Analysis of Bridge Deterioration Rates: A Case Study of the Northern Plains Region

by Denver Tolliver and Pan Lu

A bridge deterioration model is estimated from the National Bridge Inventory that explains and forecasts future condition as a function of bridge material, bridge design, operating rating classification, average daily traffic, the state where the bridge is located, and the age of the bridge. Over the 95-year analysis period, the rate of bridge deterioration with age is a third-order polynomial function. However, the relationship between condition and age is approximately linear until age 65. Holding all else constant, a bridge substructure in the Northern Plains loses approximately one-half of a condition rating point every 13 years until age 65.

INTRODUCTION

According to the United States Department of Transportation (USDOT 2008), more than 597,000 bridges located on public roads in the United States are greater than 20 feet in length. Approximately 47% of these bridges were built before 1966 (USDOT 2008), many of them during the initial interstate highway construction era. Bridges in this age category have reached or will reach their 50-year milestone during the next five years. Although 50 years was originally thought of as the design life of a highway bridge, the useful life of a bridge can be extended through diligent maintenance and rehabilitation. However, with looming deficits in the Highway Trust Fund, state and local officials are concerned about the availability of resources to extend bridge service lives and replace structurally deficient or obsolete bridges.

Knowledge of bridge deterioration rates is essential for cost-effective asset management and long-range transportation planning. In the United States, the Federal Highway Administration has developed the National Bridge Investment Analysis System (NBIAS) to analyze and forecast bridge conditions. The NBIAS analyzes deficiencies at the level of individual bridge elements using the National Bridge Inventory (NBI). The NBIAS uses a probabilistic method of modeling bridge deterioration in which transition probabilities are used to project the likelihood that a bridge element will deteriorate from its current condition to a lower condition level during a future interval. The NBIAS assumes that the probability of a bridge element deteriorating from its current condition to the next (lower) level is independent of age. However, as USDOT notes (2008, 10-30), "This assumption may not be warranted in all cases, particularly in situations in which a bridge has not been aggressively maintained over its full lifetime and/or has been subject to loadings in excess of what was anticipated when the structure was built."

The purpose of this study is to develop a model for explaining and forecasting the deterioration rates of bridges over time. Much of the research in this field has focused on predictions derived from Markov Chains using transition probabilities. In these models, the probability that a bridge (or bridge element) will be in a certain condition at time t_1 is a function of its condition at time t_0. Thus, the history of bridge deterioration in previous periods and the effects of individual factors are not explicitly considered. While Markov Chains are useful for predicting changes in individual bridge conditions over time, other methods are needed to explain variations in deterioration rates among categories of bridges and regions, and to quantify the contributions of individual factors to deterioration rates. The model described in this paper is an explanatory tool intended for strategic analysis. It builds upon previous research and illustrates how deterioration models can be estimated that account for diversity in environment, traffic, and other key factors, and how these models can be used to forecast deterioration rates for classes of bridges. The model supplements existing analysis tools and allows for strategic long-range forecasting based on bridge type, age, traffic, and other factors.

Jiang and Sinha (1989) developed a procedure to forecast bridge condition as a function of current condition and age using a third-order polynomial function, in which condition is a function of age, age squared, and the cube of age. In a multi-state study, Dunker and Rabbat (1990) analyzed bridges built between 1950 and 1987 and, in doing so, found more variation in bridge deficiencies among states than among environmental and traffic categories. The authors also determined that structural deficiency percentages decreased as the quality of the bridge material increased from timber to steel to concrete. Moreover, this pattern was independent of age. Madanat, Karlaftis, and McCarthy (1997) concluded that bridge condition is a linear function of many factors including current condition, type of bridge, environment, traffic volume, and age. Similarly, Kallen and Van Noortwijk (2006) concluded that bridge deterioration is highly dependent upon the age of the structure and that the relationship between expected bridge condition and age is a polynomial function. Kim and Koon (2010) found that age is the most significant contributor to the structural deficiency of decks and bridge superstructures in cold regions, followed by the structural characteristics of the bridge and traffic volume.

In line with previous research, the objective of this paper is to analyze bridge deterioration as a function of key variables such as age, bridge type, and material. While this study focuses on the Northern Plains, the model can be replicated in other regions using NBI data.

OVERVIEW OF MODELS AND DATA

Kim and Koon (2010) focused on the bridge deck and superstructure, which is the part of the bridge that directly supports traffic loads. In contrast, this paper focuses on the bridge substructure, which transfers loads from the superstructure to the ground. The dataset used in this analysis consists of the 2009 NBI for the states of Iowa, Minnesota, Nebraska, North Dakota, and South Dakota. These states lie in the heart of the northern Great Plains region (referred to as the Northern Plains). This is a region of severe climate with considerable variation in temperature and freeze-thaw cycles. The five states are similar topographically and climatically. Nevertheless, there are financial, economic, and geographic differences among them.

