month interval. The 24-month routine inspection interval was determined by the FHWA in 1970s solely based on engineering judgement, regardless of the current condition of the bridges and other potential effective factors such as the age of the bridges, ADT, design of the bridge, and structural materials. This uniform interval approach has resulted in a very costly and inefficient process (Nasrollahi and Washer 2015; Reising et al. 2014; Washer et al. 2016a). The United States has more than 615,000 bridges, and the routine inspections cost more than $2.7 billion each year (Zulfiqar et al. 2014).

Although the FHWA's conservative approach to define the 24-month routine inspections was understandable in the 1970s when the NBIS was developed and initiated the bridge inspection process, today, the availability of historical records of bridge characteristics and conditions allow the creation of statistical models to explain and forecast bridge deterioration based on bridge characteristics. Such statistical forecasting models can help determine if a bridge needs inspection and maintenance based on the bridge characteristics and its current condition.

A group of previous studies aimed to create frameworks and processes for bridge inspection. For example, Wang and Elhag (2008) introduced an evidential reasoning (ER) approach for bridge condition assessment, instead of visual inspections that might involve subjective judgements. Their ER framework proposes a process to identify the most important bridge components, quantify their importance's weight, and measure the bridge condition. However, as those authors mentioned, their proposed approach does not forecast future bridge conditions. Washer et al. (2016a) proposed a qualitative risk-based approach that uses a simple risk matrix to determine the proper inspection interval for a bridge based on its potential risks, their likelihoods, and consequences. Washer et al. (2016b) showed the application of their risk-based framework in two case studies.

The second group of previous studies focused on modeling and analyzing bridge deteriorations. A significant portion of papers in this category, such as those by Thompson and Johnson (2005), Robelin and Madanat (2007), Sobanjo (2011), Wellalage et al. (2015), and Wu et al. (2017), used different stochastic models based on a Markov process to explain bridge deterioration rates. Several studies used the Weibull distribution to model bridge

[1]Assistant Professor, Dept. of Civil, Environmental, and Ocean Engineering, Stevens Institute of Technology, Hoboken, NJ 07030 (corresponding author). ORCID: https://orcid.org/0000-0001-6576-3808. Email: milbeigi@stevens.edu

[2]M.Sc. Student, Dept. of Construction Management, School of Built Environment, Bowling Green State Univ., Bowling Green, OH 43403-0001. Email: ebrahim@bgsu.edu

Note. This manuscript was submitted on December 18, 2018; approved on April 4, 2019; published online on December 2, 2019. Discussion period open until May 2, 2020; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Performance of Constructed Facilities***, © ASCE, ISSN 0887-3828.

J. Perform. Constr. Facil., 2020, 34(1): 04019104

Table 1. NBIS bridge condition rating

Condition rating	Condition
9	Excellent
8	Very good
7	Good
6	Satisfactory
5	Fair
4	Poor
3	Serious
2	Critical
1	Imminent failure

deteriorations. For example, Agrawal et al. (2010) described an approach based on the Weibull distribution to create bridge components deterioration curves. Sobanjo et al. (2010) used Weibull distributions to estimate bridge failure times. Manafpour et al. (2018) also used the Weibull distribution to develop an accelerated failure time function to estimate the service life for concrete bridge decks.

Several other previous studies used alternative approaches to analyze deterioration rates. For example, Morcous et al. (2002) proposed a case-based reasoning approach to model infrastructure deterioration based on historical scenarios. Morcous et al. (2003) conducted a genetic algorithm analysis to create bridge deterioration curves for different environmental categories. Tolliver and Lu (2012) analyzed the relationship between bridge deterioration rates and age; they observed that the relationship between these two factors is linear for bridges newer than 65 years old, after which they have a polynomial relationship. Another group of previous studies attempted to quantify the optimal bridge inspection intervals. For example, Nasrollahi and Washer (2015) identified the best conventional distribution which describes the time that a bridge may stay in one specific condition.

Finally, the fourth category of previous studies related to bridge deterioration focused on identifying effective factors influencing bridge deteriorations and creating forecasting models to predict future bridge conditions. This category of previous studies is limited to only a few papers. Wang and Foliente (2008) conducted ANOVA using 2,500 inspection records of concrete deck slabs in Australia to identify major factors influencing the condition index. They observed that bridge construction year, inspection year, and inspector were statistically significant when structures were exposed to the same environment.

Kim and Yoon (2010) conducted an ordinary least-square multiple linear regression analysis using National Bridge Inventory (NBI) data of 5,289 bridges in North Dakota between 2006 and 2007 to identify critical parameters affecting bridge deteriorations in cold regions. However, their analysis is problematic. First, the bridge conditions are an ordered multinomial variable that has more than two categories, and ordinary least-square regression analysis is not an appropriate statistical tool to explain this type of response variable (Harrell 2015). Second, their categorical explanatory variables related to bridge characteristics are not complete and comprehensive. For example, their material variable has only three categories: steel, concrete, and prestressed concrete. However, the NBI data set consists of 10 categories for bridge structural materials. Their structural system variable also has only three categories: slab, girder/beam, and truss. However, the NBI data use 23 categories. Third, their data set is relatively small and limited in terms of time to generalize the observations of their study. Finally, the scope of their study was limited to identifying the effective factors related to deterioration, and they did not create a forecasting model to predict future bridge conditions based on the identified significant factors.

