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Multiscale Condition and Structural Analysis of Steel Bridge Infrastructure

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16. Abstract
The deteriorating state of the nation's highway infrastructure is well known. Yet, the data that exists or can be obtained regarding the condition and behavior of this infrastructure presently exceeds the profession's ability to make efficient use of said data. In this work, the depth and breadth of three data types (NBI data, owner inspection report data, and finite element analysis data) are integrated to identify structural characteristics leading to above- or below-average performance, after accounting for important differences in climate, use, etc. Each of these data types has been used for various applications, but this is the first known study that has systematically evaluated the inter-relationships between these data types. The piloted methodology is found to be successful. Specifically, the database that was built and corresponding analysis process is successful at identifying outliers that perform significantly better or worse than their counterparts. Furthermore, from the subset of these outliers that are selected for modeling, clear differences in the structural behavior of the good and inferior bridges were observed. Namely, the maximum stresses in the inferior bridge are the result of stress concentrations at connections, which includes the use of a bent plate to connect the transverse stiffener to cross-frame elements. A second key finding is that most of the inferior bridges are not affected by structural issues, but rather are suffering from corrosion problems. This highlights the continued need for better corrosion mitigation strategies both in initial design and in the maintenance of highway bridges.

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1. INTRODUCTION

1.1 Background

The deteriorating state of the nation's highway infrastructure is well known. Yet, the data that exists or can be obtained regarding the condition and behavior of this infrastructure presently exceeds the profession's ability to make efficient use of said data. Existing data sets span an enormous range of relative breadth and depth. For example, the breadth of the National Bridge Inventory (NBI) is comprehensive, but relatively basic with respect to structural condition. At the opposite extreme, state of the art structural models (i.e., finite element analysis) of individual structures can be created that give accurate and detailed information on the stress and displacement profiles throughout the structure under diverse loading conditions, but are only performed on rare occasions where the level of effort involved in their creation is worthwhile. Between these two extremes is element level data recorded by owners that quantifies more precise information on the severity and extent of deteriorated conditions than the NBI. Each of these data types has been used for various applications, but there are no known studies that have attempted to systematically identify and evaluate the inter-relationships between these data types.

1.2 Objective, Scope, and Organization

The objective of this project is to integrate this gradient of breadth and depth that can be described by these existing methodologies to identify structural characteristics leading to above- or below-average performance, after accounting for differences in climate, use, etc. This objective is achieved through the efforts described in the following chapters of this report. In summary:

- Chapter 2 discusses analysis of NBI data. Historical NBI data from agencies in six different climates are compiled. To create a comprehensive yet manageable database, NBI records from every three years for the entire historical record of the NBI are compiled. The latitude and longitude of each of these structures, as given in the NBI, is then associated with weather and atmospheric chemical concentration databases using GIS to fully quantify the environmental conditions at each structure. Then, multivariate regression analysis is used to describe the trends in superstructure condition rating as a function of site condition. This allows bridges that are outliers, with superstructure condition ratings significantly above or below the average condition of the population when accounting for site condition influences, to be identified. Validation of the multi-linear regression models that are developed is also presented.

- Chapter 3 discusses inspection report data. Specifically, inspection reports are requested from the owners of selected outliers identified in Chapter 2. For inferior performing bridges, the element-level data from these reports is used to separate bridges that are outliers due to structural issues from bridges that are outliers due to other causes (most typically, corrosion).

Inferior bridges due to structural issues are then candidates for further analysis via finite element analysis (as discussed in Chapter 4). For both inferior and good performing outliers, the inspection reports are also reviewed for information on the structural configuration of the bridges. This is an additional consideration in selecting bridges for further analysis so that good and inferior bridges with some similarities are selected in order to facilitate later comparisons in performance.

- Chapter 4 discusses finite element analysis data. Here the modeling of the bridges and the observed similarities and differences in the structural behavior of good and inferior performing bridges is discussed.
- Chapter 5 presents conclusions from this work and recommendations for future work.

2. ANALYSIS OF NBI DATA

2.1 Introduction and Overview

Bridge deterioration in the United States is a common issue with 9.1% of the nation's bridges being structurally deficient (ASCE, 2017). Bridge deterioration can be caused by different environmental and structural conditions. Because bridges perform differently in different climates and because of widespread corrosion issues, identifying the structural design parameters that are associated with inferior performance cannot be readily determined based on NBI data. This chapter describes developing and implementing a process for identifying outliers in the NBI data that have superstructure condition ratings significantly above and below the average condition of the population when accounting for age, average daily traffic volume, and environmental variables. In other words, bridges that have exceptionally good or inferior performance relative to other bridges subjected to the same conditions are identified.

There are two main parts to the evaluation of NBI performed in this work: (1) building the geographic information system (GIS) database to associate NBI data and environmental data and (2) performing multiple-linear regression analysis to quantify the relationship between environmental and structural condition. Six states with different climates are selected. Then National Bridge Inventory (NBI) data, atmospheric chemical concentration data, and climatic data is collected from every three years throughout the history of the NBI and associated to each bridge location using GIS. Next, multiple linear regression analysis is conducted and outliers with superstructure condition ratings above and below threshold values determined herein are identified for each year for which NBI data was analyzed. With outliers for each year identified, the frequency of each outlier over the entire range of years that are considered is summed to determine the most extreme outliers in the dataset.

2.2 GIS Database

This section contains two parts: the details of the different data types considered and the process of associating this data to bridge locations using GIS. As a result, a database of steel bridges in six states, Florida, Arizona, California, Delaware, Pennsylvania, and Montana is created that describes the NBI data, chemical data, and climate data at each steel bridge location.

2.2.1 Data types

2.2.1.1 NBI Data

Bridges were selected in six different climate categories from the International Energy Conservation Code (International Code Council, 2012) climate zone definitions, which are also being used by the Long Term Bridge Performance Program (FHWA, 2017). The six climates considered are: hot and humid, hot and dry, temperate and humid, temperate and dry, cold and humid, and cold and dry. Consequently, six corresponding states are selected based on the climate in all or part of the state, the number of steel bridges available, and the perceived ability to coordinate with the owners of these bridges in subsequent stages of the research. These corresponding states are Florida, Arizona, Delaware, California, Pennsylvania, and Montana, respectively.

NBI data is collected from every three years from 1992 to 2015 in order to result in a reasonably sized data set. While there are more than one hundred items recorded in the NBI data, the following seven items are relevant to this work.

- Item 43 (Structure Type): This is used to determine the bridge material and type of design. The structure types are limited to steel and steel continuous for stringer/multiple-beam or girder, consistent with the scope of this work.
- Item 27 (Year Built): This is used to attain the age of the bridge.
- Item 106 (Year Reconstructed): This is used to determine if the bridge has been reconstructed because this will be the effective age of at least part of the structure. Thus, to simplify and provide consistency to the data analysis, bridges that have been reconstructed are removed from the dataset.
- Item 59 (Superstructure Condition Rating (SCR)): This is used to determine the physical condition of all structural members including girders, beams, and cross frames. An integer value from 0 to 9 is used to define the superstructure condition of bridges. A 9 represents the excellent condition. A 0 means a failed condition and a 1 indicates an imminent failure condition. Because bridges in this severely poor condition are not expected to yield information useful to the research effort, bridges that are represented by 0 and 1 are removed from the dataset.
- Item 29 (Average Daily Traffic): This is used to assess the possible influence of the volume of traffic carried by the bridge.
- Item 16 and Item 17 (Latitude and Longitude): These geographic coordinates are used to locate the bridge in GIS and then to associate the structural data from the NBI with environmental data.

