Methodology for Probabilistic Modeling of Highway Bridge Infrastructure Condition: Accounting for Improvement Effectiveness and Incorporating Random Effects

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Abstract: The peculiar nature of bridge infrastructure condition data persistently poses challenges in predicting bridge component deterioration that necessitate the continued investigation of probabilistic modeling techniques. These challenges include the uncertainty that characterizes bridge condition data due to the inherent random nature of deterioration factors and the existence of other variables that are not typically measured (unobserved factors responsible for deterioration), the panel nature of the data and its consequent observation-specific correlation and heterogeneity bias, and the lack of knowledge of the type and nature of past interventions. To these ends, this paper introduces a novel probabilistic modeling methodology intended to enhance the reliability of condition prediction by defining and quantifying the types of interventions and incorporating newly introduced explanatory variables to capture the effect of these intervention types on the future deterioration of bridge components. Unlike the current probabilistic techniques, the methodology proposed in this paper duly accounts for the maintenance and intervention history of in-service bridge components in the condition modeling process to reflect the real-world nondecay deterioration of the components. This paper demonstrates how the developed methodology can be implemented to predict the probability that a bridge component is in a given condition state at any given year. The marginal effects analysis provides bridge engineers with additional information about the individual strengths of the influential factors of bridge deterioration. The developed models can be useful for various agency functions, including the monitoring of bridge component performance and predicting their remaining service lives based on the bridge design and operational and environmental attributes. **DOI: 10.1061/(ASCE)IS.1943-555X.0000389.**

Introduction

Bridge managers, faced with increased traffic demand, renewed emphasis on vulnerability issues, aging infrastructure, higher user expectations, and uncertain sustained funding for preservation and improvement, continue to seek risk-enhanced strategies for cost-effective bridge management. They seek these tools at a time when the uncertainties in funding and other decision factors are increasingly assuming a prominent role in infrastructure management discourse. As part of their efforts to achieve these objectives, agencies regularly track the physical condition of their infrastructure by carrying out either field monitoring (through sensors and inspections) and/or desk monitoring (through deterioration models) of their bridge components. In desk monitoring, the deterioration of bridge components (deck, superstructure, and substructure) is tracked using empirical bridge performance models. These performance models describe the degeneration or the change in strength of a material over time or accumulated cycles, and thus, are used to predict the changes in the structural and functional integrity of a bridge in response to various accumulated loadings, environmental conditions, and maintenance practices. Therefore, it is critical to have reliable information about the current state and future condition of bridges in devising cost-effective strategies for the maintenance, rehabilitation, and replacement (MR&R) of bridge components.

Motivation and Problem Statement

The bridge-management literature is replete with models developed to facilitate decision makers at highway agencies in project-level or network-level analysis of predicting the future condition of a specific bridge or a bridge network, grouped as deterministic and stochastic models (Veshosky et al. 1994; DeStefano and Grivas 1998; Lavrenz et al. 2015; Amin and Adey 2015; Lavrenz et al. 2016; Moomen 2016; Moomen et al. 2016; Qiao et al. 2016a, b; Saeed et al. 2016, 2017). As evidenced in the past research (Busa et al. 1985; Jiang and Sinha 1989; Stukhart et al. 1990; Bolukbasi et al. 2004; Agrawal and Kawaguchi 2009; Hatami and Morcous 2011; Moomen 2016; Saeed et al. 2017; Lu et al. 2016), most of these models are deterministic in nature. However, it is difficult to account for uncertainty using deterministic models and confidently make robust conclusions from the National Bridge Inventory (NBI) data, which is characterized by a great deal of variability.

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At the national level, increasing calls for risk-based performance evaluation and decision making in infrastructure asset management (FHWA 2012, 2016; ASCE 2016) indicate a greater awareness of the relevance of probabilistic models, which involve stochastic estimation techniques, in the quest to provide more robust and realistic predictions of future condition. This paper hypothesizes that the random occurrence, underlying uncertainty, and variation associated with deterioration factors and the NBI bridge condition data, in particular, can be addressed using an appropriately specified probabilistic model.

The most common probabilistic methodology is the Markovian model, which has been used extensively in modeling deterioration of infrastructure facilities (Bogdanoff 1978; Golabi et al. 1982; Carnahan et al. 1987; Jiang 1990; Kleywegt and Sinha 1994; Tao et al. 1994; Basheer et al. 1996; Thompson et al. 1998; Micevski et al. 2002; Abaza et al. 2004; Baik et al. 2006; Jha and Abdullah 2006; Kleiner et al. 2006; Morcous 2006; Patidar et al. 2007; Ramani 2010; Sobanjo 2011; Hasan et al. 2015). The underlying assumption in these models is that the state of the system at a given time is not dependent on the intervention/maintenance history (Kleywegt and Sinha 1994), thus assuming decay deterioration (Sobanjo 2011), assuming the effect of any improvement intervention over the bridge life is negligible. This implies that the infrastructure deteriorates without any dependence on the past intervention or maintenance history (maintenance and improvement), which does not reflect real-world practices. The validity of this rather restrictive assumption has been questioned by many past studies (Busa et al. 1985; Ramaswamy 1989; Madanat et al. 1997; Mauch and Madanat 2001; Frangopol et al. 2001; Robelin and Samer 2008; Huang 2010), and the phenomenon of state dependence has been proposed to explain the future performance of assets under the influence of past deterioration history (Ramaswamy 1989). The existing bridge-management system software packages, *PONTIS* (Thompson et al. 1998) and *BRIDGIT* (Hawk and Small 1998), contain the Markovian models, which assume that the future bridge condition is not dependent on the condition history and that only the current condition matters. This assumption has been identified as being unrealistic, and attempts have been made to address this issue by incorporating a lagged indicator explanatory variable in deterioration models. Huang (2010) argued that the Markovian model's assumption of maintenance independence continues to serve as evidence of its limited capability to adequately model bridge component deterioration.

