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INDIANA DEPARTMENT OF TRANSPORTATION
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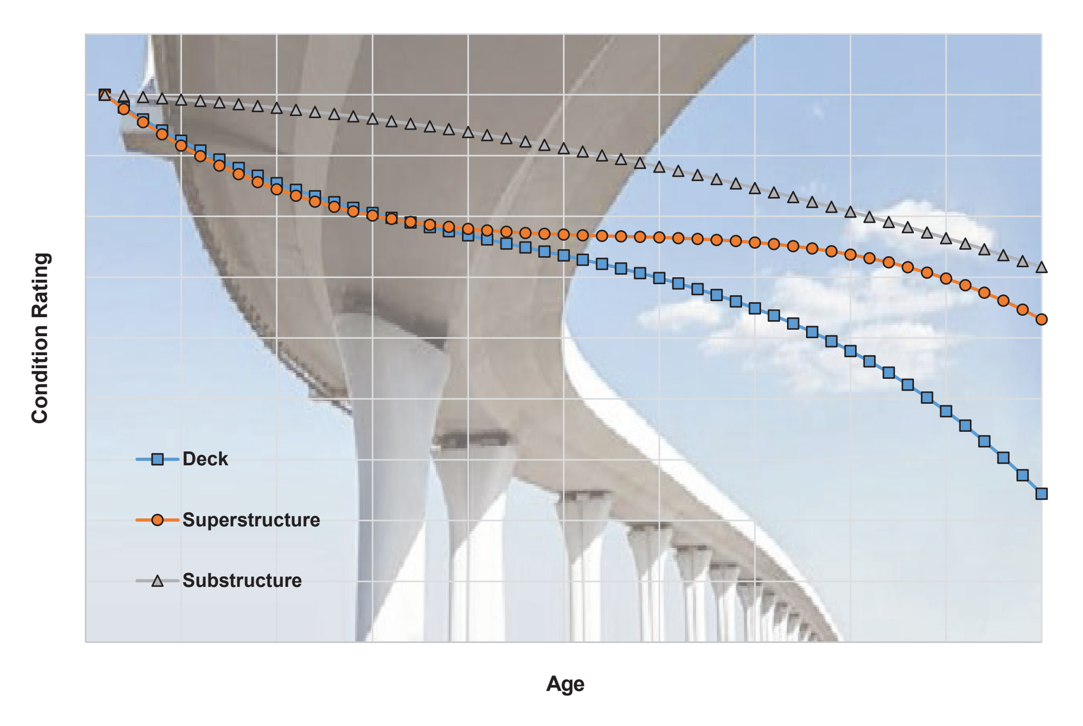
Bridge Deterioration Models to Support Indiana's Bridge Management System



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JOINT TRANSPORTATION RESEARCH PROGRAM

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16. Abstract

An effective bridge management system that is equipped with reliable deterioration models enables agency engineers to carry out monitoring and long-term programming of bridge repair actions. At the project level, deterioration models help the agency to track the physical condition of bridge elements and to specify when bridge maintenance, rehabilitation and replacement can be expected. Also, with reliable deterioration models, the agency can customize bridge repair or replacement schedules that incorporate element condition, functional obsolescence, and pre-specified performance thresholds. At the network level, component-specific deterioration models are useful for system-wide needs assessment over a specified future time horizon, and to quantifying the system-wide consequences of funding shortfalls or funding increases in terms of specified performance measures including average values of bridge condition and remaining service life.

The bridge deterioration models that are currently in use in the Indiana Bridge Management System were developed over two decades ago. Since then, significant changes have taken place in inspection methods, technologies used, advanced statistical tools for data analysis. Also, because of the lack of reliable data, such items as the truck traffic and climate conditions were not included in past modeling efforts. In recent years, these obstacles have been minimized and therefore, there is an opportunity to update the deterioration models for the various bridge components.

In addressing this research need, the present study developed families of curves representing deterioration models for bridge deck, superstructure, and the substructure. The National Bridge Inventory database was used, and the models use the NBI condition ratings as the response variable. The model families were categorized by administrative region, functional class, and superstructure material type. The explanatory variables include traffic volume and truck traffic, design type, and climatic condition, and design features. Deterministic and probabilistic models were developed.