2.2.1.2 Chemical Data

The chemical data considered in this project are Cl^-, NO_3^- and SO_4^{-2} concentrations. Higher levels of these ions may lead to accelerated corrosion and accordingly have been used in prior work (McConnell et al., 2016). These specific ions are selected because they are available via the National Atmospheric Deposition Program database. Because this data is available for multiple years and the performance over multiple years is the subject of this research, the average value from 1992 to 2015 (the same data range for which NBI data is considered) for each recording station is used.

2.2.1.3 Climate Data

The climate data considered is snowfall, precipitation, temperature, humidity, and wind obtained from the National Oceanic and Atmospheric Administration (NOAA 2016a, NOAA 2016b, and NOAA 2016c).

2.2.2 Associating NBI and Environmental Data

GIS software (ArcGIS, 2016) is used to associate the chemical and climate data with the NBI data. The specific process used to do this is that the NBI data are regarded as a "target feature" and the environmental data are regarded as "join features". The latitude and longitude from the NBI data is used to identify the closest environmental station by using the "spatial join" tool and the "closest geodesic match" option is used to match the environmental attributes to the bridges.

2.3 Data Analysis Method

The multiple linear regression analysis method is used to explore the relationship between superstructure condition rating and different variables including age of bridge, average daily traffic (ADT) carried by the bridge, chemical data, and climate data. There are four steps to this analysis that are described in the following subsections, respectively: database development, multiple linear regression model development, determining outliers, and model validation.

2.3.1 Database Development

Prior to data analysis, the output file from GIS is prepared. Because it is obvious that the effects of atmospheric ion concentrations on bridge corrosion is cumulative (i.e., a bridge built in 1965 has been subjected to more chemical effects than a bridge built in 2014), the age of each bridge is multiplied by the average chemical concentration value over the considered date range (1992 to 2015) to express the cumulative effect of age and atmospheric chemical concentrations. The age of each bridge is also multiplied by average precipitation and snowfall from 1981 to 2010 (the available data range, NOAA 2016a) to account for the cumulative effect. Superstructure condition rating is used as the dependent variable in the regression analysis and Table 2.1 shows the independent variables. In later tables, the terms "humidity" and "wind" are used to more concisely represent the average relative humidity and average wind speed.

2.3.2 Multiple Linear Regression Model Development

There are two primary steps in the model development: determining the correlation between each variable and conducting stepwise regression to obtain the multiple linear regression model. Determining the correlation between each of the variables includes determining if any of the independent variables are highly correlated with one another as well as determining the relationship (including if there is a positive or negative correlation) between each independent

Table 2.1: Independent Variables

Independent Variable	Units of Measure
Age	Years
Average Daily Traffic (ADT)	Number of vehicles per day
Cl^{-}	Mg/L*year * Number of years = Mg/L
NO_3^{-}	Mg/L*year * Number of years = Mg/L
SO_4^{2-}	Mg/L*year * Number of years = Mg/L
Precipitation	Inches/year * Number of years = In.
Snowfall	Inches/year * Number of years = In.
Temperature	Degrees Fahrenheit
Average Relative Humidity	Percent
Average Wind Speed	Miles per hour (MPH)

variable and the dependent variable. Evaluating the correlation among independent variables is important because this influences the significance of the variable in the model and may change the sign of the coefficient in front of the independent variables (Jia et al., 2009). Therefore, adding an interaction term of the two independent variables or deleting one of them should be considered. Also, determining the correlation between each independent variable and the dependent variable gives an approximate understanding of which independent variable will contribute more to the superstructure condition rating.

The forward stepwise regression method (Kabacoff, 2011) is used to develop the multiple linear regression models. This is an approach to select a final set of independent variables from many candidate variables. The criteria for selecting or not selecting a variable is based on the following three items: adjusted R-squared value, which is the percentage of variation in the dependent variable that is explained by variation in the independent variable; residual standard error, which is a measure of variation of the observation around the regression line and directly related to the adjusted R-squared value; and P value for the t-test (confidence level), which quantifies the significance of each variable to the model. The independent variable with the highest adjusted R-squared value (and thus lowest standard error residual) is initially added to the model. Then, at each step, the influence of adding each remaining variable to the model is assessed and the variable that increases the adjusted R-squared value the most is added if the variable is significant (P value$\leq$ 0.05). The process terminates when none of the remaining variables are significant.

The functional form for the resulting multiple linear regression models in this project is

$$y = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n + \varepsilon \tag{2.1}$$

where y is superstructure condition rating; x_i is each independent variable; a_i is each coefficient that describes the functional relationships between the dependent and independent variables; and ε is the variable. Different multiple linear regression models are developed for each year of NBI data in order to produce the best fit to the data as some of the independent (e.g., ADT) variables and the dependent (superstructure condition rating) variable varies with time. Furthermore, there are differences in which bridges are contained in each year of data as new bridges are built and others are taken out of service.

2.3.3 Determining Outliers

Based on the multiple linear regression equation for each year of data resulting from the process described in Section 2.3.2, an expected value of superstructure condition rating for each bridge in each year can be calculated. Then, the difference between the calculated value based on the average performance as a function of all independent variables listed in Table 2.1 and the actual value is calculated; this value is termed the error, for conciseness. Good performing bridges are those with actual superstructure condition ratings much greater than the expected value (large positive magnitude of error) while inferior performing bridges have actual values significantly below the expected values (large negative magnitude of error), based on the average condition of the population when accounting for all variables.

Next, a quantified threshold for the magnitude of error at which the bridge is considered good or inferior must be determined. The primary criteria used to determine this was to attempt to generally have at least 50 bridges that are considered good outliers and 50 bridges that are considered inferior outliers in each year of the data. This number is selected in order to evaluate the overlap in the number of times a given bridge appears as an outlier over multiple years. It is then determined that the most consistent rationale is to rank the absolute value of the errors in terms of the percentage of the data that exceeded different values of error. For example, Table 2.2 shows data from the 2015 dataset. Here it can be seen that 94.0% of the data has an error of 1.64 or greater, that 94.5% of the data has an error of 1.66 or greater, etc. Table 2.2 also shows that the number of bridges with positive error (> than the error threshold) is less than the number of bridges with negative error ($\leq$ the error threshold). In other words, there are significantly more inferior outliers than good outliers for given error value. As a result, a higher error threshold is selected for defining an inferior outlier than for defining a good outlier. Specifically, a good outlier is generally defined as one in which the error exceeds the 94.5 percentile for the dataset

Table 2.2: Example Percentile Distribution of Possible Error Thresholds for Defining Good and Inferior Bridges and Associated Number of Bridges, based on 2015 Dataset. Selected percentiles are highlighted in yellow.