To overcome the limitations of past research in this area, the effect of past interventions must be incorporated in the analysis. To do so, this paper introduces a three-step methodology:

1. Identify, from the bridge condition data, whether any of the three bridge intervention categories (repair, rehabilitation, and replacement/reconstruction) occurred at any specific year and the effectiveness of such interventions in terms of changes in the condition ratings of the bridge components (from a lower to a higher condition state after the intervention). This paper introduces a "bridge intervention matrix" for this purpose;
2. Explicitly account for the recuperation effect of these past interventions on the bridge infrastructure condition, which this paper does by specifying new explanatory variables in the deterioration model to account for these effects; and
3. Finally, the proposed method introduces into the deterioration model the effect of the length of time that a specific intervention remains effective and its changing efficacy as the age progresses and the effect on the probability of the component being in a given condition. For this purpose, bridge intervention effectiveness factors (BIEF) are introduced that reflect the post-treatment effect of a specific intervention on the probability of a bridge component being in a certain condition.

The data used in this paper combined the NBI condition data for more than 5,600 bridges over a 23-year span (1992–2014). Therefore, for each individual bridge, the data spanned either 23 years or less (for those that were built later than 1992, thus leading to an unbalanced panel). Observations of multiple phenomena measured over multiple time periods for the same entity (in this case, a bridge component), are referred to as panel data. An important issue is the consideration of specification issues, i.e., heterogeneity bias and serial correlation, in modeling the panel data, which, if left unaddressed, may lead to inconsistent, erroneous, or meaningless parameter estimates (Washington et al. 2011). Heterogeneity reflects differences across cross-sectional units (i.e., bridges, in this case) that are not suitably or completely captured in the currently available data set (i.e., an existing set of independent variables). Failure to account for heterogeneity results in biased parameter estimates. For that reason, resolving cross-sectional heterogeneity is important in panel data analysis (Greene 2008; Washington et al. 2011). The second issue is serial correlation of the disturbance terms, which affects the efficiency of regression parameter estimates. This correlation occurs in time-series data when the disturbances associated with observations in one period are dependent on disturbances from prior periods. The data used in this paper are obviously characterized by temporal correlation, mainly because the data set contains multiple observations of an individual bridge over multiple time periods. In this case, correlation of disturbance terms is a matter of concern due to likely correlation of the unobserved features, and such correlation violates the assumption of disturbance independence, resulting in erroneous standard error estimates if not accounted for. To address these issues, there is a need to estimate a random effects model to account for the variation in deterioration modeling across bridge components at different locations and across different years. This model specification introduces a bridge-specific disturbance term to account for any bridge-specific random disturbance. This correlation in the data was not addressed in early studies that modeled discrete panel deterioration data (Butt et al. 1987; Feighan et al. 1988; Jiang et al. 1988; Scherer and Glagola 1994; Madanat and Wan Ibrahim 1995) but was taken into consideration in later studies (Madanat et al. 1997).

In sum, this paper is motivated by the peculiar nature of bridge data, emerging analytical opportunities evidenced by new modeling techniques, and recent federal legislation and policy statements that encourage infrastructure agencies to pay more attention to risk-based performance evaluation and decision making. The method proposed in this paper responds to the need for highway agencies to use models that incorporate stochastic elements, specifically, probabilistic models that can provide more robust predictions of future condition.

Study Objectives

The above discussion revealed several challenges posed in the pursuit of more reliable prediction of bridge condition, which is due in part to the nature of bridge condition data. These challenges, which are discussed in more specific detail below, can impair any effort to reliably model bridge component deterioration.

First, NBI data do not include information about all the factors of bridge deterioration, such as the quality of the bridge construction materials and workmanship, the loads and axle configurations of the vehicular traffic on the bridge, the frequency and intensity of deicing applications during the winter months, and data collection error factors, such as the level of expertise of the inspectors. Therefore, a number of unobserved factors exist in bridge data whose effects on deterioration need to be considered. This paper seeks to do this using a random-effects specification.

Second, the data often do not indicate what category of intervention, if any, was carried out in a particular year (repair, rehabilitation, or replacement/reconstruction) even though the condition data occasionally show drastic jumps in condition ratings that are suggestive of some intervention. If the occurrence of a past intervention is not identified, any attempt to adequately model the component deterioration will fall short of intuitiveness and reliability. Therefore, a protocol is needed for identifying the type of intervention carried out based on the observed jump in condition ratings in a given past year. This paper develops such a protocol in the form of a bridge intervention matrix (BIM).

Third, when intervention work is found to have been carried out, there needs to be a way to account for the efficacy of that work, specifically, how long the intervention maintains the bridge component in a certain desired condition. In addition, it must be assumed that this intervention efficacy is not the same over time and is less when applied to a component in poor condition compared to the one in good condition. To address this effect, this paper introduces a new derived factor, known as the bridge intervention effectiveness factor (BIEF), which is an indicator of the length of time for which a specific improvement intervention remains in effect. The reduction of BIEF at lower condition states implies that there will be a smaller probability that the bridge component will be in a given condition state and, consequently, a greater probability that the bridge component will transition to the next lower condition state.

Finally, as the literature review suggests, attempts to model bridge data of a panel nature without the appropriate econometric specifications can yield biased and inefficient estimates. Therefore, the proposed method adopts a specification that duly addresses the panel effects.

By throwing more light on the relative and directional impacts of influential deterioration factors, this paper also presents the marginal effects of such factors on bridge deterioration. Overall, this knowledge is critical for bridge condition monitoring, repair work scheduling, long-term planning, and other management and administrative issues associated with highway bridges.