The dependent variable of the model is bridge condition rating (Table 1). In this rating scale, a brand new bridge deteriorates from excellent condition to failure via eight interim steps or levels. In this paper, bridge condition is treated as an integer-scaled variable. A change of one unit anywhere on the scale has the same statistical effect: e.g., a change from very good to good has the same statistical effect as a change from fair to poor. Although imperfect, the interpretation of bridge condition as an integer-scaled variable is acceptable because the purpose of this study is to forecast when condition ratings will change, not to assess the seriousness of the changes or the need for remedial actions. Nevertheless, a corollary issue exists: the condition ratings are scored by different people (i.e., different bridge inspectors). As a result, human (perceptual) differences are reflected in the evaluations. To some extent, these variations are captured by state indicator variables that reflect differences in inspection and maintenance policies and programs among states.

Table 1: Bridge Condition Ratings

Code	Meaning	Description
9	Excellent	
8	Very Good	No problems noted.
7	Good	Some minor problems.
6	Satisfactory	Structural elements show some minor deterioration.
5	Fair	All primary structural elements are sound but may have minor deterioration.
4	Poor	Major deterioration is occurring.
3	Serious	Deterioration has seriously affected the primary structural components of the bridge. Local failures are possible.
2	Critical	Advanced deterioration of the primary structural elements is evident. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.
1	Imminent Failure	Major deterioration is affecting the stability of the bridge. The bridge is closed to traffic but corrective action may allow it to be out back in light service.
0	Failed	The bridge is out of service and beyond corrective action.

Age is the quantitative independent variable of the model. The age of a bridge is computed as 2009 minus the year of original construction or reconstruction. Bridges tend to deteriorate consistently with time. Theoretically, the rate of loss is a polynomial function. This hypothesis is based on two suppositions: (1) The rate of loss may be modest and nearly linear until a bridge's condition deteriorates to fair. Then, more maintenance and repairs are implemented to keep the bridge safe and operational. These improvements may slow the rate of condition loss with time. (2) Once a bridge is in serious condition it may continue in light service for some time under close scrutiny via posting (e.g., limiting the traffic loads) and spot repairs.

While there are logical arguments for a polynomial form, it must fit the data. As shown in Figure 1, a plot of mean substructure rating against age exhibits a third-degree polynomial form up to 95 years. Around age 65, the graph turns up temporarily, and then down again. After age 95, the observations begin to spread out. These are very old bridges. Many of them were built before standardization of designs. Not surprisingly, the variance within this group is quite significant. While Figure 1 suggests that a polynomial form is appropriate, the rate of deterioration is approximately linear until age 65.

The substructure model consists of five effects: bridge type, bridge design, bridge operating rating, average daily traffic (ADT group), and the state where the bridge is located. The values or levels of these effects are summarized in Table 2. The effects are defined as indicator or dummy variables. They shift the intercept of the regression, thereby creating many unique levels or categories—e.g., concrete bridges in Iowa with operating ratings > 80,000 pounds and ADT greater than 5,000 trips. Each category has its own unique intercept. However, the slope (or rate of change in substructure rating with age) is the same after controlling for bridge type, design, operating rating, ADT group, and state.

Figure 1: Plot of Substructure Condition Rating by Age

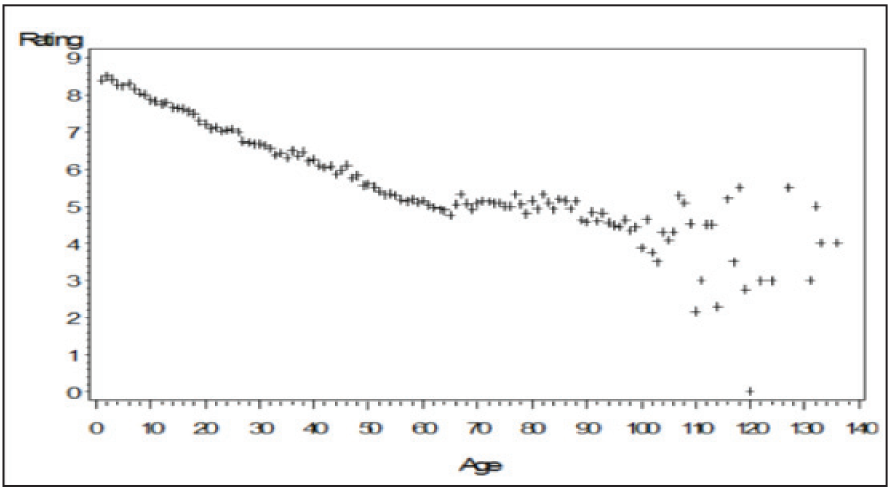


Table 2: Class Level Information

Class	Levels	Values
Bridge Type	4	Concrete, Steel ,Timber, Other
Bridge Design	8	HS_15, HS_20, HS_20+, HS_25, H_10, H_15, H_20, Other
Operating Rating	4	40 kips, 60 kips, 80 kips, > 80 kips (1 kip=1,000 lb)
ADT Group	4	0-100; 101-1,000; 1,001-5,000; > 5,000
State	5	IA, MN, ND, NE, SD

In this analysis, railroad and pedestrian bridges have been eliminated from the dataset. The remaining bridges consist of three material types (concrete, steel, and timber), plus an “other” category which includes mixed and masonry bridges. Bridge design consists of seven main categories (HS-15, HS-20, HS-20+, HS-25, H-10, H-15, and H-20), plus an “other” category. These designs reflect prototypical truck configurations and loading patterns. A prefix of H denotes a single-unit truck, whereas HS denotes a tractor pulling a semitrailer. For H bridges, the numeric suffix represents the gross weight in tons of a single-unit truck. For example, H-20 denotes a truck with a gross weight of 20 tons. In comparison, the numeric suffix of HS vehicles represents the assumed weight on the first two axle sets of the truck. For example, HS-20 signifies a truck with a total of 20 tons on the tractor’s axles. The ADT volume groups consist of 0–100, 101–1,000, 1,001–5,000, and greater than 5,000 vehicles per day. The state variable includes five classes and captures differences attributable to the bridge’s geographic and jurisdictional location.