Percentile	Error Threshold	# of Bridges, >Error Threshold	# of Bridges, <=Error Threshold
94.0%	1.64	73	152
94.5%	1.66	62	144
95.0%	1.69	50	138
95.5%	1.74	41	128
96.0%	1.78	30	120
96.5%	1.84	22	109
97.0%	1.91	15	98
97.5%	2.02	11	83
98.0%	2.09	8	67
98.5%	2.24	5	52
99.0%	2.46	3	35
99.5%	2.75	0	19
99.6%	2.90	0	15
99.7%	2.95	0	12
99.8%	3.23	0	8
99.9%	3.78	0	4

for that year and an inferior outlier is generally defined as one in which the error exceeds the 98.0 percentile for the dataset for that year. Exceptions to this are discussed in Chapter 3.

Once the outliers are identified in this way, the number of times a bridge appears as an outlier in all years of the database is summed. The bridges with the largest sums are considered to be the outliers within the entire database.

2.3.4 Model Validation

Model validation is performed to check the appropriateness of model by checking if the multiple linear regression analysis satisfies the four statistical assumptions underlying the model. These assumptions are that the errors should be normally distributed, zero mean, constant variance and independent. Results of this validation are presented in Section 2.4.4.

2.4 Results

This section presents this results of each of the four steps of the data analysis method described in Section 2.3: developing the database, creating the multiple linear regression model, identifying the outliers, and validating the model.

2.4.1 Database Development

Table 2.3 shows an excerpt of the database, where the various data types that have been integrated using GIS are reported for representative bridges in a representative year. This serves as the raw data for developing the multi-linear regression model for each year in the following step.

2.4.2 Model Development

As a result of the forward stepwise approach described in Section 2.3.2, a multi-linear regression model is created for each year of data in the database. As an example, the 2015 model is described by Equation 2.2 along with the variables and coefficients in Table 2.4.

$$Superstructure\ condition\ rating = a_0 + \Sigma a_n x_n \tag{2.2}$$

Table 2.3: Excerpt of Structural and Environmental Database

State	Structure ID	Year Built	Age (Years)	ADT (# of Vehicles Per Day)	SCR	Average Relative Humidity (Percent)	Average Wind Speed (Miles Per Hour)	Temperature (Degrees Fahrenheit)	Precipitation (In)	Snowfall (In)	NO_3^- (Mg/L)	Cl^- (Mg/L)	SO_4^{2-} (Mg/L)
4	740	1965	50	200	6	53	6	51	1116	3690	44	6	24
4	741	1965	50	100	6	53	6	51	1116	3690	44	6	24
4	816	1966	49	200	6	41	8	53	510	157	61	8	40
4	843	1965	50	5967	7	53	6	51	1116	3690	44	6	24
4	844	1965	50	100	3	53	6	51	1116	3690	44	6	24
4	845	1965	50	7902	5	41	8	56	351	405	62	8	41
4	863	1965	50	1000	7	35	6	71	750	10	44	6	24
4	885	1965	50	1537	5	36	8	67	672	0	48	7	41
4	887	1965	50	2466	6	36	8	67	672	0	48	7	41
4	889	1965	50	2300	6	53	6	55	548	200	44	6	24
4	890	1965	50	2300	7	53	6	53	548	200	44	6	24
4	893	1965	50	12000	7	35	6	66	608	15	45	25	35
4	894	1965	50	8100	7	35	6	71	533	15	45	25	35
4	896	1966	49	500	6	53	6	44	1135	3768	43	5	24
4	921	1966	49	8116	7	53	6	75	188	0	43	5	24
4	923	1966	49	800	7	53	6	69	369	5	43	5	24
4	926	1966	49	50	7	53	6	69	369	5	43	5	24
4	930	1968	47	1800	5	41	8	55	406	259	58	8	39
4	931	1967	48	600	7	41	8	55	415	264	60	8	39
4	941	1965	50	1600	7	35	6	71	492	0	45	25	35
4	944	1965	50	200	7	35	6	71	525	0	45	25	35
4	945	1965	50	3000	7	35	6	71	525	0	45	25	35

Table 2.4: Coefficients and Variables for 2015 Model

Variable	Description	Coefficient	Value
---	Constant	a_0	7.721
x_1	Age	a_1	-4.53E-02
x_2	ADT	a_2	1.47E-06
x_3	Cl^-	a_3	-6.57E-02
x_4	SO_4^{-2}	a_4	-6.35E-03
x_5	Temperature	a_5	2.03E-02
x_6	Humidity	a_6	-4.06E-03
x_7	Wind	a_7	-4.82E-02
x_8	Cl^-: Age	a_8	1.59E-03

The 2015 model is created using seven variables with associated coefficients, one interaction item, Cl^-: Age (which is the product of the two variables), and one constant item, a_0, to obtain the predicted superstructure condition rating. All variables included are significant based on the P value for the t-test being smaller than 0.05. Compared to the ten independent variables identified in Table 2.1, NO_3^-, snowfall, and precipitation are not included in the model. NO_3^- is excluded because it has a high correlation with SO_4^{-2} and using SO_4^{-2} but not NO_3^- in the model provides a better fit to the data. Snowfall is excluded because snowfall is correlated with temperature and using temperature but not snowfall provides a better fit to the data. Precipitation is not included because when adding this, it and the previously selected humidity variable became not significant. Because the chemical concentration data is expressed as the product of the atmospheric concentration and the age of the structure, the coefficient for Cl^- became positive when adding this term along with age, due to the high correlation between these two variables. Therefore, an interaction term that is the product of Cl^- and age (Cl^-: Age) is added to the model, which results in Cl^- having a logical negative coefficient. Models for other years are reported in Table 2.5. This shows that the 2015 model is a representative model, with similarities to other models (such as age, Cl-, and temperature being used in all models), but each model has differences to the 2015 model (such as including precipitation). Other models also contain interaction terms denoted by ":", indicating the product of two variables.

Table 2.5 also reports the variables used in the model for each year in the database and the corresponding residual standard error and adjusted R-squared. The relatively low adjusted R-

Table 2.5: Multiple Regression Analysis for Each Year Considered

Year	Model	Residual Standard Error	Adjusted R^2
1992	SCR = f(Age+ CL^-+Temperature+Precipitation+Wind)	1.0490	0.1071
1995	SCR = f(Age+ CL^-+Temperature+Precipitation+Wind)	0.9916	0.1655
1998	SCR = f(Age+ CL^-+Temperature+Precipitation+Humidity+ CL^-:Age)	0.9306	0.3045
2001	SCR = f(Age+ADT+ CL^-+Temperature+Precipitation+Wind+Precipitation:Age)	0.9742	0.2829
2004	SCR = f(Age+ADT+ CL^-+Temperature+Precipitation+Humidity+Wind+ CL^-:Age)	0.9585	0.3120
2007	SCR = f(Age+ADT+ CL^-+Temperature+Precipitation+Humidity+ CL^-:Age)	0.9314	0.3022
2010	SCR = f(Age+ADT+ CL^-+Temperature+Precipitation+Humidity+ CL^-:Age)	0.8565	0.3756
2013	SCR = f(Age+ADT+ CL^-+Temperature+Precipitation+Wind+ CL^-:Age)	0.8610	0.4015
2015	SCR = f(Age+ADT+ CL^-+Temperature+SO4+Humidity+Wind+ CL^-:Age)	0.8641	0.3790

squared values are expected given the tremendous amount of scatter than exists in NBI SCR. The residual standard error measures variation of the observations around the regression line. That indicates the strength of fit by reporting how far off the model is. Another observation of the model results shown in Table 2.5 is that the models describing newer NBI records have lower residual standard error and higher adjusted R-squared values, perhaps indicating greater inspection consistency in more recent years.