Data Collection and Collation

The data in this paper were compiled by combining the NBI bridge condition data over a 23-year span from 1992 to 2014; for bridges built after 1992, the length of time between the built year of the bridge to 2014 was considered in the analysis. Only state highway bridges were used. Thus, a total of 106,413 observations were available. The information on the explanatory variables included bridge data, location data, environmental data, and traffic load data. The bridge-specific data obtained from the NBI database and the Indiana Bridge Management System (IBMS) included bridge geometric characteristics (e.g., total deck width, bridge length, and vertical clearance under the bridge) and functional class. The bridge location was determined by the county, route, and milepost reference. Identifying the bridge spatial locations allowed the association of specific environmental characteristics and traffic loadings to each bridge. Climate data obtained from the National Oceanic and Atmospheric Administration (NOAA) and the INDIPAVE 2000 database included the following information: annual precipitation, temperature, number of hot days, number of cold days, freeze-thaw cycles, and air-freezing index. Climate information exists in aggregated form for each county and is typically assigned to each bridge given the average conditions in the county where the bridge is located. To account for the maintenance and intervention history of bridge components in the condition modeling and to reflect the real-world nondecay deterioration, the intervention types were first identified based on the change in the bridge component condition rating in the NBI data set and then were explored for statistical significance during the model estimation. The development process of these intervention types and new variables identifying maintenance and intervention actions is discussed in detail in the next section.

Bridge Intervention Matrix and Bridge Intervention Effectiveness Factors

To analyze the post-treatment effect of different types of interventions on component condition, the year of the bridge maintenance and the performance jump due to that intervention as well as the performance trend after the intervention are needed. However, these data are not directly available from current data sources, and the only relevant information in the NBI database is the year of last rehabilitation. Also, the NBI database lacks detailed information on the past intervention history of each bridge component.

To overcome this limitation, a new approach was developed for preparing the data to address the effects of past intervention work. For each component, the performance jump (i.e., sudden increase in the condition rating) was measured by tracking the condition change each year between 1992 and 2014, and the type of intervention applied (repair, rehabilitation, and component replacement or bridge reconstruction) was identified based on the measured magnitude of the performance jump (Fig. 1). For example, in the NBI data where a sudden increase in the deck condition rating by two units (from five to seven) was observed in a certain year, it was assumed that deck rehabilitation occurred in that year. In the matrix below, rehab refers to rehabilitation, rep refers to replacement and rec to reconstruction and repair refers to routine or minor maintenance. Validation of the BIM matrix was carried out using a small sample of bridge project contracts where the intervention

From condition states	To condition states: 9	8	7	6	5	4	3	2	1
9									
8	Repair								
7	Repair	Repair							
6	Rep/ Rec	Rehab	Repair						
5	Rep/ Rec	Rep/ Rec	Rehab	Repair					
4	Rep/ Rec	Rep/ Rec	Rehab	Rehab	Repair				
3	Rep/ Rec	Rep/ Rec	Rehab	Rehab	Rehab	Repair			
2	Rep/ Rec	Rep/ Rec	Rehab	Rehab	Rehab	Repair	Repair		
1	Rep/ Rec	Rep/ Rec	Rehab	Rehab	Rehab	Repair	Repair	Repair	

Fig. 1. Bridge intervention matrix

type was known. Then the intervention type as suggested by the BIM matrix and the actual intervention type were compared. The results showed that 92% of the time, the BIM matrix correctly indicated the type of intervention that occurred. This finding lent greater confidence in applying the matrix to the entire population.

The post-treatment effect of each intervention category was then analyzed to incorporate past intervention as an explanatory variable in the deterioration model. By tracking the post-treatment condition for each component, the number of years taken for the bridge component to revert to its pretreatment condition was counted and recorded in the database. For example, if the deck condition improved from 5 to 7 in a certain year and deteriorated from 7 to 5 ten years later, the efficacy duration or the number of effective years for this intervention was counted as 10 years. For each intervention type, the average efficacy duration was calculated for all components that received that type of intervention (Table 1).

The effect of intervention refers to the continuously decreasing effect of bridge improvement interventions on the probability of a bridge component being in a certain condition. The intervention effect is assumed to be maximum (i.e., 1.00 or 100%) at the first year of intervention ($n = 0$) and continuously decreases for a specific period (i.e., average number of years between the intervention year to the year when condition drops). This specific period for each intervention type is called average efficacy (duration in years), shown in Table 1. The average efficacy was obtained for each intervention type using the NBI data set. The BIEF refers to the decreasing rate of the intervention effect. If it is assumed that the intervention effect is negligible when it falls below 1%, then BIEF can be calculated as $(1\%)^{1/n}$ while the intervention effect after n years of the intervention application is given by $100\% \times (\mathrm{BIEF})^n$. The intervention efficacy (duration) is therefore defined as the period over which the intervention remains effective. The intervention types defined in this manner were considered in the proposed modeling framework to account for the postintervention effectiveness of the improvement.

Table 1. Bridge Intervention Effectiveness Factors (BIEF) and the MR&R Efficacy Duration

Bridge component	Intervention category	Average efficacy (duration in years)	BIEF	Number of observations
Deck	Repair	09	0.6	2,070
	Rehabilitation	13	0.7	1,053
	Replacement	16	0.75	652
Superstructure	Repair	11	0.66	2,202
	Rehabilitation	14	0.72	338
	Replacement	15	0.74	382
Substructure	Repair	12	0.68	832
	Rehabilitation	14	0.72	126
	Replacement	15	0.74	259

Dependent Variable

The dependent variable represents the probability of a bridge component being in a certain condition state at a certain age. All the explanatory variables with positive signs imply that the probability of a bridge being in a higher condition state is higher with an increasing magnitude of these factors while negative signs indicate that it is more likely for bridge components to be in lower condition states with an increasing magnitude of these factors. The condition state is an aggregation of one or more NBI ratings and is a discrete variable ranging from 1 to 4 (Table 2). Table 3 contains the number of observations available for each condition state of the three bridge components.

Explanatory Variables

Data availability considerations, a priori expectations about the effects of predictors and existing empirical work on bridge condition modeling, led to the choice of explanatory variables for the models in this paper. The explanatory variables included bridge

Table 3. Number of Observations for Condition States of All Three Components

Condition states	Designation	Number of observations		
		Deck	Superstructure	Substructure
4	Excellent	18,351	18,652	18,513
3	Good	46,096	55,158	57,631
2	Fair	29,723	23,138	22,701
1	Poor	12,078	9,454	7,549

Table 2. Classification of Bridge Condition Using Condition States

Description of NBI ratings[a]	NBI rating	Condition state	Description of condition state
As new.	9	4	Excellent
No problems noted.	8		
Some minor problems noted.	7	3[b]	Good
Structural elements show some minor deterioration.	6	2[b]	Fair
All primary structural elements are sound but may have minor section loss, cracking, spalling or scour.	5	1	Poor
Advanced section loss, deterioration, spalling or scour.	4		
Loss of section, deterioration, spalling or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.	3		
Advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.	2		
Major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put back in light service.	1		
Bridge is out of service. Beyond corrective action.	0		

[a]Source: FHWA (1995).
[b]Interior or intermediate categories refer to Condition States 2 and 3.