The operating rating is a working estimate of the load capacity of a bridge in terms of maximum gross vehicle weight. Four classes are used in this study: ≤ 40,000 pounds, 40,001–60,000 pounds, 60,001–80,000 pounds, and > 80,000 pounds. The operating rating is to some extent a function of bridge design. However, the operating rating provides unique information that is not necessarily captured in the design classification. As illustrated in Table 3, H-15 bridges in the Northern Plains are distributed among all rating classes. In this paper, material, design, and operating rating are used to collectively describe the quality dimensions of a bridge. The operating rating is defined in levels rather than as a continuous variable. While the operating rating may be adjusted somewhat over time, it is not likely to change category unless the bridge is considered structurally insufficient.

Table 3: Operating Ratings of H-15 Bridges in the Northern Plains (Thousands of Pounds)

Maximum Operating Rating	40	60	80	> 80
Percent of Bridges	8%	23%	41%	28%

SUBSTRUCTURE MODEL

The essential purpose of the model is to forecast substructure condition rating as a function of age, bridge type, bridge design, operating rating, traffic, and location. Because of the relationships shown in Figure 1, two models are estimated: a linear model appropriate for bridges 65 years and younger and a polynomial model applicable to bridges ≤ 95 years of age. A summary of the polynomial regression is presented in Table 4. The model is estimated from 47,812 observations.

Table 4: Regression Summary for Polynomial Substructure Model

Dependent Variable	*Substructure Rating*
Number of Observations Used	47,812
Degrees of Freedom (DF)	47,788
F-Value	2,623
F-Test for Model Fit (Prob. > F)	<.0001
R-Square	0.5580
Adjusted R-Square	0.5578
Coefficient of Variation	16.68

Variation in bridge condition is measured by the sum of the squared deviations—i.e., the sum of squares. The F-value is a ratio of the sum of squares explained by the regression model, divided by the model's degrees of freedom, to the sum of squares not explained by the model, divided by the error degrees of freedom. If the regression model explains little of the variation in bridge condition, the F-value will be small. On the other hand, if the model explains much of the variation in condition rating, the F-value will be large, as it is in this case (i.e., 2,623). Actually, the value (of 2,623) is quite large and the probability of observing such a large value when the null hypothesis is true (e.g., the regression model is not a substantially better predictor than the mean) is extremely small—i.e., a probability of less than .0001. Of course, the F-value doesn't indicate which variables are most significant and if all of the effects are statistically meaningful. These topics are discussed next.

Incremental Sum of Squares and Tests for Main Effects

Although the substructure model is based on theory, it must still be determined if the theoretical effects are statistically significant in the Northern Plains dataset. Main effects are evaluated using Type I and Type III sums of squares (SS). Type I sum of squares are computed by sequentially adding variables to a model (one at a time) and computing the reduction in the error sum of squares attributable to each. In comparison, Type III sum of squares reflect the incremental contribution of a variable when it is added to a model that already includes all other variables. For this reason, Type III effects are often referred to as partial sums of squares. For both types, an F statistic is used to compute a probability based on the null assumption that the added effect does not significantly improve the model. As shown in Table 5, the sum of squares tests are highly significant for all five effects with probability values of less than .0001, meaning the variables improve the explanatory power of the model.

Table 5: Incremental Sum of Squares Tests for Polynomial Substructure Model

	Probability of > F-Value	
Source	**Type I SS**	**Type III SS**
State	<.0001	<.0001
Bridge Type	<.0001	<.0001
Bridge Design	<.0001	<.0001
Operating Rating	<.0001	<.0001
ADT	<.0001	<.0001

Coefficient of Variation and R-Square

The coefficient of variation (CV) is 16.68 (Table 4). It is computed by dividing the standard error of the regression by the mean of the dependent variable (substructure condition rating), and multiplying by 100 to express this ratio as a percentage. The coefficient of variation has a range of 0 to 100, with lower values indicating a model with good fit to the data. It is a key indicator of the precision of the model and the widths of prediction intervals. In this case, the CV is relatively low, which bodes well for prediction.

The R-square is the ratio of the sum of squares explained by the regression model to the total sum of squares. A higher R^2 is preferred, ceteris paribus. Intuitively, the R^2 of 0.558 in Table 4 means that the model explains nearly 56% of the variation in substructure condition rating. Why is the R^2 not higher? Although the effects attributable to bridge type, bridge design, operating rating, traffic volume, and state are captured in the model, many individual bridge effects are not. Fixed bridge effects such as quality controls and conditions during initial construction, the frequency of inspections, the inspectors, the maintenance program used and the amount of maintenance funds available, the frequency of unusual loadings, and deicing practices (e.g., how frequently has the bridge been exposed to chemicals?) are not included in the NBI database and cannot be compiled from other sources and merged with the NBI records.