2.4.3 Determining Outliers

The difference between expected and actual values is computed for each bridge for each year in the database, which is termed the error. Then different possible thresholds for the error at which the bridge is considered to be an outlier are evaluated based on the absolute value of the error corresponding to different percentiles of the data for the given year as described in Section 2.3.3. Based on the defined threshold criteria discussed in Section 2.3.3 (generally the 94.5 percentile of error quantifies a good performing outlier and the 98.0 percentile quantifies an inferior outlier; exceptions to this are discussed in Chapter 3), the outliers are determined as described in Section 2.3.3, by summing the number of years in which a given bridge is quantified as an outlier. Tables 2.6 and 2.7 summarize the results of this analysis for good and inferior performing bridges, respectively, by listing all bridges that are classified as an outlier in more than one year of data.

2.4.4 Model Validation

There are four assumptions made in the prior analysis. The degree to which these assumptions are satisfied primarily affects the accuracy of using the model to make predictions about other data based on the existing data (Kabacoff, 2011). While the present models are not used for prediction purposes, the four assumptions are nonetheless evaluated for completeness.

The four assumptions are that the residuals have linearity, constant variance, normality, and independence. The residuals represent the difference in the estimated and observed values (i.e., the error). The residuals are generally assessed for set of values of independent variables. A set values of independent variables is represented by the variable $X_i = (x_{1i}, x_{2i}, \ldots)$. Then, the multilinear regression model can be expressed as:

Table 2.6: Good Performing Outliers

Structure Number	2015	2013	2010	2007	2004	2001	1998	1995	1992	Outlier Score
GP1	1	1	1		1	1	1			6
GP2	1	1	1		1	1	1			6
GP3		1	1		1	1	1			5
GP4	1	1	1		1					4
GD1	1		1		1	1				4
GA1	1	1	1							3
GA2	1	1	1							3
GA3					1	1	1			3
GA4					1	1	1			3
GA5					1	1	1			3
GA6					1	1	1			3
GA7					1	1	1			3
GA8					1	1	1			3
GA9					1	1	1			3
GD2			1		1	1				3
GP5						1	1	1		3
GP8					1	1	1			3
GP9					1	1	1			3
GP10						1	1	1		3
GA10					1		1			2
GA11		1	1							2
GA12						1	1			2
GC1					1	1				2
GD3					1	1				2
GD4					1	1				2
GD5					1	1				2
GD6					1	1				2
GD7					1	1				2
GD8					1	1				2
GD9						1	1			2
GD10						1	1			2
GD11	1	1								2
GD12					1	1				2
GM1					1	1				2
GM2			1		1					2
GM3					1	1				2
GP6		1	1							2
GP7	1		1							2
GP11						1	1			2

$$y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \quad (2.3)$$

where y_i is the predicted value, β_0 and β_1 are constants and ε_i is the residual (error), which is intended to have the characteristics of a random variable if the model assumptions are true. The additional meaning of these assumptions and extent to which these assumptions are satisfied is herein evaluated for the multiple linear regression model for 2015, as an example.

- Normality

The normality assumption is that the residuals at each set of values of the independent variables are normally distributed. Creating a normal probability plot of the residuals is an effective way to check this assumption. A normal probability plot compares the distribution of sample data to

Table 2.7: Inferior Performing Outliers: (a) with Outlier Score ≥ 3

Structure Number	2015	2013	2010	2007	2004	2001	1998	1995	1992	Outlier Score
IC1	1	1	1		1	1	1			6
IM1				1	1	1	1	1	1	6
IP1			1		1	1	1	1	1	6
IC2	1	1		1	1	1				5
IC3	1			1	1	1	1			5
IC4	1			1	1	1	1			5
IC5	1	1	1	1	1					5
IM2	1	1	1	1		1				5
IP2					1	1	1	1	1	5
IC6	1		1	1	1					4
IC7	1	1	1		1					4
IC8	1	1	1						1	4
IC9	1				1	1	1			4
IF1	1		1	1			1			4
IF2		1	1	1	1					4
IP3	1	1	1		1					4
IA1	1	1	1							3
IA2	1	1		1						3
IA3	1	1				1				3
IC10	1		1	1						3
IF3			1	1	1					3
IP4	1	1	1							3
IP5	1	1	1							3
IP6	1	1					1			3
IP12	1	1	1							3
IP13	1	1	1							3
IP14	1	1	1							3
IP15	1	1						1		3
IP16			1		1	1				3
IP17						1	1	1		3
IP18						1	1	1		3

Table 2.7: Inferior Performing Outliers: (b) with Outlier Score = 2

Structure Number	2015	2013	2010	2007	2004	2001	1998	1995	1992	Outlier Score
IA4	1	1								2
IA5	1	1								2
IC11						1	1			2
ID1	1	1								2
ID2	1	1								2
ID3		1		1						2
ID4								1	1	2
ID5								1	1	2
IM3			1	1						2
IM4							1	1		2
IF4	1	1								2
IP7	1	1								2
IP8	1	1								2
IP9		1	1							2
IP10			1		1					2
IP19	1		1							2
IP20	1	1								2
IP21	1	1								2
IP22	1	1								2
IP11	1	1								2
IP23	1	1								2
IP24	1	1								2
IP25					1	1				2
IP26					1	1				2
IP27			1		1					2
IP28			1		1					2
IP29		1	1							2
IP30		1	1							2
IP31		1	1							2
IP32		1	1							2
IP33		1	1							2
IP34		1	1							2
IP35			1					1		2
IP36			1			1				2
IP37						1	1			2
IP38						1	1			2
IP39							1	1		2
IP40							1	1		2
IP41							1	1		2

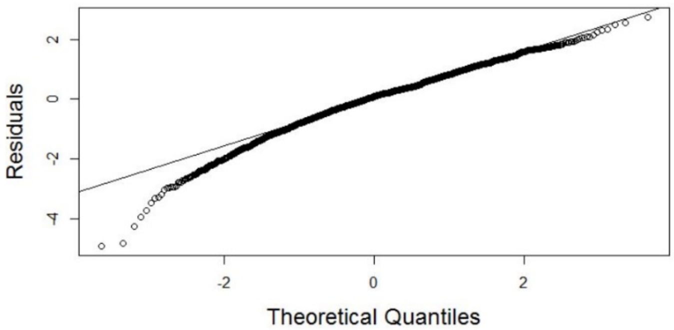

Figure 2.1: Normal Probability Plot of Residuals

a theoretical standard normal distribution by plotting the residuals versus the theoretical quantiles, as shown in Figure 2.1. Quantiles are associated with values below which a certain proportion of sample data fall. For example in standard normal distribution, 0.5 corresponds to the 0 quantile meaning that 50% of the data are below the 0 quantile and 0.95 corresponds to the 1.64 quantile meaning that 95% of the data is below the 1.64 quantile. These quantile values can be found according to a standard normal probability table.

In Figure 2.1, the y-axis is the value of the residuals from the sample data and the x-axis is the quantile of the corresponding probability of whether or not the sample value is exceeded in a theoretical normal distribution. Then, if the sample data (residuals) are normally distributed, the points form a straight line. Therefore, whether the normal probability plot of residuals is a straight line or not is used to check the normality assumption.