Table 4. Summary of Explanatory Variables

Variables	Description	Mean
Age	Bridge age, years	37.27 (19.64[a])
Interstate indicator	1 if bridge is on interstate system, 0 otherwise	27%
Urban indicator	1 if bridge is located in an urban area, 0 otherwise	30%
Warm region indicator	1 if bridge is located in a warm climate region, 0 otherwise	33%
High freeze-thaw cycles indicator	1 if freeze-thaw cycles >60, 0 otherwise	22%
Waterway indicator	1 if service under the bridge is water, 0 otherwise	66%
Steel indicator	1 if superstructure material is steel, 0 otherwise	40%
Deck protection layer indicator	1 if deck protection layer exists, 0 otherwise	45%
Deck repair indicator	1 if deck is repaired, 0 otherwise	2.71%
Deck rehabilitation indicator	1 if deck is rehabilitated, 0 otherwise	1%
Deck replacement indicator	1 if deck is replaced/reconstructed, 0 otherwise	0.85%
Superstructure repair indicator	1 if superstructure is repaired, 0 otherwise	2.85%
Superstructure rehabilitation indicator	1 if superstructure is rehabilitated, 0 otherwise	0.64%
Superstructure replacement indicator	1 if superstructure is replaced/reconstructed, 0 otherwise	0.47%
Substructure repair indicator	1 if substructure is repaired, 0 otherwise	2.28%
Substructure rehabilitation indicator	1 if substructure is rehabilitated, 0 otherwise	0.60%
Substructure replacement indicator	1 if substructure is replaced/reconstructed, 0 otherwise	0.45%

[a]Standard deviation.

age, regional variable, bridge superstructure material type, highway functional class, interventions and their post-treatment effect (developed from NBI condition data), service under bridge and climate effects (measured in terms of freeze-thaw cycles). Deck deterioration is impacted by different levels and rates of salt application, but there is no data available on these rates at each bridge. However, various qualitative regional and climatic variables were used as proxies to implicitly account for this. This paper also considered the bridge condition (measured in terms of the current condition rating and the switching state in the last inspection period), and intervention history (measured in terms of the number of years from the last reconstruction/replacement year to the current year). The explanatory variables in Table 4 were found to be statistically significant at 5% level in the estimated models.

Methodological Approach

Model Specification

Due to the discrete ordinal nature of dependent variable, the ordered probit modeling approach was used to estimate the future deterioration of bridge components. The application of this model for determining the bridge condition can be explained by the latent variable concept, which is used as a basis for modeling data of an ordinal nature (Washington et al. 2011). The latent variable accounts for conditions that are not observable by bridge inspectors, such as the internal process of bridge component deterioration. However, the bridge components can manifest themselves and be observed as excellent, good, fair, and poor through the field inspection. Assume that the latent performance is represented by a variable V. This unobserved variable is typically specified as a linear function for each observation, such that

$$V_{ig} = \beta_{ig} X_{ig} + \varepsilon_{ig} + \phi_i \tag{1}$$

Where β = vector of the estimable parameters; X = vector of exogeneous variables determining the discrete ordering for observation n; subscript i = bridges; and subscript g indexes the group of observations generated by each bridge. The error term, ε, is considered as consisting of two parts: a traditional error term unique to each observation ε_{ig} and a bridge-specific random effect disturbance term ϕ_i (assumed to be normally distributed with mean 0 and variance σ^2). To test for correlation between observations generated by each single bridge, the Hausman test statistic, σ, is estimated to check whether the random effects formulation is significant or not (Hausman 1978). Panel data modeling issues are addressed by the random effects specification, which allows for a bridge-specific disturbance term (in addition to an overall disturbance term) to account for random disturbances specific to each bridge. Eq. (1) cannot be estimated directly since V is not directly observable. To estimate Eq. (1), measurement Eq. (2) is used, which maps this latent variable V to y

$$y = m \text{ if } \mu_m \leq V \leq \mu_{m+1} \tag{2}$$

where $m = 1, 2, 3, 4$ (refers to condition states)

So, observed ordinal, y, in Eq. (2) can be expanded as

$$\left.\begin{array}{l} y = 1(\text{poor}) \text{ if } V \leq \mu_0 \\ y = 2(\text{fair}) \text{ if } \mu_0 < V \leq \mu_1 \\ y = 3(\text{good}) \text{ if } \mu_1 < V \leq \mu_2 \\ y = 4(\text{excellent}) \text{ if } V \geq \mu_3 \end{array}\right\} \tag{3}$$

Each μ is an estimable parameter (called as a threshold) that defines y, which corresponds to integer ordering. μ_0 is set equal to zero, which implies that only two thresholds are needed (i.e., m–2 = 4–2 = 2) as shown in Fig. 2. The μ parameters are estimated jointly with the model parameters β; this leads to estimating

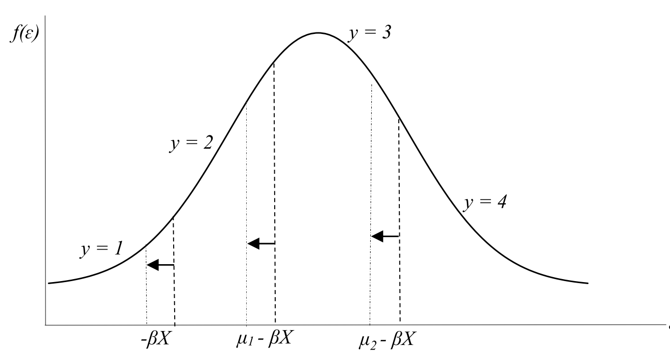

Fig. 2. Ordered probit model, an increase in βX and $\mu_0 = 0$

the probability of i specific ordered responses for each observation n, setting up an assumption of ε to be normally distributed across the observations with mean $= 0$ and variance $= 1$.