Parameter Signs and Estimates

The estimates from the substructure model are shown in Table 6. Both the slope and intercept must be used to forecast bridge condition loss. However, before this calculation can be attempted, a specific intercept for the type of bridge and location must be computed. An HS-20 concrete bridge in Nebraska with an operating rating of 80,000 pounds and 500 ADT is used as an example. The specific intercept is computed as $6.69952 + 0.96394 + 0.27807 + 0.74999 - 0.21229 + 0.33922 \approx 8.8$. Six terms are reflected in this calculation: the model intercept (6.69952), the intercept shift attributable to Nebraska (0.96394), the intercept shift attributable to material type (0.27807), the intercept shift attributable to bridge design (0.74999), the intercept shift attributable to operating rating (−0.21229), and the intercept shift attributable to ADT (0.33922). In effect, the parameter estimate of each class variable is added to the intercept to compute a specific intercept for the type and design of bridge and traffic class within the state of interest. In this example, a new HS-20 concrete bridge is predicted to have a condition rating of 6.9 after 40 years (which is computed as $(8.8 + (-0.06988) \times 40 + 0.0005827 \times 40 \times 40 + (-0.00000135) \times 40 \times 40 \times 40)$). In other words, the bridge is expected to be in satisfactory condition with only minor problems.

Another example is an H-15 timber bridge in Iowa with an operating rating of 80,000 pounds and 50 ADT. The intercept is calculated as $6.69952 + 0.21546 + 0.25732 - 0.21229 + 0.26792 \approx 7.23$. This calculation involves only five terms: the model intercept (6.69952), the intercept shift attributable to Iowa (0.21546), the intercept shift attributable to bridge design (0.25732), the intercept shift attributable to operating rating (−0.21229), and the intercept shift attributable to ADT (0.26792). There is no adjustment factor or shift for bridge material. This is because timber serves as the base material of the model.

In the regression model, the effects of a class level are interpreted in relation to the base. The effect of the base level is subsumed in the intercept. As shown in Table 6, the parameter estimates of concrete, steel, and other bridges have positive signs, indicating that these bridges deteriorate at slower rates than timber bridges (ceteris paribus). The adjusted intercept for H-15 timber bridges in Minnesota with operating ratings of 60,001–80,000 pounds and less than 100 ADT can be used in conjunction with the coefficients of age to estimate condition over time. For example, this type of bridge is expected to have a substructure condition rating of 5.31 after 40 years. In other words, H-15 timber bridges in Minnesota with operating ratings of 60,001–80,000 pounds and < 100 ADT are expected to be in fair condition after 40 years of service. While the primary structural elements of these bridges are expected to be sound, they may exhibit minor deterioration.

Standard Errors

As shown in Table 6 (Column 3), the standard errors of all variables are small in relation to the estimated values. This is a desirable outcome. However, the standard errors may be suspect unless the variance of the regression is consistent over the entire range of the dependent variable.

Non-constant variance (heteroscedasticity) is common in regression analysis. In most instances, the form of heteroscedasticity is unknown and cannot be ascertained from the data. In such cases, the variance is said to be inconsistent, meaning it is not a function of an independent variable and does not increase or decrease monotonically. The regression coefficients (i.e., the parameter estimates) are not biased by heteroscedasticity. However, there are two potential issues: (1) Regression coefficients estimated from sample data may no longer be efficient (e.g., minimum variance estimators). (2) The standard errors may be affected. As a result, hypothesis tests may be unreliable.

The first issue is not a concern for this study because the parameters are estimated from population data. Nevertheless, to detect and account for inconsistent variance, heteroscedasticity-consistent errors are computed under the assumption that the variance is not constant. These standard errors are shown in Column 6 of Table 6. A comparison of Columns 3 and 6 shows only minor differences between the two sets of standard errors, suggesting mild inconsistency. This inference is bolstered by Figure 1, which suggests that the variance is relatively constant until age 95.

Probability Values and Inferences

In this study, the Northern Plains database constitutes the inventory or population of publicly owned bridges. Because an inventory is available, sampling variability is not an issue. Nevertheless, it is beneficial to envision the Northern Plains dataset as a large sample of bridges that do (or could) exist in the region. This visualization allows hypothesis tests that provide intuitive insights concerning the statistical significance of particular effects and sampling variability. For each variable, the null hypothesis is that the partial effect attributable to the variable is statistically insignificant. For indicator variables, this means that the intercept shift attributable to the variable is not significantly different from zero. For quantitative variables, the null hypothesis is that the partial slopes are not significantly different from zero.