In Figure 2.1, the normal probability plot of residuals is a straight line except some extreme negative residuals at the bottom left. Thus, the error terms are not very normally distributed (Kabacoff, 2011). This is likely to be due to not removing the abnormal values (outliers) at the onset of the analysis given that the goal of this work was to identify whether SCR is truly an outlier when viewed relative to its environment. Thus, even though the assumption is not well satisfied, there is not anticipated to be any negative consequences of this for the present purposes of identifying outliers.

- Linearity

The linearity assumption is that the mean of residuals at each set of values of the independent variables is zero. This is termed the linearity assumption because if the mean of residuals is zero for all sets of independent variables (X_i), the mean value of y_i will be a value that results in a linear function between X_i and y_i.

Creating a scatter plot of residuals versus estimated values is a common method for evaluating this assumption. If the mean of each residual at each set of values of the independent variables

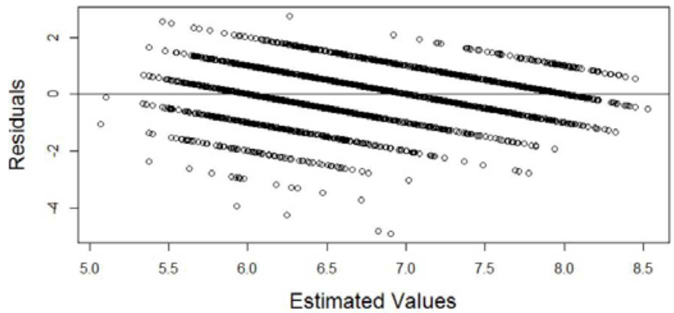

Figure 2.2: Residuals versus Estimated Values Plot

is 0, the data will fall into a fixed region around the horizontal axis. Figure 2.2 shows all points except some extreme negative residuals at bottom fall into the fixed region around 0. Furthermore, while it is not a precise evaluation that the average of the residuals at all combinations of the independent variables is zero, it is noted that the average of residuals for the entire dataset is 0.00000. Therefore, the linearity assumption is satisfied. It is noted that the diagonal pattern to the data in Figure 2.2 is likely associated with the fact that the actual values are integers.

- Equal Variance

The equal variance assumption is that the residuals at each set of values of the independent variables have equal variances. If the variance at each set of values of the independent variables is equal, the data will fall into a fixed region around 0 line with the distribution of the values of the residuals being similar at all estimated values. From Figure 2.2, all points generally fall into a horizontal region between ±3. Therefore, the equal variance assumption is satisfied.

- Independence

Independence means the dependent variable for each set of values of the independent variables is uncorrelated with others. In the present dataset, each dependent variable, bridge superstructure condition rating, is uncorrelated with others because each bridge does not influence other bridges. Therefore, the assumption of independence is satisfied.

Thus, it is concluded the model assumptions are sufficiently validated for use of this model for the present purposes.

2.5 Discussion and Conclusions

Based on a review of the models in Table 2.5 and the resulting outliers in Table 2.6 and Table 2.7 for good and inferior bridges, respectively, it is observed that there are two sets of models, 1992 to 1995 versus 1998 to 2015. Within each of these time periods, the models describe similar deterioration trends. The later models also result in a better fit to the data, perhaps due to more uniform standards now being applied to SCR.

The inspection reports for selected outliers that have been identified through the process described in this chapter are requested from their owners, as described in Chapter 3. The element-level data from these reports is used to initially confirm that this process does result in identifying bridges with exceptionally good or inferior performance and then used to identify inferior performing bridges with structural defects for finite element analysis in later stages of this work. The goal of the finite element analysis is to evaluate the potential differences in stress distribution between good and inferior bridges, as described in Chapter 4.

3. ANALYSIS OF INSPECTION REPORT ELEMENT LEVEL DATA

After good and inferior performing bridges are identified as outliers based on the combined analysis of the NBI and climate data presented in Chapter 2, inspection reports from these bridges are requested from their owners in order to review the element level data. This allows for confirmation that bridges previously determined to be good outliers are in relatively good condition. This also permits a more refined assessment of the inferior characteristics of bridges that are identified as inferior outliers. For example, bridges that have inferior performance due to corrosion or over-height trucks impacting highway overpasses can be separated from bridges that have inferior performance due to structural issues such as fatigue cracks or distortion. Reviewing the inspection reports also allows for more detailed information about bridge geometry to be determined for all bridges, which allows for the population of bridges to be compared and contrasted. As a result, bridges that are the best candidates for more detailed analysis via finite element analysis are identified.

This chapter first describes the criteria that are used to request specific inspection reports from owners. Then a summary of these reports are given. Lastly, the rationale for selecting specific bridges for more detailed finite element analysis are described.

3.1 Criteria for Requesting Inspection Reports

From the larger population of good and inferior performing bridges that are identified in Chapter 2, the inspection reports of a subset of these bridges is requested. Subsets are selected to create a more manageable workload for the owners. The criteria used to identify this subset is the bridges' year built, the extent to which it is quantified as an outlier (i.e., based on the sum values in Table 2.6 and Table 2.7), and the owner of the bridge. In general, the bridge is considered an outlier if its error threshold is in the 94.5 percentile or above for good performing bridges and in the 98.0 percentile or above for inferior performing bridges (as is described in Tables 2.6 and 2.7). For clarity, the sums representing the number of years of data in which the bridge is classified as an outlier (shown in Tables 2.6 and 2.7) are herein referred to an "outlier score". The owner is a criteria in order to geographically balance the subset of bridges further considered and to explore the possibility of requesting more bridges from agencies that have provided timely information in past experience, which would facilitate maintaining the research schedule. As a result, different criteria are applied to the data in Table 2.6 and Table 2.7 based on the owner. Within each agency, newer bridges that are the most significant outliers, as quantified by their outlier score are selected. Newer bridges are prioritized in order to focus the research on the most current design and detailing practices as consistent with the overall research objective of possibly revealing new information about current practice.

The resulting criteria for requesting the inspection reports of good and inferior performing bridges for each agency is shown in Table 3.1 and Table 3.2, respectively. Based on these criteria, inspection reports for 32 good performing and 40 inferior performing bridges are requested from six different agencies.

The 28 good and 22 inferior bridges for which inspection reports are able to be obtained from their owners are listed in Table 3.3 and Table 3.4, respectively. Tables 3.3 and 3.4 use the same labeling convention that was used in Table 2.6 and 2.7: G or I represents a good or inferior performing bridge, respectively; the second letter indicates the first letter of the state agency owner; and the final number is an arbitrary identifier.

3.2 Inspection Report Summary

3.2.1 Inspection Report Format

In current standard inspection reports, bridges are represented by the National Bridge Elements (NBE) (AASHTO, 2010). Because only the superstructure of steel stringer/ multi beam bridges and steel girder bridges (FHWA, 1995) are considered in this project, the steel bridge superstructure elements of interest are those listed in Table 3.5.