Huang (2010) listed 11 potential effective factors such as age, ADT, and number of spans of a bridge. Next, he conducted an ANOVA test to examine the significance of those factors on the age of a concrete deck when it deteriorates. He then created an artificial neural network (ANN) model to predict the future bridge deck conditions based on those 11 factors and historical data in Wisconsin. However, the prediction accuracy of his model was only 75.3%, which is not high enough to present a reliable forecasting model.

Ghonima (2017) defined the deterioration rate (DR) factor as the difference between the bridge conditions after deterioration divided by the time that the bridge stayed in the first condition before the deterioration. He observed that the DR factor ranges between 0.056 (i.e., the bridge stayed in the same condition for approximately 18 years before its condition decreases one unit) and 2 (i.e., the bridge condition drops two units after only 1 year staying in the first condition). He coded these two extreme DRs as 0 and 1 and conducted a logistic regression analysis to examine effects of bridge characteristics on the probability of low or high deterioration rate. This statistical approach is also subject to several critical issues. First, the DR is not a categorical variable and can be anything between its two extreme values. Therefore, coding the extreme values and conducting a logistic regression analysis is not justified. Second, the model does not clearly predict future bridge conditions based on the NBIS conditions. Third, that author reported that the prediction accuracy of the model is only 70.2%, which is considerably low for a sensitive topic such as bridge deterioration prediction.

Review of the previous studies indicates that little is known about empirically analyzing the effects of bridge characteristics such as age, ADT, design, and materials on variations in bridge deterioration conditions and proper statistical forecasting models that predict future bridge conditions based on their characteristics. These gaps in knowledge make it difficult to empirically and statistically determine if a bridge needs to be inspected for potential maintenance based on its characteristics and current condition. If the future condition of a bridge is predicted accurately, the costly routine inspections with uniform intervals can be avoided. The objective of this study is to create a causal forecasting model that predicts the future condition of a bridge based on its characteristics and current condition. Detailed information about characteristics and inspection records of more than 28,000 bridges in the state of Ohio from 1992 to 2017 were collected. An ordinal regression analysis was conducted to analyze the bridge characteristics, identify statistically significant bridge characteristics influencing bridge deterioration, and predict the probability that a bridge deteriorates from its current condition to lower conditions based on its characteristics.

The outcomes of this study will help transportation agencies, bridge owners, and decision makers (1) empirically identify the bridge characteristics that have statistically significant contributions in: explaining deteriorations of a bridge; (2) predict the future deterioration condition of a bridge based on its characteristics; and (3) assign inspection resources more efficiently to the bridges that require attention instead of routine inspections with uniform intervals. This will result in saving millions of dollars that can be invested in other infrastructure development projects.

The remainder of this paper is structured as follows: First, the research methodology and steps conducted in this study are described. Next, the characteristics of the NBI data set used in this study are reviewed. The proposed methodology is then applied to the Ohio NBI data set to create the ordinal regression model. Next, the results are presented, and goodness of fit and prediction power of the model are analyzed. Finally, the outcomes of this study are summarized, and future works are recommended.

Methodology

Ordinal regression analysis was used to identify statistically significant bridge characteristics that can explain variations in bridge deterioration conditions. An ordinal regression model, which is also called a multinomial logit model or conditional choice model, is the extended version of the logistic regression model. The response variable in an ordinal regression model is an ordered multinomial variable that has more than two categories. The explanatory variables can be either numerical and/or categorical.

In the created ordinal regression model in this study, the response variable is the bridge condition, which is a categorical variable ranging from 1 to 9, with 1 indicating the worst condition and 9 indicating the best condition. The explanatory variables are the bridge characteristics. The overall mathematical expression of the ordinal regression is as follows:

$$F_j = \frac{e^{\alpha_j+\beta_1 X_1+\cdots+\beta_k X_k}}{1+e^{\alpha_j+\beta_1 X_1+\cdots+\beta_k X_k}} \tag{1}$$

where F_j = cumulative probability that the future bridge condition is in condition j or lower; $X_i = i$th explanatory variable; and α and β = coefficients in the model.

An ordinal regression analysis uses the maximum likelihood estimation (MLE) method to estimate the coefficients in the model. The MLE method is an iterative process that determines the coefficients by maximizing the chance that the model accurately explains variations in the response variable. After estimating the coefficients, the contribution of each explanatory variable in the model is statistically tested using a hypothesis test that examines whether the expected value of a variable's coefficient is statistically different from zero. If the probability (i.e., p-value) that the coefficient of a variable is equal to zero is less than the significance level, one can reject the null hypothesis (i.e., the coefficient is zero) and consider that explanatory variable a statistically significant variable in the model. Otherwise, the variable does not have a statistically significant contribution in explaining the response variable and should be eliminated from the model. The significance level is determined based on the desired accuracy and sensitivity. The typical recommended significance level is 5% (Craparo 2007).