Table 6: Parameter Estimates and Probabilities of Polynomial Substructure Model

					Heteroscedasticity Consistent		
Variable	**Parameter Estimate**	**Standard Error**	**t-value**	**Prob. > |t|**	**Standard Error**	**t -value**	**Prob. > |t|**
Intercept	6.69952	0.06279	106.70	<.0001	0.06834	98.03	<.0001
State							
IA	0.21546	0.01884	11.44	<.0001	0.01880	11.46	<.0001
MN	0.24442	0.02163	11.30	<.0001	0.02132	11.46	<.0001
ND	0.56697	0.02521	22.49	<.0001	0.02588	21.91	<.0001
NE	0.96394	0.01984	48.59	<.0001	0.01987	48.51	<.0001
SD							
Bridge Type							
Concrete	0.27807	0.07893	3.52	0.0004	0.08111	3.43	0.0006
Other	0.62834	0.04791	13.11	<.0001	0.05431	11.57	<.0001
Steel	0.30238	0.06479	4.67	<.0001	0.07469	4.05	<.0001
Timber							
Bridge Design							
H_10	0.38573	0.07788	4.95	<.0001	0.08522	4.53	<.0001
H_15	0.25732	0.01844	13.95	<.0001	0.02056	12.52	<.0001
H_20	0.52047	0.01832	28.41	<.0001	0.01906	27.30	<.0001
HS_15	0.46521	0.07549	6.16	<.0001	0.08971	5.19	<.0001
HS_20	0.74999	0.01737	43.18	<.0001	0.01854	40.45	<.0001
HS_20+	0.85103	0.03509	24.25	<.0001	0.02927	29.08	<.0001
HS_25	0.78127	0.03051	25.61	<.0001	0.02811	27.80	<.0001
Other							
Operating Rating							
≤ 40 kips	-1.21700	0.01960	-62.09	<.0001	0.02428	-50.13	<.0001
≤ 60 kips	-0.65158	0.01895	-34.38	<.0001	0.02099	-31.05	<.0001
≤ 80 kips	-0.21229	0.01426	-14.88	<.0001	0.01441	-14.73	<.0001
> 80 kips							
ADT Class							
0-100	0.26792	0.02072	12.93	<.0001	0.01850	14.48	<.0001
101-1,000	0.33922	0.02144	15.82	<.0001	0.01898	17.87	<.0001
1,001-5,000	0.24224	0.02197	11.03	<.0001	0.01865	12.99	<.0001
> 5,000							
Age	-0.06988	0.00205	-34.03	<.0001	0.00205	-34.02	<.0001
Age^2	0.00058270	0.00005206	11.19	<.0001	0.00005371	10.85	<.0001
Age^3	-0.00000135	3.82726E-7	-3.52	0.0004	4.046894E-7	-3.33	0.0009

The t-values shown in Column 4 of Table 6 are computed by dividing the parameter estimates in Column 2 by the corresponding standard errors in Column 3. The heteroscedasticity-consistent t-values in Column 7 are computed by dividing the parameter estimates in Column 2 by the corresponding heteroscedasticity-consistent errors in Column 6. The probability values (or p-values) associated with the t-statistics are shown in Columns 5 and 8, respectively. With two exceptions, the p-values shown in Column 8 of Table 6 indicate less than a one in 10,000 chance of observing t-values as large as those observed if the null hypotheses are true. The p-values for concrete bridges and the cube of age indicate less than a one in 1,000 chance of observing t-values as large as those observed when the null hypotheses are true. Moreover, the p-values for age and age squared are highly significant. If the second and third terms of the polynomial model were unimportant, the probability values associated with these t-ratios would be much higher. In effect, the tests confirm the polynomial functional form. Clearly, all the effects in the model are highly significant. Moreover, the mild inconsistency in variance does not affect the hypothesis tests.

Class Variable Effects

The coefficients of concrete, steel and other bridges are positive. As noted earlier, these coefficients are interpreted relative to timber bridges, the type of material reflected in the intercept. The positive signs indicate that substructure ratings should be higher over time for these types of bridges than for timber bridges. Similarly, the coefficients of all bridge designs (HS-15, HS-20, HS-20+, HS-25, H-10, H-15, and H-20) are positive, meaning that substructure ratings should be higher over time for these designs than for bridges included in the "other" category. However, the signs of the operating ratings are negative and must be interpreted in relation to bridges with operating ratings greater than 80,000 pounds. The negative signs suggest that bridge substructure rating is expected to decrease with operating rating, ceteris paribus. This is because the operating rating is a reflection of the design quality of a bridge and its capability to accommodate modern truck traffic. Finally, the signs of the ADT class variables (0–100, 101–1,000, and 1,001–5,000 vehicles per day) are all positive in relation to the base level (greater than 5,000 vehicles per day), suggesting that traffic contributes to loss of condition rating over time.

Because the predictions are ratio scaled, they include fractional results. In effect, they provide information about when a bridge is in transition from one condition level to the next. For example, a bridge with a predicted condition rating of 6.8 is likely to stay in satisfactory condition for several years. In contrast, a bridge with a predicted condition rating of 6.05 is on the verge of transitioning from satisfactory to fair.

Forecasting Methods

A manual method of forecasting bridge condition ratings can be devised using the parameters in Table 6. The specific intercepts for each combination of bridge type, design, and ADT group are shown in Table 7 for bridges in North Dakota with operating ratings of 60,001 to 80,000 pounds. The values are rounded to two digits to facilitate calculation.