Each element is inspected to determine its condition state with respect to various possible defects. In the Bridge Element Inspection Guide Manual, there are four types of defects for steel superstructures, namely: corrosion, cracking, connection and load capacity and four different

Table 3.1: Criteria for Selecting Specific Good Performing Bridges

State	Criteria
DE	All with 92 percentile and above error threshold and: (1) outlier score >= 4 or (2) outlier score with sum of 3 or 2 and built in 1982 or later
PA	All with 94.5 percentile and above error threshold and: (1) outlier scores >=4 or (2) outlier score with sum of 3 or 2 and built in 1982 or later
AZ	All with 94.5 percentile and above error threshold and outlier scores with of 3 (which was maximum score for this population)
FL	NA
MT	All with 94.5 percentile and above error threshold
CA	All with 94.5 percentile and above error threshold

Table 3.2: Criteria for Selecting Specific Inferior Performing Bridges

State	Criteria
DE	All with 92 percentile and above error threshold
PA	All with 98 percentile and above error threshold and: (1) outlier score >=4 or (2) outlier score of 3 or 2 and built in 1982 or later
AZ	All with 98 percentile and above error threshold and outlier score of 3 or 2
FL	All with 98 percentile and above error threshold
MT	All with 98 percentile and above error threshold
CA	All with 98 percentile and above error threshold and: (1) outlier score >= 3 or (2) outlier score of 2 and built in 1982 or later

condition states (CS) for each defect (AASHTO, 2010). Table 3.6 summarizes the four condition states for each possible defect. In some states, like Delaware (DeLDOT, 2017) and Montana (MDOT, 2015), additional defects are included, such as distortion and damage with four condition states for these defects.

3.2.2 Data from Subject Bridges

The inspection reports for each bridge listed in Table 3.3 and 3.4 is reviewed to determine each bridge's defects, the extent of those defects if applicable, and more information about the structural layout of each structure. This is summarized in Table 3.7 and Table 3.8 for the good and inferior bridges, respectively. A label of "NA" indicates that the information is not available from the inspection reports available to the researchers.

For the good performing bridges, the goals of the review of the inspection reports are to confirm that the bridges are good performing as suggested by the prior data analysis, to document any defects in these structures, and to identify one or more bridges that are candidates for finite element analysis of the structural behavior of the structure. The ideal candidate for such modeling is one that is free from defects so that it satisfies the philosophical intent of being a good performing bridge and has relatively simple geometry while also being of modest size in order to facilitate modeling that can be executed and processed efficiently in the next phase of work.

Table 3.3: Good Performing Bridges for which Inspection Reports are Received

Structure Number	Year Built	Outlier Score
GD1	1981	4
GD2	1968	3
GD3	1972	2
GD4	1970	2
GD5	1967	2
GD6	1966	2
GD7	1971	2
GD8	1971	2
GD9	1967	2
GD10	1967	2
GD11	1982	2
GD12	1971	2
GP1	1965	6
GP2	1967	6
GP3	1965	5
GP4	1967	4
GP5	1983	3
GP6	1996	2
GA3	1965	3
GA4	1966	3
GA5	1968	3
GA6	1968	3
GA7	1966	3
GA8	1966	3
GA9	1967	3
GM1	1968	2
GM2	1968	2
GM3	1972	2

Table 3.4: Inferior Performing Bridges for which Inspection Reports are Received

Structure Number	Year Built	Outlier Score
ID1	2006	2
ID2	1967	2
ID3	1980	2
ID4	1975	2
ID5	1975	2
IP2	1979	5
IP3	1991	4
IP4	1985	3
IP5	1985	3
IP6	1984	3
IP7	2008	2
IP8	1997	2
IP9	1997	2
IP10	1997	2
IF1	1966	4
IF2	1990	4
IF3	1991	3
IF4	1973	2
IM1	1970	6
IM2	2004	5
IM3	1975	2
IM4	1971	2

Table 3.5: Steel Bridge Superstructure Elements Considered

Element #	Units	Element Title	Description
107	(L.F.)	steel open girder/beam	steel open girder units including stiffeners regardless of protective system
113	(L.F.)	steel stringer	steel stringers that support the deck in a stringer floor beam system regardless of protective system
881	(EA)	steel diaphragm	steel diaphragms regardless of protective system

Table 3.6: Condition State Definitions for Defects (AASHTO, 2011)

Defect	Condition States			
	1	2	3	4
Corrosion	None.	Freckled Rust. Corrosion of the steel has initiated.	Section Loss. Steel pitting is evident without impact on load capacity.	The condition is beyond the limits established in condition state three (3) and /or warrants a structural review to determine the strength or serviceability of the element or bridge.
Cracking/ Fatigue	None.	Arrested Cracks Exist. Cracks with arrest holes, doubling plates or similar in place.	Moderate Exists. Identified cracks that are not arrested or otherwise addressed.	
Connections	Sound.	Sound. Connections are in place and functioning as intended.	Isolated Failures. Missing bolts/rivets, broken welds or a severed connection.	
Load Capacity	No Reduction.	No Reduction.	No Reduction.	

Table 3.7: Summary of Good Performing Bridges' Inspection Data

Structure ID	Defects	Span	Girder	Comments	Results
GD1	corrosion	3	7	geometry complicated: many girders	ignore
GD2	corrosion	1	NA	unclear structural layout	ignore
GD3	corrosion	2	5	geometry complicated: many girders	ignore
GD4	corrosion	3	6	geometry complicated: many girders	ignore
GD5	corrosion	5	12	geometry complicated: many girders and spans	ignore
GD6	corrosion	4	11	geometry complicated: many girders	ignore
GD7	corrosion	2	4	geometry complicated: curved	ignore
GD8	corrosion	2	4	geometry complicated: curved	ignore
GD9	corrosion	3	6	geometry complicated: many girders	ignore
GD10	corrosion	3	6	geometry complicated: many girders	ignore
GD11	corrosion	1	4	99% CS1	select
GD12	corrosion	1	10	geometry complicated: many girders	ignore
GA3	corrosion	5	NA	78.2 % CS1	ignore
GA4	corrosion	4	NA	100% CS3	ignore
GA5	corrosion	4	NA	100% CS2	ignore
GA6	corrosion, distortion, damage	3	NA	damage caused by vehicle impact	ignore
GA7	corrosion, distortion, damage, connection	3	NA	damage caused by vehicle impact	ignore
GA8	corrosion, damage	3	NA	damage caused by vehicle impact	ignore
GA9	corrosion, distortion	5	NA	distortion caused by vehicle impact	ignore
GM1	corrosion	1	7	60% CS2	ignore
GM2	damage	2	NA		ignore
GM3	corrosion	4	6	91.7% CS1	ignore
GP1	corrosion	3	5	geometry complicated: many spans	ignore
GP2	no defects observed	2	2	SCR = 8 (no condition state data)	possible future work
GP3	corrosion	3	5	geometry complicated: many spans	ignore
GP4	no defects observed	1	6	SCR = 8 (no condition state data)	possible future work
GP5	no defects observed	2	6	steel cross frame diaphragms have rust	ignore
GP6	no defects observed	1	6		ignore