It is recommended not to remove all nonsignificant variables in one step (Webster 2013). The best subset of explanatory variables is identified using a backward-elimination algorithm in which all potential explanatory variables are entered into the model first and coefficients are calculated using MLE. P-values of the explanatory variables are calculated then, and if there is at least one explanatory variable with the p-value of greater than the significance level (i.e., 5%), then the explanatory variable with the greatest p-value is subtracted from the model. Next, the coefficients for the remaining explanatory variables are calculated again using MLE method, and p-values are calculated. This process continues until there is no explanatory variable that has a p-value greater than the significance level. Detailed information regarding ordinal regression model development, MLE method, significance level, and calculating p-values is available in various statistical books such as those by Friedman et al. (2001), Webster (2013), and James et al. (2013).

Several steps were followed to create the ordinal regression model:

1. Conduct a literature review and study the NBI data set to identify a potential list of bridge characteristics (i.e., explanatory variables) such as age, ADT, deck area, and material for modeling the variations of bridge deterioration conditions.
2. Collect detailed information about more than 28,000 bridges in the state of Ohio from 1992 to 2017.
3. Prepare the data set, identify unusual observations (i.e., outliers), and remove (or refine) theses data points from the data set.
4. Randomly select 80% of the data as the training data set, construct the ordinal regression model, and apply backward-elimination algorithm to identify the statistically significant bridge characteristics on bridge condition.
5. Verify the model by analyzing goodness of fit using conformance.
6. Validate the model and measure its prediction power using the remaining 20% of data (i.e., test data set) that was not used in the model creation.

NBI Data Set

The FHWA publishes the NBI that is a publicly available data set consisting of detailed information about all bridges in the United States. Currently, recorded data from 1992 to 2017 are available (FHWA 2018). The NBI contains more than 130 types of information about each bridge. The following bridge characteristics are selected as the potential explanatory variables in the ordinal regression model based on previous studies (i.e., Wang and Foliente 2008; Kim and Yoon 2010; Huang 2010; Ghonima 2017) and engineering judgement:

- Age: Typically, it is assumed that as bridges get older, their deterioration rates increase. Therefore, age of a bridge might be an important explanatory variable. This is a numerical variable that is measured in years in the NBI data.
- ADT: A bridge's ADT represents its planned utilization. On the one hand, greater ADTs may result in faster deterioration. On the other hand, ADT is a critical factor in the design of a bridge. Bridges with higher ADTs are designed and constructed stronger to tolerate more severe situations. Therefore, they may be more resistant against deterioration. A bridge's ADT may change over time due to changes in traffic demands. The NBI data include the annual ADT for each bridge. This annual ADT variable is considered in this study in order to capture changes in the ADT records. The unit of this numerical variable is the number of cars per day.
- Truck ADT: Trucks and heavy vehicles may have more significant impacts on bridge deterioration. Therefore, the truck ADT is considered as a separate potential explanatory variable. Similar to the ADT variable, Truck ADT is measured in number of trucks per day.
- Deck area: The size of a bridge can be one of the bridge characteristics that explain variations in bridge deterioration. There is no quantified bridge size factor. Therefore, deck area is considered a proxy for the size of a bridge. This numerical variable is measured in square meters in the NBI data.
- Current condition of the bridge: Previous studies showed that deterioration rate increases over time when a bridge depreciates (Nasrollahi and Washer 2015). Therefore, the current condition of a bridge might be a very important potential explanatory variable that can explain future bridge conditions. The current condition of a bridge is an ordinal variable and can be one of the nine numbers defined by the NBIS procedure (Table 1).
- Length of structure improvement: This variable shows the size of major maintenance operations done on a bridge and is measured in meters. On the one hand, if the maintenance operations are done essential improvements with a proper quality, a greater

Table 2. NBIS structural materials categories

Code	Structural material type
1	Concrete
2	Concrete continuous
3	Steel
4	Steel continuous
5	Prestressed concrete
6	Prestressed concrete continuous
7	Wood or timber
8	Masonry[a]
9	Aluminum
0	Other[a]

[a]This category is not used in highway bridges. Therefore, it was removed from the analysis.

Table 3. NBIS structural systems categories

Code	Structural system
01	Slab
02	Stringer/multibeam or girder
03	Girder and floor beam system
04	Tee beam
05	Box beam or girders—multiple
06	Box beam or girders—single or spread
07	Frame (except frame culverts)
08	Orthotropic[a]
09	Truss—deck
10	Truss—thru
11	Arch—deck
12	Arch—thru
13	Suspension[a]
14	Stayed girder[a]
15	Movable—lift[a]
16	Movable—bascule[a]
17	Movable—swing[a]
18	Tunnel[a]
19	Culvert[a]
20	Mixed types[a]
21	Segmental box girder[a]
22	Channel beam[a]
00	Other[a]

[a]This category is not used in highway bridges. Therefore, it was removed from the analysis.

length of structure improvement may result in slower deterioration in the future. On the other hand, if the maintenance operations are not fundamental and long-term solutions, it may show that the bridge is not in a proper condition and that it may deteriorate faster in the future. The unit of this variable in the NBI data is in meters.