The formulations for the probability of a bridge component being in poor (condition state = 1), fair (condition state = 2), good (condition state = 3), and excellent (condition state = 4) condition states are as follows:

$$\left.\begin{aligned} P[y=1] &= \Phi[-\beta X] \\ P[y=2] &= \Phi[\mu_1-\beta X]-\Phi[-\beta X] \\ P[y=3] &= \Phi[\mu_2-\beta X]-\Phi[\mu_1-\beta X] \\ P[y=4] &= 1-\Phi[\mu_3-\beta X] \end{aligned}\right\} \tag{4}$$

where $\Phi(.)$ = cumulative normal distribution, given as

$$\Phi(\mu)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\mu}\mathrm{EXP}\left[-\frac{1}{2}w^2\right]dw \tag{5}$$

While evaluating and explaining the influence of the individual estimated parameters in ordered probit models, a positive value of variable x_k's parameter estimate β_k implies that an increase in x_k will increase the probability that the observation falls in the highest category (i.e., $y = 4$, which represents the excellent condition state) and decreases the probability that it falls in the lowest category (i.e., $y = 1$, which represents the poor condition state). One shortcoming associated with ordered probit models is the interpretation of interior/intermediate categories (i.e., $y = 2$, $y = 3$) (Fig. 2). The effect of a positive or negative β_k on the probabilities of these interior categories has not been established. This difficulty could be attributed to the location of the thresholds where the areas between the shifted thresholds may cause probabilities to increase or decrease after shifts to the right or to the left. Therefore, the estimation results could be interpreted by stating that an increase in x_k increases the likelihood that the component is in excellent condition and decreases the likelihood that it is in poor condition. For this reason, marginal effects analysis was conducted to acquire a good sense of the direction of the influence on the interior categories.

Marginal Effects Analysis

To quantify the strength of the effects of the influential factors and to obtain a good sense of the direction of the influence on the interior condition state categories ($y = 2$, $y = 3$), marginal effects analysis was carried out for each condition state. With regard to the indicator variables, their marginal effects on the response variable were calculated as the difference in the estimated probabilities, with their value changing from zero to one while all other variables were assumed to be at their arithmetic means. For continuous variables, the effects were calculated from the partial derivatives as follows:

$$\frac{\partial P(y=1)}{\partial X}=-\phi(-\beta X)\beta' \tag{6}$$

$$\frac{\partial P(y=2)}{\partial X}=[\phi(\mu_0-\beta X)-\phi(\mu_1-\beta X)]\beta' \tag{7}$$

$$\frac{\partial P(y=3)}{\partial X}=[\phi(\mu_1-\beta X)-\phi(\mu_2-\beta X)]\beta' \tag{8}$$

$$\frac{\partial P(y=4)}{\partial X}=-\phi(\mu_2-\beta X)\beta' \tag{9}$$

where P $(y = m)$ = probability of response category m; $\phi(\cdot)$ = standard normal density; and all other terms are as defined earlier. The marginal effects for each response category refer to a change in the outcome probability of each threshold category P $(y = m)$ given a unit change in a continuous variable, x. A positive marginal effect for a specific condition state indicates an increase in probability for that state, while a negative value corresponds to a decrease in probability for that condition state in response to an increase in the explanatory variable. A large marginal effect indicates that the variable, expressed in the given units, has a relatively large effect on a bridge's condition state while a relatively small marginal effect indicates a relatively minimal effect.

Estimation Results and Discussion

The model estimation results are summarized in Table 5. The overall model fit was measured in terms of McFadden statistic, ρ^2, the values of which are 0.270 for the deck, 0.232 for the superstructure, and 0.271 for the substructure. The results, which are in agreement with previous studies (Lavrenz et al. 2015, 2016; Moomen 2016; Moomen et al. 2016; Qiao et al. 2016a, b; Saeed et al. 2016, 2017), show that the components on older bridges are more likely to be in fair and poor condition as indicated by the negative sign of coefficient of the age variable. Further, the positive signs of the interstate indicator for both the deck and the superstructure indicate that bridges on interstate highways have a higher probability that their deck and superstructure are in poor and fair condition, which is likely because the high traffic loading on interstates outweighs the higher design standard of those bridge components for that class of highways. However, this variable was not significant in the substructure deterioration model, which is not surprising because compared to the deck and superstructure, the substructure is more sheltered from the direct damaging effects of truck loading. The urban variable has a positive sign for all three components, which indicates a higher probability of a good and excellent condition of bridges located in urban areas because this variable is likely to be associated with superior design or more frequent and careful maintenance on urban bridges. Also, for all three bridge components, the two climate-related variables were found to be very influential: the positive sign of the warm region indicator variable indicates that bridges in the warmer regions have lower deterioration rates; and for the high freeze-thaw cycle (HFTC: number of freeze-thaw cycles exceeding 60), the negative sign suggests that higher levels of this variable are associated with higher deterioration, which is intuitive. The waterway indicator variable represents the type of service under bridges and is significant for superstructure and substructure with a negative sign, which suggests that the deterioration is generally higher for bridges that cross waterways compared to those that cross highways or railways. Besides age, the most influential variable is the intervention type, which consistently has a positive sign, suggesting that the probability of a bridge component being in a good condition is higher when it has received some intervention. The effect of a replacement is largest, followed by rehabilitation and repair. Further, the effect of each intervention type decreases continually and dissipates at the effective year (as defined earlier) of that intervention type.