Table 3.8: Summary of Inferior Performing Bridges' Inspection Data

Structure ID	Defects	Span	Girder	Comments	Results
ID1	corrosion, connection and diaphragms corrosion	12	8	geometry complicated: many girders and spans	ignore
ID2	corrosion, distortion and diaphragms corrosion	4	8	distortion (span 3)	select
ID3	corrosion, damage and diaphragms corrosion	2	8	damage caused by impact	ignore
ID4	corrosion, distortion and diaphragms corrosion	2	5	distortion caused by corrosion (span 1), distortion caused by impact (span 2)	ignore
ID5	corrosion and diaphragms corrosion	5	5	geometry complicated: many girders and spans	ignore
IM1	corrosion	NA	NA	culvert	ignore
IM2	corrosion	1	4		ignore
IM3	distortion	1	NA	unclear structural layout	ignore
IM4	corrosion, cracking	2	5	cracking due to impact	ignore
IF1	corrosion	3	NA		ignore
IF2	NA	NA	NA	terminus for a ferry	ignore
IF3	NA	NA	NA	terminus for a ferry	ignore
IF4	NA	NA	NA	culvert	ignore
IP2	corrosion	1	5		ignore
IP3	corrosion	1	10	geometry complicated: many girders	ignore
IP4	corrosion	1	5		ignore
IP5	corrosion	1	8		possible future work
IP6	corrosion	1	7		ignore
IP7	damage, collision	1	10	damage caused by impact	ignore
IP8	corrosion	1	4		ignore
IP9	corrosion	1	5		ignore
IP10	corrosion	1	4		ignore

For the interior performing bridges, the primary goals of the review of the inspection reports are to confirm that the bridges are inferior performing as suggested by the prior data analysis by documenting the types and extent of defects in these structures and to identify one or more bridges that are candidates for finite element analysis of the structural behavior of the structure. The candidate for such modeling is one that has distortion or cracking defects with the distortion or cracking caused by structural behavior (as opposed to impacts from over-height vehicles for example) and is ideally of modest size in order to facilitate modeling (same as with the good performing bridge criteria).

3.3 Selecting Specific Bridges for Structural Modeling

The data in Table 3.7 is reviewed to identify a good performing bridge for further evaluation using finite element analysis. As can be seen by the data reported in Table 3.7, the majority of the bridges are relatively large, having multiple spans. Furthermore, all of the bridges have some type of defect. None of these defects are structural, but rather are typically corrosion defects. Vehicle impacts are also the cause of some defects. With these facts in mind, Bridge GD11 is selected for further evaluation because of its relatively modest size and because only 1% of the bridge is in a condition state other than 1 with this 1% being due to corrosion rather than structural problems. The structural plans for this bridge are then requested from the owner.

The data in Table 3.8 is reviewed to identify an inferior performing bridge for further evaluation using finite element analysis. As can be seen by the data reported in Table 3.8, the majority of these bridges also have corrosion defects. In fact, the option for a bridge with defects related to structural behavior is limited to only Bridge ID2. Thus, this bridge is selected for finite element modeling and analysis and the structural plans for this structure are requested from the owner.

4. FINITE ELEMENT ANALYSIS DATA

4.1 Methodology

4.1.1 Modeling Process

Building the finite element models starts with drawing the geometry in Abaqus CAE v. 6.14-1, the pre- and post-processing software associated with the commercial finite element software Abaqus. This geometry consists of lines with geometric coordinates that represent the geometry of the bridges. The line geometry is then used to create an element mesh. Once the mesh has been created, boundary and loading conditions are then applied to nodes on the element mesh. The completed model is then processed and post-processed.

4.1.2 Element Selection

All elements (girder flanges and webs, stiffeners, cross-frames, deck, haunch, and connection plates) are modeled using a multipurpose reduced-integration four-node shell element, labeled as type S4R in Abaqus. These elements have 3 translational and 3 rotational degrees of freedom and are selected based on successful past performance and validation of this element type for this type of modeling (e.g., Radovic, 2017).

4.1.3 Element Connections

Connections between all steel components is achieved by merging coincident nodes where members and member components intersect. Composite action between the concrete deck and steel girders is modeled using Abaqus' tie constraint to specify connectivity between the surfaces of the top flanges, haunches, and concrete decks. Both types of connections constrain translations and rotations of the connected nodes or surfaces, respectively.

4.1.4 Material Modeling

Concrete and steel are the materials that are modeled for the purpose of this study. The concrete is modeled as isotropic linear elastic material with an elastic modulus computed based on the compression strength prescribed in the design documents for the structures. The steel is modeled as elastic-plastic isotropic material with a yield plateau equal to the minimum yield strength specified in the design documents and strain-hardening. All input is input in accordance with Abaqus requirements that plastic material input to be expressed in terms of true stress and logarithmic plastic strain. True stress (σ_T) is defined as the ratio of the external load to the instantaneous cross-sectional area of the loaded element and can be related to engineering stresses by Eqn. 4.1:

$$\sigma_T = \sigma_E(1 + \epsilon_E), \tag{4.1}$$

where σ_E is engineering stress and ϵ_E is engineering strain. Engineering strain (ϵ_E) is related to logarithmic plastic strain (ϵ_{ln}) by Eqn. 4.2:

$$\epsilon_{ln} = \ln(1 + \epsilon_E) - \frac{\sigma_T}{E_s}, \tag{4.2}$$

where E_s is the modulus of elasticity of steel. For small deformations, the difference between engineering and true stress is negligible. However, as strains exceed the elastic limit, the change in cross-sectional area increases, resulting in true stresses that can be significantly higher that engineering stresses.

4.1.5 Boundary Conditions

Boundary conditions are applied to the nodes of the bottom flange cross-sections where physical supports exist. In order to simulate the actual translation and rotation constraints, all of these nodes are constrained in the vertical direction. In addition, in order to model the supports at fixed bearings, the nodes at the transverse center of corresponding bottom flange cross-sections are constrained longitudinally (x-direction) and laterally (z-direction). In order to model the supports at expansion bearings, the nodes at the transverse center of corresponding bottom flange cross-sections are constrained only laterally (z-direction). These nodes are constrained in the lateral direction to avoid instability problems in the analysis and to more accurately simulate the physical boundary conditions. Only the nodes at the transverse center of the bottom flange cross-sections, versus the entire bottom flange cross-section, are constrained in the longitudinal and transverse directions in order to avoid the effect of constraining minor axis rotation if the entire line of nodes is constrained. Otherwise, unrealistically large lateral bending strains would occur at this location.

4.1.6 Loading

The applied load consisted of self-weight in addition to an AASHTO HS20 design truck, with back, middle, and front axle loads of 32,000 lb, 32,000 lb and 8,000 lb respectively, spaced longitudinally at 14 ft and wheel lines spaced at 6 ft. For GD11, which is a single-span bridge, the load was centered on the bridge deck. For ID2, which consists of four continuous spans, the load is centered on one of the interior spans. This provides a relatively consistent and convenient basis for comparison between the two models. It should not be implied that this is the overall worst-case load position for all components of all bridges.

4.1.7 Completed Models

Figs. 4.1 and 4.2 show the completed mesh, with the deck hidden in order for the steel superstructure to be seen, for bridges GD11 and ID2, respectively.