- Age from reconstruction: This variable shows how many years ago the most recent reconstruction operation was done. Although the age of a bridge was considered as a potential explanatory variable, the age from the last major reconstruction might be a factor in explaining bridge deterioration as well. This variable is measured in years in the NBI data.

The deterioration rate of a bridge might be related to the design characteristics of the bridge as well. The following six potential explanatory variables represent the design characteristics of a bridge from different perspectives:

- Structural materials: Different types of materials may have different deterioration rates. The NBI categorizes the bridge structural material types into 10 groups as presented in Table 2.

Table 4. NBIS deck materials categories

Code	Deck material type
1	Concrete cast-in-place
2	Concrete precast panels[a]
3	Open grating
4	Closed grating
5	Steel plate
6	Corrugated steel
7	Aluminum[a]
8	Wood or timber
9	Other

[a]This category is not used in highway bridges. Therefore, it was removed from the analysis.

- Structural systems: The type of design and/or construction of a bridge might be a bridge characteristic that has impact on its deterioration. In other words, some types of structural systems may have different deterioration rates. The NBI categorizes bridge structural systems into 23 groups as presented in Table 3. However, some of the categories are not used in highway bridges, which are the focus of this study. Those categories, which are clearly denoted in the table, were removed from the analysis before the backward-elimination process.
- Deck material: The NBI also categorizes the deck material types into nine groups as presented in Table 4. However, not all deck material categories are available in highway bridges.
- Number of spans in the main structure of a bridge: Number of spans in the main part of a bridge is another bridge design characteristic that is considered as a potential explanatory variable to explain bridge deterioration.
- Number of spans in the approach segments of a bridge: Number of spans in the approach parts of a bridge is another bridge characteristic available in the NBI data set that is considered a potential explanatory variable in this study.
- Maximum length of span: The NBI data contain the maximum length of spans in a bridge. This factor shows another design characteristic of a bridge. This variable is measured in meters.

With more than 28,000 bridges recorded in 2016, Ohio has the second highest number of bridges in the country after Texas. The Ohio NBI data set is used in this study.

Data Preparation and Cleaning

Bridges can be categorized based on their type of service, such as highway, railroad, and waterway. Highway bridges constitute 92.4% of all bridges in Ohio. This study focuses on highway bridges. For cleaning the data set, first, miscoded records with value of 0 or N for variables such as bridge condition, ADT, and deck area were removed from the data set. This data-cleaning operation led to the removal of approximately 8% of the original data.

Deterioration of a bridge results in a transition from a higher condition rating to a lower condition rating. Therefore, typically, a bridge stays in its current condition or transitions to a lower condition rating unless it undergoes rehabilitation or there is an error in data collection. Because the focus of this study is deterioration through time, upward transitions from lower ratings to higher ratings should be removed from the data set. Using the historical NBI data of Ohio from 1992 to 2017, 494,757 acceptable transitions (i.e., steady or downward transitions) including detailed information about the bridges were identified and used for the ordinal regression analysis.

Then, 80% of the data (i.e., 395,804 transitions) were randomly selected as the training data set and used to create the ordinal regression model, identify the statistically significant variables, and estimate the coefficients of the model. The remaining 20% of the data were used to validate the model and evaluate its prediction power.

Finally, the potential explanatory variables should be checked for multicollinearity issues (i.e., if two or more explanatory variables in a regression model are highly correlated, the results might be misleading). Variance inflation factor (VIF) (Webster 2013) was calculated for each potential explanatory variable to diagnose any multicollinearity issue. The results indicate that ADT and Truck ADT are highly correlated (their Pearson correlation is 77%) and cannot be used together in the model. ADT is a more general proxy for live loads affecting a bridge; therefore, the Truck ADT variable is eliminated from the model development process.

Ordinal Regression Analysis

The potential explanatory variables are plugged into the ordinal regression model to explain variations of bridge conditions. A backward-elimination algorithm (Webster 2013) was applied to check which potential explanatory variables are statistically significant in the model and determine the best combination (i.e., subset) of potential explanatory variables that can best model and predict future bridge conditions. Table 5 presents the final result of the backward process, including statistically significant variables, their coefficients, odds rations, and p-values. A 5% level of significance was considered when checking if the explanatory variables are statistically significant.

The results of the backward process show that age, ADT, deck area, current condition of the bridge, length of structure improvement, age from reconstruction, structural materials, and maximum length of span are statistically significant in the ordinal regression model. The binary variables representing the categories of structural systems do not show a consistent effect on explaining the variations of bridge conditions. The binary variables for slab, girder and floor beam system, tee beam, multiple box beam or girders, truss-deck, and truss-thru are statistically significant in the model. However, binary variables for stringer/multibeam or girder, single or spread box beam or girders, frame, arch-deck, and arch-thru are not statistically significant and were removed from the model. Regarding the deck material types, the binary variables for corrugated steel and wood/timber categories are statistically significant. However, the other categories do not have statistically significant power to explain the variations in bridge conditions. The explanatory variables that are not statistically significant and were removed from the model during the backward-elimination process, such as Truck ADT, number of spans in main section, and number of spans in approach sections, are not presented in Table 5.