Suppose the bridge of interest is a concrete HS-25 bridge with more than 5,000 ADT. The expected condition rating after 25 years is $8.11 + (-0.06988) \times 25 + 0.0005827 \times 625 + (-0.00000135) \times 15{,}625 \approx 6.7$. In this example, the bridge is in the upper portion of the satisfactory interval. Suppose, instead, that the bridge of interest is a steel H-15 bridge in the highest traffic category. The expected condition rating of this bridge after 25 years is $7.61 + (-0.06988) \times 25 + 0.0005827 \times 625 + (-0.00000135) \times 15{,}625 \approx 6.21$. In this example, the bridge is in the lowest portion of the satisfactory interval.

Table 7: Specific Intercepts for Bridge Type, Design, and ADT Groups in North Dakota

Applicable to Operating Ratings of 60,001–80,000 Pounds				
	ADT Volume Group			
Bridge Type/Design	**0-100**	**101-1000**	**1001-5000**	**>5000**
Concrete: HS-15	8.07	8.14	8.04	7.80
Concrete: HS-20	8.35	8.42	8.32	8.08
Concrete: HS-20+	8.45	8.52	8.43	8.18
Concrete: HS-25	8.38	8.45	8.36	8.11
Concrete: H-10	7.99	8.06	7.96	7.72
Concrete: H-15	7.86	7.93	7.83	7.59
Concrete: H-20	8.12	8.19	8.09	7.85
Concrete: Other	7.60	7.67	7.57	7.33
Other: HS-15	8.42	8.49	8.39	8.15
Other: HS-20	8.70	8.77	8.67	8.43
Other: HS-20+	8.80	8.87	8.78	8.53
Other: HS-25	8.73	8.80	8.71	8.46
Other: H-10	8.34	8.41	8.31	8.07
Other: H-15	8.21	8.28	8.18	7.94
Other: H-20	8.47	8.54	8.45	8.20
Other: Other	7.95	8.02	7.92	7.68
Steel: HS-15	8.09	8.16	8.06	7.82
Steel: HS-20	8.37	8.45	8.35	8.11
Steel: HS-20+	8.48	8.55	8.45	8.21
Steel: HS-25	8.41	8.48	8.38	8.14
Steel: H-10	8.01	8.08	7.98	7.74
Steel: H-15	7.88	7.95	7.86	7.61
Steel: H-20	8.14	8.22	8.12	7.88
Steel: Other	7.62	7.70	7.60	7.36
Timber: HS-15	7.79	7.86	7.76	7.52
Timber: HS-20	8.07	8.14	8.05	7.80
Timber: HS-20+	8.17	8.24	8.15	7.91
Timber: HS-25	8.10	8.17	8.08	7.84
Timber: H-10	7.71	7.78	7.68	7.44
Timber: H-15	7.58	7.65	7.55	7.31
Timber: H-20	7.84	7.91	7.82	7.57
Timber: Other	7.32	7.39	7.30	7.05

Linear Substructure Model

The purpose of this model is to allow easy forecasting of the loss of substructure condition rating with age. However, it is important to remember that this model is estimated on a subset of bridges: those 65 years of age and younger. Therefore, the slope coefficient applies only within this range. The results are summarized in Table 8, while the parameter estimates are displayed in Table 9. Age is the primary variable of interest. It has a coefficient of −0.0382. This suggests that the substructure condition ratings of bridges 65 years and younger are expected to decline by 0.5 units in 13 years and by one full unit in 26 years, ceteris paribus.

Table 8: Regression Summary for Linear Substructure Model: Age ≤ 65

Dependent Variable	*Substructure Rating*
Number of Observations Used	40770
Degrees of Freedom (DF)	40748
F-Value	2,211
F-Test for Model (Prob. > F)	<.0001
R-Square	0.5327
Adjusted R-Square	0.5324
Coefficient of Variation	15.692

Multicollinearity

Multicollinearity exists when one or more of the independent variables are highly correlated with each other. In a multiple regression analysis, multicollinearity is a question of degree. It is most problematic when the calculation of one independent variable depends upon another, or when two effects are mutually exclusive. Extensive multicollinearity may cause several problems: (1) The standard errors of the estimates may become inflated. As a result, hypothesis tests may be unreliable. Because of inflated errors, a variable that is actually important may fail a hypothesis test. (2) The estimates of the parameters may be conditional upon other variables. Consequently, the parameter estimates of several variables may change if a highly correlated variable is dropped from or added to the model.

The bridge substructure model exhibits only mild multicollinearity. This conclusion is based on the variance inflation factor (VIF), which is computed by regressing one independent variable against all others and using the R^2 from that regression (R_j^2)—i.e., $VIF = 1/(1 - R_j^2)$. Opinions vary widely about how much multicollinearity can be tolerated. One suggestion is that variables with VIFs of less than 10 may be contributing some unique explanatory information to the model, especially if the p-values are low (Kutner, Nachtsheim, and Neter 2004). However, more conservative rules of thumb suggest that VIFs ≥ 5.0 may indicate problems. The VIF scores of the 21 independent variables in the model range from 1.10 to 4.23 with a median value of 1.79, which suggests that multicollinearity is not an issue, even by conservative standards.