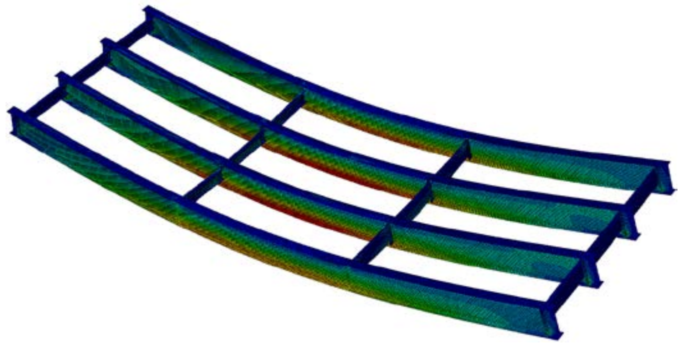

Figure 4.1: Finite Element Model for Bridge GD11

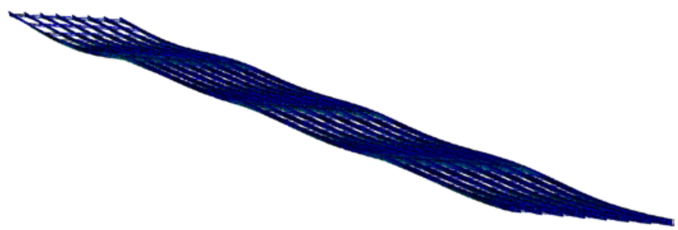

Figure 4.2: Finite Element Model for Bridge ID2

4.2 Results

4.2.1 Stress Results

Selected stress results from the two models are reported in Table 4.1. Specifically, the maximum von Mises stresses (S_{VM}) throughout the model, maximum S_{VM} occurring in the girders, and maximum directional stresses along the two local coordinate systems for each of the shell elements (S_{11} and S_{22}) are reported for each model. The von Mises stresses are computed by the Abaqus post-processing software according to the standard equation for predicting yielding according to the von Mises yield criterion, which is given in Equation 4.1.

$$S_{VM} = \sqrt{\frac{(S_{11}-S_{22})^2+{S_{11}}^2+{S_{22}}^2}{2}} \tag{4.1}$$

In other words, if the result of Equation 4.1 exceeds the yield stress, yielding is expected. In general, this equation is a convenient metric for considering and comparing different multi-axial stress states. For the girder elements in this work, S_{11} represents the longitudinal direction and S_{22} represents the perpendicular direction in the plane of the element (i.e., the transverse direction for girder flange elements and the vertical direction for web elements). The S_{11} and S_{22} values reported in Table 4.1 are the maximum absolute values of these quantities that are obtained in the models.

Table 4.1 shows that the maximum girder stress in ID2 is twice the maximum girder stress in GD11. However, this difference is not surprising given assumed differences in yield stress. The girder flanges of ID2 have a nominal yield stress of 70 ksi. It is assumed that the GD11 girders are fabricated from A36 or A7 based on the inferred age of girders. Thus, the yield stress of ID2 is approximately twice the yield stress of GD11 and thus twice the girder stress is a logical result.

Another logical result is that for GD11 (the good performing bridge), the maximum S_{VM} stress is in the girders. This occurs at a logical location, in the bottom flange at midspan of one of the interior girders. In contrast, the maximum S_{VM} stress in ID2 (the inferior performing bridge) occurs in a bent connection plate between a cross-frame and a vertical stiffener on an exterior girder at Pier 1. This stress is twice the maximum girder stress in ID2 and four times the maximum stress in GD11.

The maximum stress components in the local element directions for ID2 also occur in connecting elements. The maximum S_{11} value for ID2 occurs at the end of a bottom chord of the end diaphragm connecting to an exterior girder. The maximum value of S_{22} on ID2 occurs at the same location as the maximum S_{VM}, a bent connection plate between a transverse stiffener and cross-frame connecting to an exterior girder at Pier 1. It is noted that the cross-frames connecting this exterior girder to the adjacent interior girder contain a smaller top chord than all other cross-frames, which may be a reason why the highest stresses are associated with this girder and its connecting members.

For GD11, the maximum value of S_{11} occurs at the same location where the maximum S_{VM} value is observed, in the bottom flange at midspan of an interior girder. The maximum value of S_{22} for GD11 occurs in the web of an exterior girder adjacent to a diaphragm connection.

Table 4.1: FEA Stress Results Summary

Bridge	Maximum S_{VM} (psi)	Maximum S_{VM} in girders (psi)	S_{11} (psi)	S_{22} (psi)
GD11	9332	9332	9332	9291
ID2	40419	20399	37200	40929

4.2.2 Displacement Results

Selected displacement results from the two models are reported in Table 4.2. Specifically, the maximum overall displacement and maximum displacement in each of the three global coordinate directions used in the models are reported. Here, the 1-direction represents the longitudinal direction, the 2-direction is the vertical direction, and the 3-direction is the transverse direction.

Considering that the two bridges have significantly different span lengths and span configurations, significant differences in vertical displacement are expected. However, the differences in longitudinal and transverse displacements clearly indicate that ID2 is subjected to significantly more distortion than GD11. In fact, the transverse displacement in ID2 is 40 times the maximum transverse displacement in GD11.

4.2.3 Concluding Comments

The FEA results successfully capture differences in the behavior of the good and inferior bridges that are modeled which could be correlated with differences in the structural condition of these two bridges. The good performing bridge (GD11) is found to have stress and displacement results that follow common assumptions of structural response. Namely, the maximum stress occurs at midspan of the bottom flange and out-of-plane displacements are minimal. In contrast, the inferior performing bridge (ID2) is found to have significant stress concentrations in connecting elements between the girders and the cross-frames, which create stresses that are twice the maximum bending stress in the girders. The transverse displacements observed in this bridge is also significantly larger than the good performing counterpart. Both of these FEA observations correlate with the distortion observed in the field conditions of GD11.

Table 4.2: FEA Displacement Results Summary

Bridge	U (in.)	U_1 (in.)	U_2 (in.)	U_3 (in.)
GD11	0.541	0.140	0.537	0.015
ID2	3.499	0.507	3.478	0.647

5. CONCLUSIONS

5.1 Summary

This work consists of three primary parts: building a database integrating structural and environmental data of steel bridges and analyzing this data to determine outliers with respect to structural performance relative to each bridges' environment; reviewing owner inspection reports of the outliers; and creating and analyzing finite element models of a representative good and inferior outlier. This methodology is piloted as a potential means to identify structural characteristics leading to above- or below-average performance, after accounting for differences in climate, use, etc.

5.2 Key Findings

The piloted methodology is found to be successful. Based on the database that is built and analyzed, owner inspection reports for 50 bridges are reviewed. This review shows that the database and corresponding analysis process is successful at identifying outliers that perform significantly better or worse than their counterparts. Furthermore, from the subset of these outliers that are selected for modeling, clear differences in the structural behavior of the good and inferior bridges were observed. Namely, the maximum stresses in the inferior bridge are the result of stress concentrations at connections, which includes the use of a bent plate to connect the transverse stiffener to cross-frame elements.

A second key finding is that most of the inferior bridges are not affected by structural issues, but rather are suffering from corrosion problems. This highlights the continued need for better corrosion mitigation strategies both in initial design and in the maintenance of highway bridges.

5.3 Future Work

The finding that the inferior bridge that is modeled using finite element analysis has significant stress concentrations could be viewed as somewhat intuitive. In the future, it is envisioned that the developed methodology could be used to screen for the unique structural features of outlier bridges, and the modeling could be reserved for the purpose of confirming whether intuitive findings such as these are proven true or false. This would enable the piloted methodology to be used for maximum efficiency in identifying the structural characteristics of bridges with significantly above- or below-average performance relative to their environments.

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