Table 5 also provides the coefficients for the significant explanatory variables. The coefficient of an explanatory variable shows that for a one-unit increase in the explanatory variable, the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale while the other variables in the model are held constant. A more informative way to interpret explanatory variables in the ordinal regression model is to use odds ratios that describe the contribution of the variable from a cumulative perspective. The odds ratio of an explanatory variable is calculated by exponentiating its coefficient (i.e., $e^{\text{coefficient}}$). The odds ratio of an explanatory variable indicates that for a one-unit increase in the variable, the probability that the bridge ends up in a condition level lower than a specific condition versus transitioning to that specific condition or any condition levels greater than that specific condition is odds ratio times larger, given the other variables are held constant in the model.

Table 5. Results of the ordinal regression model

Predictor	Coefficient	P-value	Odds ratio
Constant 1	8.52892	0.000	—
Constant 2	15.0406	0.000	—
Constant 3	20.8308	0.000	—
Constant 4	27.3041	0.000	—
Constant 5	32.7319	0.000	—
Constant 6	39.1656	0.000	—
Constant 7	45.0654	0.000	—
Constant 8	51.1754	0.000	—
Age (years)	0.0022747	0.000	1.002277
ADT (cars per day)	−0.000003	0.000	0.999997
Deck area (m^2)	0.0000245	0.000	1.000024
Current condition	−5.79727	0.000	0.003036
Length of structure improvement (m)	0.0003147	0.031	1.000315
Age from reconstruction (years)	0.0006652	0.010	1.000665
Structural material types			
Concrete	−0.455684	0.000	0.634014
Concrete continuous	−0.587711	0.000	0.555597
Steel	−0.29115	0.006	0.747404
Steel continuous	−0.390837	0.000	0.67649
Prestressed concrete	−0.468695	0.000	0.625818
Prestressed concrete continuous	−0.425662	0.000	0.653337
Wood or timber	−0.595512	0.000	0.55128
Structural systems			
Slab	0.136551	0.000	1.146314
Girder and floor beam system	0.075452	0.023	1.078371
Tee beam	0.159442	0.000	1.172856
Box beam or girders—multiple	−0.196557	0.000	0.821554
Truss—deck	0.213538	0.006	1.238051
Truss—thru	0.182573	0.000	1.200302
Deck material types			
Corrugated steel	0.216657	0.000	1.241918
Wood or timber	0.205754	0.000	1.22845
Maximum length of span (m)	−0.0048277	0.000	0.995184

For example, if there are two exact identical bridges from any perspective, but one of them is just 1 year older than the other one, the proportional probability that the older bridge transitions to Condition 3 or lower versus the chance that it stays in a condition level greater than Condition 3 is 1.002277 times greater than this proportional probability for the younger bridge. The same interpretation can be used for categorical and binary variables too. For example, if there is a bridge with a slab structural system and another identical bridge but with a structural system that is not significant in the model (e.g., frame), the likelihood that the first bridge transitions to condition levels lower than a specific level, say Condition 4, versus staying in that specific condition or greater, is 1.146314 times greater than this proportional probability for the second bridge. More detailed information regarding ordinal regression models and interpretation of their variables is available from Harrell (2015).

In general, an odds ratio greater than 1 indicates that if all other variables are held constant in the model, then with an increase in the explanatory variable, overall, the probability that the bridge transitions to a lower condition level is greater than that of it staying in a higher condition level. An odds ratio of age greater than 1 indicates that if all other variables are held constant in the model, with an increase in the age variable, the probability that the bridge will transition to a lower condition level is greater than staying in a higher condition level. In other words, when a bridge gets older, the probability of its deterioration increases. Similarly, the odds

J. Perform. Constr. Facil., 2020, 34(1): 04019104

ratio of the age from reconstruction variable is greater than 1, indicating that if there are two similar bridges with respect to all explanatory variables except the age of their reconstruction, the one which has undergone rehabilitation most recently has a slower deterioration.

The length of structure improvement has an odds ratio of greater than 1. This illustrates that if all other factors are held constant, a bridge that needed a greater extent of reconstruction operations has a higher chance of deterioration in the future. This is an interesting observation indicating that the quality of rehabilitation and reconstruction operations are not perfect. Therefore, reconstructed bridges have greater deterioration rates than bridges that did not need major reconstructions.

The odds ratio of the current condition variable is considerably lower than 1. This indicates that if all factors are held constant, an increase in the current condition decreases the probability of deterioration. In other words, depreciated bridges have a higher chance of deterioration to lower levels. This observation is consistent with what Nasrollahi and Washer (2015) observed in their studies.

The deck area variable, which was considered as a proxy for size of a bridge, has an odds ratio greater than 1, indicating that if all factors are held constant, the rate of deterioration is higher when bridges are larger. Finally, a lower than 1 odds ratio of the ADT variable indicates that if all other factors are held constant, bridges that are designed for greater ADTs have slower deterioration rates. ADT plays a significant role in designing bridge structural connection specifications. Structural connections in bridges with greater ADTs are designed and constructed stronger to tolerate more severe situations and are more resistant against deteriorations. This observation is completely consistent with the Section 3.4.1 of AASHTO *Bridge Design Specifications* (AASHTO 2014).