Regarding the importance of the random effects, it is noteworthy that the random effect (Hausman test) parameter (σ) is significantly different from zero, with a parameter estimate of 1.057 and a t-statistic of 13.17 for the deck model; a parameter estimate of 1.168 and a t-statistic of 10.37 for the superstructure model; and

Table 5. Model Estimation Results

Variables	Parameter estimate	t-statistic
Deck deterioration model		
Constant	2.618	10.77
Age	–0.043	–9.66
Interstate indicator	–0.057	–4.98
Urban indicator	0.040	3.43
Warm region indicator	0.570	2.64
High freeze-thaw cycle indicator	–0.193	–3.88
Deck protection indicator	1.104	5.26
Deck repair indicator	1.434	4.86
Deck rehabilitation indicator	2.418	6.23
Deck replacement indicator	4.750	7.55
Threshold		
μ_1	1.561	23.11
μ_2	3.733	32.5
Random effect (Hausman test) parameter, σ	1.057	13.17
McFadden statistic for model evaluation, ρ^2	—	0.270
Superstructure deterioration model		
Constant	4.376	8.70
Age	–0.055	–7.82
Interstate indicator	–0.433	–6.53
Urban indicator	0.143	3.07
Warm region indicator	0.367	4.04
High freeze-thaw cycles indicator	–0.115	–3.27
Steel indicator	–0.014	–4.54
Waterway indicator	–0.180	–2.23
Superstructure repair indicator	1.002	5.90
Superstructure rehabilitation indicator	1.800	7.67
Superstructure replacement indicator	5.104	9.11
Threshold		
μ_1	1.433	33.70
μ_2	3.970	41.33
Random effect (Hausman test) parameter, σ	1.168	10.37
McFadden statistic for model evaluation, ρ^2	—	0.232
Substructure deterioration model		
Constant	5.084	11.17
Age	–0.066	–9.80
Urban indicator	0.050	2.86
Warm region indicator	0.532	3.96
High freeze-thaw cycles indicator	–0.128	–2.02
Waterway indicator	–0.033	–3.19
Substructure repair indicator	1.088	6.48
Substructure rehabilitation indicator	1.971	9.31
Substructure reconstruction indicator	4.070	11.74
Threshold		
μ_1	1.715	34.84
μ_2	4.683	47.61
Random effect (Hausman test) parameter, σ	1.260	11.32
McFadden statistic for model evaluation, ρ^2	—	0.271

a parameter estimate of 1.260 and a t-statistic of 11.32 for the substructure model. This high level of significance clearly shows that estimating the model with random effects is valid and that ignoring the correlation in disturbances among the individual participant bridge condition ratings would result in serious model specification errors and could lead to inconsistent parameter estimates.

Marginal Effects

The marginal effect refers to the approximate amount of change in the probability of a bridge component being in a certain condition state in response to a unit change in the explanatory variable when all other explanatory variables are held constant at their respective population means. The average marginal effects for these models are presented in Table 6. As mentioned, marginal effects provide information about the magnitude of the change in probability for all condition categories (poor, fair, good, and excellent). As can be seen in the first row in Table 6, a one-unit increase in the bridge's age (one year) results in an average 0.0043 increase in the probability of the bridge deck being in Condition State 1, a 0.0068 increase in the probability that the bridge deck would be in Condition State 2, a 0.0049 decrease in the probability that it would be in Condition State 3, and a 0.0062 decrease in the probability that it would be in Condition State 4. These results indicate that the newly introduced variables for intervention category occurrence were the most influential variables on the performance of each of the three bridge components. The analysis also quantified the extent of this influence in terms of the probability of being in a given condition state, which varied across the three intervention categories. This influence was measured by analyzing the difference in the marginal effects values of these interventions for each condition state. Regarding the deck, the replacement intervention was found to be 96 and 230% more influential than rehabilitation and repair, respectively, on the probability that the deck is in excellent condition. For the superstructure, the replacement intervention was found to be 183 and 409% more influential than rehabilitation and repair, respectively, on the probability that the superstructure is in excellent condition. For the substructure, the replacement intervention was found to be 106 and 274% more influential than rehabilitation and repair, respectively, on the probability that the substructure is in excellent condition.

Development of Deterioration Curves

After the models were estimated for all three components, probabilistic deterioration curves were developed with the component's condition and age while keeping the other explanatory variables at their desired values. Using Eq. (7), the estimated coefficients of each explanatory variable and the thresholds (μ_1, μ_2), the probability of each bridge component being in each condition state was calculated. For each condition state, the deterioration curves for the bridge deck, superstructure, and substructure were developed separately based on the model results under two extreme scenarios (the most and the least favorable scenarios), as shown in Figs. 3–5. The x-axis is the component age (number of years after construction), and the y-axis is the probability of the bridge component being in a certain condition state. The two extreme scenarios were defined as the most favorable and the least favorable based on the inputs given in Table 7. Other desired values of explanatory variables specific to a bridge asset can also be used in the model to develop a deterioration curve while varying the age for each condition state.

The simulation plots in Figs. 3–5 quantify, for each of the three bridge components, the extent of the probability of the bridge component being in a good or excellent condition state decreases over time and, identifies the point (age) when this probability becomes lower than the probability of being in a fair or poor condition state. For each of the three bridge components, the location of this turning point was investigated for the bridges in the most favorable settings as well as those in the least favorable settings. The results, as expected, confirm that the turning point occurs much later in the most favorable scenario compared to the least favorable scenario. This was the pattern observed for each of the three bridge components; however, the time