CONCLUSION

A model for estimating substructure deterioration rates, which has good statistical properties and a relatively low coefficient of variation has been developed. The regression model includes five main effects: bridge material, bridge design, operating rating classification, average daily traffic, and the state where the bridge is located. These effects are represented through indicator or dummy variables that shift the intercepts of the regression, creating many unique levels or categories. Although each category has its own unique intercept, the slope (or rate of change in condition rating with age) is the same after controlling for bridge type, design, operating rating, ADT group, and state. Over the 95-year analysis period, the rate of deterioration is a third-order polynomial function, which is consistent with previous findings. However, the relationship between condition and age is linear up to 65 years. Holding all else constant, a bridge substructure in the Northern Plains loses approximately one-half of a rating point every 13 years until age 65.

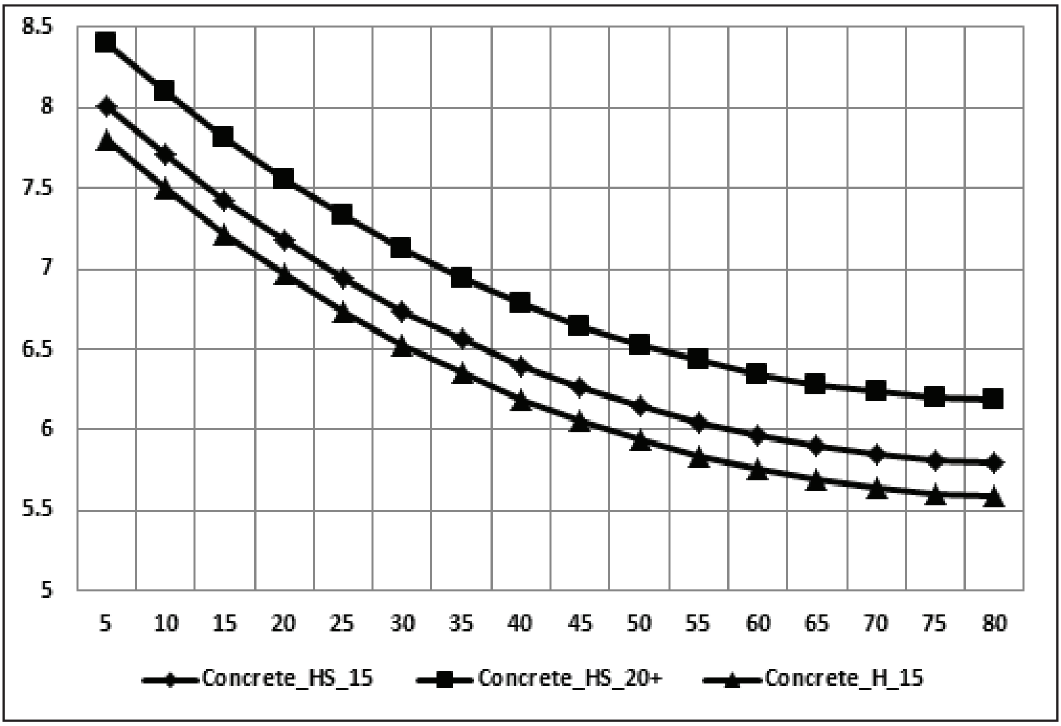
Table 9: Parameter Estimates and Probabilities of Linear Substructure Model: Age ≤ 65

Variable	Parameter Estimate	Standard Error	t-value	Pr > |t|	Heteroscedasticity Consistent Standard Error	t-value	Pr > |t|
Intercept	6.23460	0.06639	93.92	<.0001	0.07732	80.63	<.0001
State							
IA	0.26809	0.02021	13.26	<.0001	0.02044	13.12	<.0001
MN	0.25929	0.02302	11.26	<.0001	0.02253	11.51	<.0001
ND	0.61568	0.02686	22.92	<.0001	0.02769	22.23	<.0001
NE	0.98498	0.02187	45.04	<.0001	0.02198	44.81	<.0001
SD							
Bridge Type							
Concrete	0.28486	0.08635	3.30	0.0010	0.09381	3.04	0.0024
Other	0.67458	0.05633	11.98	<.0001	0.06866	9.82	<.0001
Steel	0.35378	0.07782	4.55	<.0001	0.09311	3.80	0.0001
Timber							
Bridge Design							
H_10	0.25013	0.11168	2.24	0.0251	0.12321	2.03	0.0423
H_15	0.28616	0.01941	14.74	<.0001	0.02245	12.75	<.0001
H_20	0.48593	0.01849	26.28	<.0001	0.01980	24.54	<.0001
HS_15	0.52719	0.08324	6.33	<.0001	0.10294	5.12	<.0001
HS_20	0.76971	0.01765	43.61	<.0001	0.01915	40.19	<.0001
HS_20+	0.87432	0.03505	24.95	<.0001	0.02976	29.38	<.0001
HS_25	0.88668	0.02998	29.58	<.0001	0.02780	31.89	<.0001
Other							
Operating Rating							
≤ 40 kips	-1.27792	0.02300	-55.55	<.0001	0.03069	-41.64	<.0001
≤ 60 kips	-0.68362	0.02096	-32.62	<.0001	0.02400	-28.48	<.0001
≤ 80 kips	-0.23620	0.01473	-16.03	<.0001	0.01509	-15.65	<.0001
> 80 kips							
ADT Class							
0-100	0.31876	0.02056	15.51	<.0001	0.01878	16.98	<.0001
101-1,000	0.37676	0.02132	17.67	<.0001	0.01936	19.46	<.0001
1,001-5,000	0.25202	0.02176	11.58	<.0001	0.01890	13.34	<.0001
> 5,000							
Age	-0.03820	0.0004279	-89.28	<.0001	0.0004889	-78.14	<.0001