The developed ordinal regression model can forecast future deterioration conditions of a bridge using its characteristics (i.e., explanatory variables in the regression model). For example, the bridge with structure number (i.e., ID) 501190 was 14 years old in 2016 with ADT of 5,557, deck area of 4,317.6 m^2, maximum length of span of 35 m, stringer/multibeam or girder structural system, prestressed concrete continuous structural material type, and concrete cast-in-place deck material. The bridge was in Condition 8 in 2016. The outcomes of the ordinal regression model show that the probability that this bridge stays in Condition 8 after 1 year is 85.34%. There is a 14.61% chance that this bridge transitions to Condition 7 in the next year, and the likelihood that the bridge deteriorates to Condition 6 or lower is less than 0.0005%.

Typically, Condition 3 or lower is considered as the caution condition. If a bridge is in the caution condition, it is scheduled for rehabilitation (Nasrollahi and Washer 2015). Therefore, transportation agencies may inspect a bridge if the probability that the bridge transitions to Condition 3 or lower is greater than the risk tolerance of the agency. For example, the bridge with Structure number 2503751 was 46 years old in 2016 with ADT of 4,200, deck area of 1,599.5 m^2, maximum length of span of 45.7 m, stringer/multibeam or girder structural system, steel continuous structural material type, and concrete cast-in-place deck material. The bridge was in Condition 4 in 2016. The outcomes of the ordinal regression model indicate that the probability that this bridge deteriorates to Condition 3 or lower is 5.83%. Therefore, if the risk tolerance of the bridge owner, for example, is 5%, it is a good idea to inspect the bridge. Different agencies with various risk tolerances and caution condition thresholds can follow the same approach using the developed model.

Verification and Goodness of Fit of the Model

The Somers' D statistic is one of the most common measures of goodness of fit for ordinal regression models (O'Connell 2006). This statistic shows how the predicted values of the ordinal response variable are associated with the actual values of the ordinal response variable. The association is defined based on concordance and discordance. Concordance and discordance measure the agreement between pairs of the actual bridge conditions and predicted bridge conditions based on their relative orders. The Somers' D value varies in the range of -1 and $+1$. Large absolute values of the Somers' D statistic indicate the model has a high goodness of fit and predictive ability. Detailed information about the Somers' D statistic and its applications were reviewed in many previous studies, including those by Somers (1962), O'Connell (2006), and Göktas and Isçi (2011).

The results of the ordinal regression analysis in this study indicate that the Somers' D statistics of the created model for bridge deterioration conditions is 0.94, which is significantly high. This indicates that the identified statistically significant explanatory variables can properly and accurately explain variations in the bridge deterioration conditions, and the developed ordinal regression model has a considerably high prediction power.

The high prediction power of the model also indicates that the identified explanatory variables provide enough information to create a powerful causal forecasting model. Therefore, even if there are other potential explanatory variables that could not be identified or quantified for the model, one can still rely on the model and its prediction power. This is a very important point because someone may argue that there might be other explanatory variables such as environmental factors (e.g., temperature, precipitation, and distance from wetlands) that were not considered in the model. It might be a correct argument, but the scope of the data used in this study is intentionally limited to the NBI data, which are freely and publicly available to all transportation agencies, bridge owners, and researchers. The high prediction power of the model indicates that the NBI data could capture a significant percentage of the variations in bridge conditions.

Validation and Prediction Accuracy of the Model

As mentioned previously, 20% of the data were not used for the model development to be considered as the test data set. The test data set that was randomly selected consists of 98,953 transitions within the time period of 1992 to 2017. In this section, the test data set is used to validate the model and assess its prediction power. Table 6 presents the proportions of actual transitions observed in the test data set. Table 7 gives the proportions of the predicted transitions calculated using the ordinal regression model. For example,

Table 6. Proportions of the actual transitions in the test data set

Original condition	Condition after transition (%)								
	9	8	7	6	5	4	3	2	1
9	4.26	0.65	0.11	0.06	0.01	0.01	0.00	0.00	0.00
8	0.00	11.77	1.41	0.28	0.04	0.02	0.00	0.00	0.00
7	0.00	0.00	21.88	2.74	0.24	0.07	0.01	0.01	0.00
6	0.00	0.00	0.00	28.11	2.03	0.40	0.03	0.01	0.00
5	0.00	0.00	0.00	0.00	12.75	1.37	0.10	0.02	0.01
4	0.00	0.00	0.00	0.00	0.00	8.11	0.50	0.07	0.01
3	0.00	0.00	0.00	0.00	0.00	0.00	2.20	0.10	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.56	0.00
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07

Table 7. Proportions of the predicted transitions in the test data set using the ordinal regression model

Original condition	Condition after transition (%)								
	9	8	7	6	5	4	3	2	1
9	4.42	0.66	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	11.88	1.65	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	22.03	2.90	0.01	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	27.13	3.44	0.01	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	12.66	1.57	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	7.79	0.90	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	2.07	0.23	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.54	0.02
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07

Table 8. Results of the paired t-test

Variable	Result	
	Actual transitions (Table 6)	Predicted transitions (Table 7)
Mean	0.022	0.022
Variance	0.0033	0.0032
Pearson correlation	0.998	
Hypothesized mean difference	0	
T-statistic	-6.54×10^{-15}	
Critical t-value	2.69	
P-value	1	

Table 6 demonstrates that 4.26% of the recorded transitions in the test data set were from Condition 9 to Condition 9. Table 7 indicates that when the ordinal regression model was used to predict the probabilistic future bridge conditions based on the bridge characteristics and their current conditions, 4.42% of the predicted transitions was from Condition 9 to Condition 9.