Table 6. Marginal Effects

Variables	$y = 1$ (poor)	$y = 2$ (fair)	$y = 3$ (good)	$y = 4$ (excellent)
	Marginal effects for the deck model			
Age	0.0043	0.0068	–0.0049	–0.0062
Interstate indicator	0.0058	0.0091	–0.0067	–0.0082
Urban indicator	–0.0039	–0.0063	0.0045	0.0058
Warm region indicator	–0.0518	–0.0907	0.0546	0.088
Freeze-thaw cycles indicator	0.0201	0.0301	–0.0238	–0.0265
Deck protection layer indicator	–0.1065	–0.1685	0.1091	0.1659
Deck repair indicator	–0.1426	–0.228	0.1643	0.2063
Deck rehabilitation indicator	–0.2396	–0.383	0.2761	0.3466
Deck replacement indicator	–0.4707	–0.7523	0.5422	0.6807
	Marginal effects for the superstructure model			
Age	0.0043	0.0076	–0.0034	–0.0085
Interstate indicator	0.0372	0.0588	–0.0341	–0.0619
Urban indicator	–0.0108	–0.0195	0.008	0.0223
Warm region indicator	–0.027	–0.0497	0.0181	0.0585
Freeze-thaw cycles indicator	0.0093	0.0158	–0.0078	–0.0173
Steel indicator	0.0012	0.002	–0.0009	–0.0023
Waterway indicator	0.0136	0.0244	–0.01	–0.028
Superstructure repair indicator	–0.0779	–0.1365	0.0613	0.1531
Superstructure rehabilitation indicator	–0.1399	–0.2452	0.1101	0.275
Superstructure replacement indicator	–0.3968	–0.6955	0.3123	0.78
	Marginal effects for the substructure model			
Age	0.0028	0.009	–0.0022	–0.0096
Urban indicator	–0.0021	–0.0068	0.0016	0.0073
Warm region indicator	–0.0208	–0.0701	0.0094	0.0815
High freeze-thaw cycles indicator	0.0057	0.0177	–0.0052	–0.0182
Waterway indicator	0.0014	0.0045	–0.0011	–0.0049
Substructure repair indicator	–0.0465	–0.1481	0.037	0.1576
Substructure rehabilitation indicator	–0.0843	–0.2684	0.0671	0.2856
Substructure reconstruction indicator	–0.1741	–0.554	0.1385	0.5896

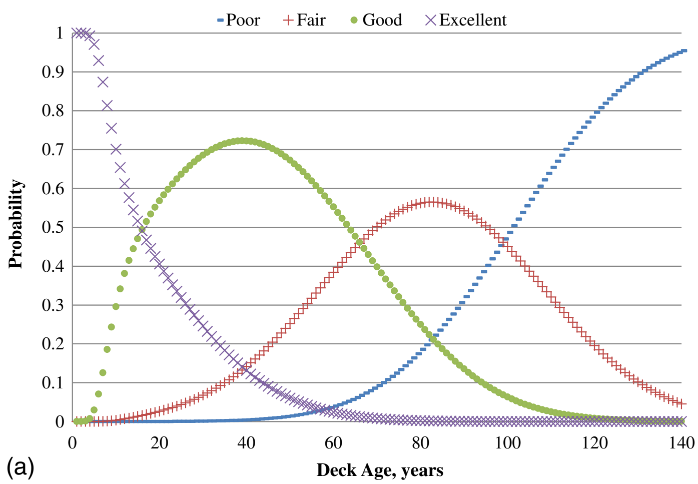

Fig. 3. Probabilistic deck deterioration curves: (a) Scenario I: most favorable levels of explanatory factors; (b) Scenario II: least favorable levels of explanatory factors

difference between the two turning points for the most and the least favorite scenarios was larger for the bridge deck compared to the superstructure or substructure. This was expected because bridge decks generally appear to be more sensitive to the agents of deterioration, as confirmed in the marginal effects analysis section of this paper.

Moreover, it can be observed from the probability plots (Figs. 3–5) that after a certain time of the bridge construction, the probability of the bridge deck/superstructure/substructure being in poor or fair condition would exceed the probability of being in at least good or excellent condition. In this paper, this time is defined as the good-to-fair transition (GFT) time. The GFT time was generally highest for the deck, followed by the superstructure and the substructure. In the most ideal environment, the GFT times were almost the same across the three component types, and under the least ideal conditions, the GFT time of the superstructure and substructure were 100 and 148%, respectively. The bridge deck exhibited the largest GFT time difference between the most and least

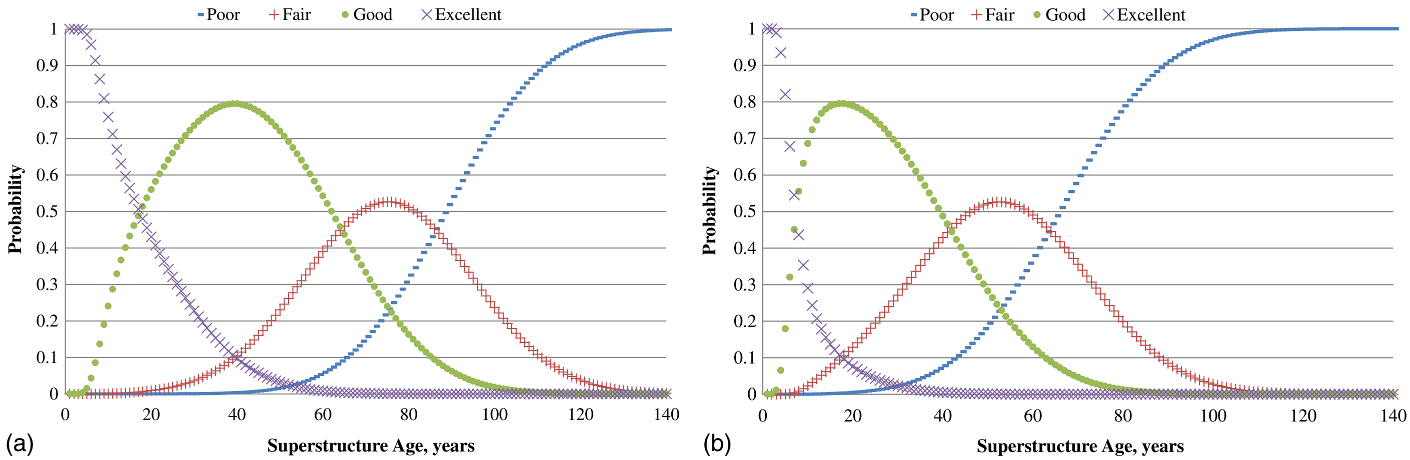

Fig. 4. Probabilistic superstructure deterioration curves: (a) Scenario I: most favorable levels of explanatory factors; (b) Scenario II: least favorable levels of explanatory factors