As shown in Figure 2, a concrete HS-20 plus bridge in North Dakota with 500 ADT and an operating rating greater than 80,000 pounds is projected to have a substructure condition rating of 6.65 after 40 years and 6.28 after 65 years of service. In comparison, a concrete HS-15 bridge in the same categories is projected to have a substructure condition rating of 6.26 after 40 years and 5.90 after 65 years of service. A bridge in one of the lower design categories (H-15) is expected to have a substructure condition rating of 6.05 after 40 years and 5.69 after 65 years of service. Specific curves for more than 2,500 unique combinations of bridge design, material, operating rating, and state can be generated from the model. No interaction terms (e.g., bridge type and age) were statistically significant.

The model developed in this study can be used to estimate deterioration rates for subsets or classes of bridges defined by bridge material, design, operating rating, average daily traffic, and state. The model is appropriate for system and subsystem planning in which the objective is to provide agency managers with strategic information. However, the model should not be used for project evaluation, where specific consideration of individual bridge elements and local factors is essential.

Figure 2: Substructure Condition Ratings for North Dakota Concrete Bridges with 101-1,000 ADT and Operating Ratings > 80,000 pounds



In conclusion, it is important to summarize the key information not available for this study: (1) The history and timing of maintenance expenditures for each bridge are unknown. While maintenance expenditures are reflected in the deterioration rates, they are not explicitly represented as variables in the model. (2) The condition ratings are scored by different people. As a result, human variations are reflected in the evaluations. (3) Many individual bridge effects such as the frequency of unusual loadings, maintenance, deicing practices, and initial and extreme conditions are not reflected in the models. (4) More detailed models are possible by predicting the conditions of individual bridge elements. However, this approach would require many individual regression equations and is beyond the scope of this paper.

References

Dunker, K.F. and B.G. Rabbat. "Highway Bridge Type and Performance Patterns." *Journal of Performance of Constructed Facilities* 4(3), 1990: 161-173.

Jiang, M. and K. C. Sinha. "Bridge Service Life Prediction Model Using the Markov Chain." *Transportation Research Records* 1223, Transportation Research Board, Washington, D.C., 1989.

Kallen, M.J. and J.M. Van Noortwijk. "Statistical Inference for Markov Deterioration Models of Bridge Conditions in the Netherlands." P.J. Cruz, D.M. Frangopol, and L.C. Neves, eds. *Bridge Maintenance, Safety, Management, Life-Cycle Performance and Cost: Proceedings of the Third International Conference on Bridge Maintenance, Safety and Management*. London: Taylor & Francis (2006): 535-536.

Kim, Y.J and D.K. Yoon. "Identifying Critical Sources of Bridge Deterioration in Cold Regions Through the Constructed Bridges in North Dakota." *Journal of Bridge Engineering* 15, (2010): 542-552.

Kutner, M., C. Nachtsheim, and J. Neter. *Applied Linear Regression Models*, 4th edition. McGraw-Hill Irwin, New York, NY, 2004.

Madanat, S. M., M.G. Karlaftis, and P.S. McCarthy. "Probabilistic Infrastructure Deterioration Models with Panel Data." *Journal of Infrastructure Systems* 3, (1997): 4-9.

U.S. Department of Transportation. *2008 Status of the Nation's Highways, Bridges, and Transit: Performance Report to Congress.* Washington, D.C., 2010.

***Denver Tolliver** is director of the Transportation & Logistics program and associate director of the Upper Great Plains Transportation Institute at North Dakota State University. He is also the director of the five-university Mountain-Plains Consortium, which is one of USDOT's designated university transportation centers. He holds doctoral and master's degrees from the Virginia Polytechnic Institute in environmental design & planning and urban & regional planning, respectively. Since 1989, Tolliver has been awarded $23 million in competitive research grants from federal and state agencies and private industries to conduct highway, railway, waterway, and multimodal analyses. He recently received the 2011 Institute of Transportation Engineers award for Innovation in Transportation Education.*

***Pan Lu** is a doctoral student in the Transportation & Logistics program at North Dakota State University, and currently serves as a graduate research assistant. She also works as a research analyst at the Upper Great Plains Transportation Institute. She received her B.S. in engineering economics from North China Electric Power University of Beijing in 2002. Her current research interests include GIS application in transportation, asset management, multimode transportation efficiency analysis, and transportation resiliency analysis. Lu's recent research activities include road impacts of agriculture product flows, multimodal transportation fuel efficiency analysis, pavement performance modeling, multi-objective pavement preservation decision making, and bridge performance studies.*