If Tables 6 and 7 are statistically identical, it can be concluded that the ordinal regression model has a statistically significant prediction power. A paired t-test is conducted to examine whether these two tables are identical or not. The paired t-test examines if the mean difference between two sets of observations is zero (Dodge 2008). Table 8 presents the results of the paired t-test, which indicate the two tables are highly correlated (i.e., 99.8%) and the p-value is considerably high. Therefore, the null hypothesis, namely that the average of the differences between the paired probabilities in these two tables are equal to 0, cannot be rejected. In other words, these two tables can be considered statistically identical. This outcome is consistent with the high goodness of fit that was observed in the preceding section. On average, there is a 0.16% difference between the proportions of the actual transitions in Table 6 and proportions of the predicted transitions in Table 7.

Conclusion and Future Works

In this study, an ordinal regression analysis was conducted to model and explain variations in bridge deterioration conditions using bridge characteristics such as age, ADT, deck area, structural material, structural system, deck material, maximum length of spans, and current deterioration condition of the bridge. Historical NBI data of more than 28,000 bridges in the state of Ohio were collected, prepared, and used to create the ordinal regression model. The ordinal regression model identifies the bridge characteristics that have statistically significant power to explain bridge deteriorations. The model uses those bridge characteristics to explain the variations in the bridge conditions and predict probability of transition from the current deterioration condition of the bridge to any other possible conditions in the next year. The results showed that the Somers' D statistics of the model is 0.94, indicating that the model has a significantly high goodness of fit. The results of the validation and forecasting process show that the model has a significantly high prediction power, and the forecasted transitions are statistically identical with actual transitions even at a 1% significance level.

The forecasting model provides useful information about expected future bridge conditions to help decision makers decide if they need to inspect and perhaps plan to maintain a bridge or not. The outcomes of this study can help bridge owners and transportation agencies assign maintenance resources more efficiently and invest the millions of dollars currently funding unnecessary inspections into much-needed infrastructure development projects.

The primary contributions of this study to the body of knowledge are (1) identifying bridge characteristics that have statistically significant power to explain deterioration of a bridge, (2) creating an ordinal regression model to predict the probabilities of deterioration to different conditions based on the bridge characteristics, and (3) developing a systematic approach to assist decision makers determine if a bridge needs inspection instead of costly and inefficient routine inspections with uniform intervals.

It should be pointed out that the forecasting model only calculates the probabilities of deterioration to different conditions. The proposed approach is a flexible tool that can be adjusted based on users' strategies and risk tolerance. The final decision regarding whether a bridge needs inspection depends on the decision makers' risk tolerance and judgement, which determine if those calculated probabilities indicate an inspection is required or not. Moreover, this study does not suggest maintaining a bridge as late as possible or any other time window. Designing cost-effective maintenance strategies and finding optimal rehabilitation times are potential topics for future studies.

Although this study was conducted using the NBI data from the state of Ohio, the proposed empirical research approach can be used for similar data sets in the other states and internationally. Empirically analyzing and comparing bridge deteriorations in different states is another potential topic for future studies.

References

AASHTO. 2014. *AASHTO LRFD bridge design specifications*. 7th ed. Washington, DC: AASHTO.

Agrawal, A. K., A. Kawaguchi, and Z. Chen. 2010. "Deterioration rates of typical bridge elements in New York." *J. Bridge Eng.* 15 (4): 419–429. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000123.

Craparo, R. M. 2007. "Significance level." In Vol. 3 of *Encyclopedia of measurement and statistics*, 889–891. Thousand Oaks, CA: Sage.

Dodge, Y. 2008. *The concise encyclopedia of statistics*. New York: Springer.

FHWA (Federal Highway Administration). 1988. *Revisions to the National Bridge Inspection Standards (NBIS)*. Tech. Advisory 5140.21. Washington, DC: FHWA.

FHWA (Federal Highway Administration). 2012. *Bridge inspector's reference manual (BIRM)*. Report No. FHWA NHI 12-049. Washington, DC: FHWA.

FHWA (Federal Highway Administration). 2018. "National Bridge Inventory (NBI)." Accessed December 18, 2018. https://www.fhwa.dot.gov/bridge/nbi.cfm.

Friedman, J., T. Hastie, and R. Tibshirani. 2001. Vol. 1 of *The elements of statistical learning*. New York: Springer.

Ghonima, O. 2017. "Statistical modeling of United States highway concrete bridge decks." Doctoral dissertation, Dept. of Civil Engineering, Univ. of Delaware.

Göktas, A., and Ö. Isçi. 2011. "A comparison of the most commonly used measures of association for doubly ordered square contingency tables via simulation." *Metodoloski zvezki* 8 (1): 17.