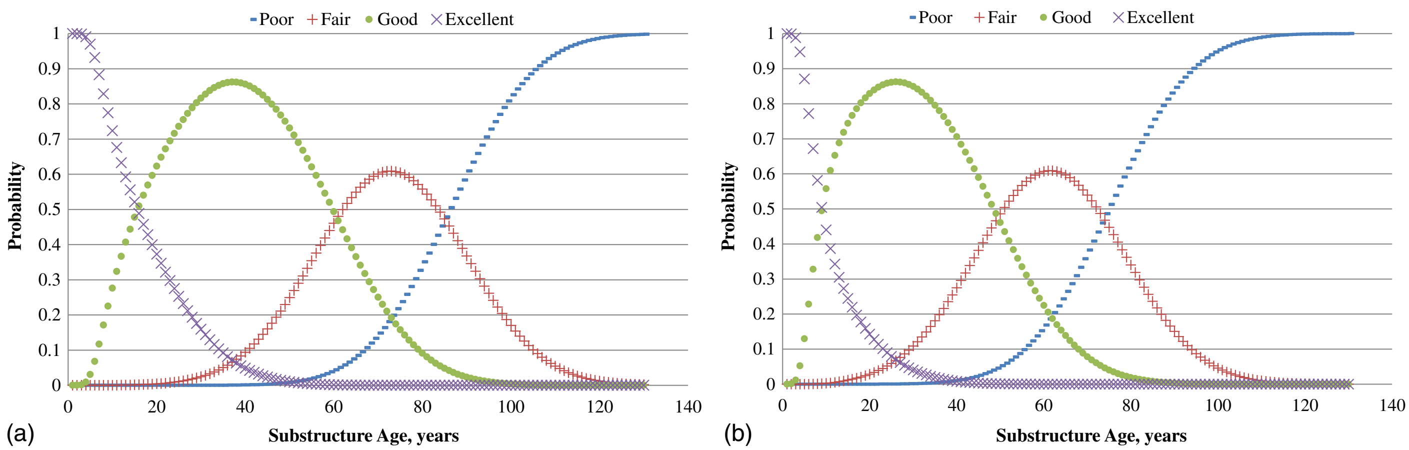

Fig. 5. Probabilistic substructure deterioration curves: (a) Scenario I: most favorable levels of explanatory factors; (b) Scenario II: least favorable levels of explanatory factors

Table 7. Summary of Inputs for Two Extreme Scenarios

Bridge component	Probability plot under the most favorable scenario	Probability plot under the least favorable scenario
Deck	Not interstate	Interstate
	In urban area	Not in urban area
	In warm region	Not in warm region
	No high freeze-thaw cycle	Has high freeze-thaw cycle
	With deck protection	No deck protection
Superstructure	Not interstate	In interstate
	In urban area	Not in urban area
	In warm region	Not in warm region
	No high freeze-thaw cycle	Has high freeze-thaw cycle
	Material type is concrete	Material type is steel
	Service under the bridge is not waterway	Service under the bridge is waterway
Substructure	In urban area	Not in urban area
	In warm region	Not in warm region
	No high freeze-thaw cycle	Has high freeze-thaw cycle
	Service under the bridge is not waterway	Service under the bridge is waterway

favorable conditions compared to superstructure or substructure, which was likely due to the greater vulnerability of the deck to the external factors (traffic and climate) compared to the other two components.

For each bridge component, the GFT times were estimated for each of the two extreme scenarios: the most favorable and the least favorable, respectively, as follows: deck: 64 and 21 years; superstructure: 64 and 42 years; and substructure: 62 and 52 years.

Summary and Conclusions

This paper introduced an ordered probit random effects model that duly addresses the observation-specific correlation and heterogeneity bias associated with the panel data modeling. The model was shown to be capable of accounting for the identified types of past intervention activities and their postapplication effectiveness. The main contributions of this paper are (1) the development and incorporation of new variables, specifically, indicator variables representing the categories of past repair, rehabilitation, and replacement of the bridge component; (2) using existing NBI condition data to ascertain if and when such interventions took place in the history of the component; and (3) proven accurate measurement of the effects of interventions on the postintervention condition of the bridge components and accounting for such effects in the deterioration model.

Using the developed models, this paper also conducted simulations for several case scenarios that helped visualize the trend of the predicted probabilities of sojourning in any condition state. The simulation plots quantified the extent to which the probability of the bridge component being in good or excellent condition decreased over time and at a certain point (age) became lower than the probability of the component being in fair or poor condition. The year at which this turning point occurred was investigated for bridges in the most favorable settings (light traffic, mild climate, deck protection, and so on) as well as for those in the least favorable settings. It was observed that the turning point for the bridges in the most favorable settings occurred much later compared to those in the least favorable scenarios. This pattern was noticed for each of the three bridge components; however, the time difference between the two turning points for the most and the least favorable scenarios was larger for the bridge deck compared to the superstructure or substructure. This was expected because the bridge deck generally appears to be the most sensitive to the agents of deterioration compared to the other two components, which was subsequently confirmed in the marginal effects analysis in this paper.

The results of the marginal effects analysis indicated that the newly introduced variables for each intervention category occurrence were the most influential on the performance of each of the three bridge components. The analysis also quantified the extent to which this influence varied across the three intervention categories. The replacement category was by far the most influential at 230% more influential than the least influential intervention category (repair) for decks; 409% more influential than the repair category for superstructures; and 275% more influential than the repair category for substructures. Each of the three variables had negative impacts on the probability of the bridge component being in poor or fair condition and positive impacts on the probability of the bridge component being in excellent or good condition. These results are intuitive since the condition of the bridge component will be improved to a certain degree after a repair or rehabilitation activity or component replacement, and the performance jump would depend on the type of intervention. Typically, the jump is larger if the intervention is more intensive, such as a rehabilitation or replacement.

The developed probabilistic modeling framework in this paper can be applied by highway agencies for the development of more robust deterioration models to monitor the performance of their bridge components and to predict their remaining lives based on attributes of the bridges and their operating environment. Although the models and analysis presented in this paper were based on data from the state of Indiana, the general framework can be applied to other states or public agencies. The methodology also can be used to develop deterioration models for other infrastructure types. It is expected that the data-driven approaches and results of this paper can provide agencies a more reliable tool to predict the condition of the main bridge components and to enhance their bridge MR&R decision making processes.

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