Harrell, F. E. 2015. "Ordinal logistic regression." In *Regression modeling strategies*. Cham, Switzerland: Springer.

Huang, Y. H. 2010. "Artificial neural network model of bridge deterioration." *J. Perform. Constr. Facil.* 24 (6): 597–602. https://doi.org/10.1061/(ASCE)CF.1943-5509.0000124.

James, G., D. Witten, T. Hastie, and R. Tibshirani. 2013. Vol. 112 of *An introduction to statistical learning*. New York: Springer.

Kim, Y. J., and D. K. Yoon. 2010. "Identifying critical sources of bridge deterioration in cold regions through the constructed bridges in North Dakota" *J. Bridge Eng.* 15 (5): 542–552. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000087.

Manafpour, A., I. Guler, A. Radlińska, F. Rajabipour, and G. Warn. 2018. "Stochastic analysis and time-based modeling of concrete bridge deck deterioration." *J. Bridge Eng.* 23 (9): 04018066. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001285.

Morcous, G., Z. Lounis, and M. S. Mirza. 2003. "Identification of environmental categories for Markovian deterioration models of bridge decks." *J. Bridge Eng.* 8 (6): 353–361. https://doi.org/10.1061/(ASCE)1084-0702(2003)8:6(353).

Morcous, G., H. Rivard, and A. M. Hanna. 2002. "Modeling bridge deterioration using case-based reasoning." *J. Infrastruct. Syst.* 8 (3): 86–95. https://doi.org/10.1061/(ASCE)1076-0342(2002)8:3(86).

Nasrollahi, M., and G. Washer. 2015. "Estimating inspection intervals for bridges based on statistical analysis of National Bridge Inventory data." *J. Bridge Eng.* 20 (9): 04014104. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000710.

O'Connell, A. A. 2006. Vol. 146 of *Logistic regression models for ordinal response variables*. Thousand Oaks, CA: Sage.

Reising, R. 2014. *Risk-based bridge inspection practices*. M.S. dissertation, Dept. of Civil Engineering, Purdue Univ.

Robelin, C. A., and S. M. Madanat. 2007. "History-dependent bridge deck maintenance and replacement optimization with Markov decision processes." *J. Infrastruct. Syst.* 13 (3): 195–201. https://doi.org/10.1061/(ASCE)1076-0342(2007)13:3(195).

Sobanjo, J., P. Mtenga, and M. Rambo-Roddenberry. 2010. "Reliability-based modeling of bridge deterioration hazards." *J. Bridge Eng.* 15 (6): 671–683. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000074.

Sobanjo, J. O. 2011. "State transition probabilities in bridge deterioration based on Weibull sojourn times." *Struct. Infrastruct. Eng.* 7 (10): 747–764. https://doi.org/10.1080/15732470902917028.

Somers, R. H. 1962. "A new asymmetric measure of association for ordinal variables." *Am. Sociol. Rev.* 27 (6): 799–811. https://doi.org/10.2307/2090408.

Thompson, P. D., and M. B. Johnson. 2005. "Markovian bridge deterioration: Developing models from historical data." *Struct. Infrastruct. Eng.* 1 (1): 85–91. https://doi.org/10.1080/15732470412331289332.

Tolliver, D., and P. Lu. 2012. "Analysis of bridge deterioration rates: A case study of the northern Plains region." *J. Transp. Res. Forum* 50 (2): 87–100.

Wang, X., and G. Foliente. 2008. "Identifying bridge structural condition development trends via categorical inspection condition rating with case studies." *Struct. Infrastruct. Eng.* 4 (6): 449–466. https://doi.org/10.1080/15732470600924656.

Wang, Y. M., and T. M. Elhag. 2008. "Evidential reasoning approach for bridge condition assessment." *Expert Syst. Appl.* 34 (1): 689–699. https://doi.org/10.1016/j.eswa.2006.10.006.

Washer, G., R. Connor, M. Nasrollahi, and J. Provines. 2016a. "New framework for risk-based inspection of highway bridges." *J. Bridge Eng.* 21 (4): 04015077. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000818.

Washer, G., R. Connor, M. Nasrollahi, and R. Reising. 2016b. "Verification of the framework for risk-based bridge inspection." *J. Bridge Eng.* 21 (4): 04015078. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000787.

Webster, A. 2013. *Introductory regression analysis with computer application for business and economics*. New York: Routledge.

Wellalage, N. K. W., T. Zhang, and R. Dwight. 2015. "Calibrating Markov chain–based deterioration models for predicting future conditions of railway bridge elements." *J. Bridge Eng.* 20 (2): 04014060. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000640.

Wu, D., C. Yuan, W. Kumfer, and H. Liu. 2017. "A life-cycle optimization model using semi-Markov process for highway bridge maintenance." *Appl. Math. Modell.* 43 (Mar): 45–60. https://doi.org/10.1016/j.apm.2016.10.038.

Zulfiqar, A., M. Cabieses, A. Mikhail, and N. Khan. 2014. *Design of a bridge inspection system (BIS) to reduce time and cost*. Farifax, VA: George Mason Univ.