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EXECUTIVE SUMMARY

BRIDGE DETERIORATION MODELS TO SUPPORT INDIANA'S BRIDGE MANAGEMENT SYSTEM

Introduction

An effective bridge management system that is equipped with reliable deterioration models enables agency engineers to carry out monitoring and long-term programming of bridge repair actions, and therefore has uses at both project and network levels. At the project level, deterioration models help the agency to track the physical condition of bridge elements and to specify when bridge maintenance, rehabilitation, and replacement should be implemented. Also, with reliable deterioration models, the agency can customize bridge repair or replacement schedules that incorporate element condition, functional obsolescence, and pre-specified performance thresholds. At the network level, component-specific deterioration models are useful for system-wide needs assessment over a specified future time horizon, and for quantifying the system-wide consequences of funding shortfalls or funding increases in terms of specified performance measures that include the average bridge condition and remaining service life.

The bridge deterioration models that are currently in use in the Indiana Bridge Management System were developed over two decades ago. Since then, significant changes have taken place in inspection methods, technologies used, and statistical tools for data analysis. Also, because of the lack of reliable data, such items as truck traffic and climate conditions were not included in the past. In recent years, these obstacles do not exist, and therefore there is an opportunity to update the deterioration models for the various bridge components.

This study was commissioned by the Indiana Department of Transportation (INDOT) to address this research need. The study developed families of curves representing deterioration models for bridge deck, superstructure, and substructure. The National Bridge Inventory (NBI) database was used, and the models have the NBI condition ratings as their response variables. The model families were categorized by administrative region, functional class, and superstructure material type. The explanatory variables include traffic volume and truck traffic, climatic condition, and design type and features.

Findings

This study used the NBI database to develop families of deterioration curves for the bridge deck, superstructure, and substructure components. The study confirmed that environmental variables play a significant role in bridge deterioration. For several of the deterioration models, the climate variables of freeze index, number of freeze-thaw cycles, and average precipitation were found to be significant predictors of bridge component deterioration.

Compared to the superstructure and substructure, deck deterioration was found to be more affected by traffic loading. It was also observed that bridge components that had undergone some repair since their construction exhibited patterns of deterioration that were different when compared to those that had not received any such repairs, which can be explained by the salubrious effect of the repair actions. Also, for the same bridge material type and traffic loading, there were generally some differences in deterioration across the Indiana regions, but this was not always the case.

Implementation

The research product was designed to facilitate implementation of the study product (that is, the bridge deterioration models) in the bridge management system. This was done to demonstrate that they are appropriate and useful for the purpose for which they are intended. With the study product, INDOT is expected to be in a better position to monitor the condition of its bridges for purposes of bridge management, and also to generate the necessary input data for its bridge management system software packages. A reliable set of deterioration models can improve the processes and procedures for bridge rehabilitation scheduling, and thus help to avoid the relatively lower levels of service associated with mistimed (hastened or deferred) rehabilitation or reconstruction. Improved deterioration models will provide greater confidence in the decisions made by INDOT regarding bridge investments.

It is expected that the primary user and implementer of the study product will be the bridge management office of the Indiana Department of Transportation.

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1. INTRODUCTION

1.1 Study Background

Deterioration models establish the current and future deterioration patterns of bridge elements over time. A bridge management system that is equipped with reliable deterioration models can assist bridge engineers with the tasks associated with long-term programming, planning, and needs assessment at both the project and network levels. At the project level, bridge engineers can utilize these models to track the physical condition of the bridge deck, superstructure, and substructure and thereby provide guidance in predicting the year at which a component's condition reaches agency-specified thresholds for rehabilitation or replacement. At the network level, bridge engineers use these deterioration models to measure the accumulated repair needs of the individual bridge components that, combined with activity cost models, can determine the system-wide financial needs over a specified futue time horizon. Deterioration models also play key roles in other agency business processes, such as highway cost allocation and asset valuation. These functions are facilitated utilized when the bridge manager is capable of reliably predicting the physical condition of each bridge component at any future date.

The bridge deterioration models currently used in the Indiana BMS were developed over two decades ago. Since then, there have been significant changes in construction techniques and technologies, materials, condition inspection methods, and loading patterns. The past few decades also have seen several opportunities, including advancements in statistical techniques for data analysis and model building. In addition, in the past few decades, there has been a surge in data resources in terms of the volume and variety of data types and items and data integrity and reliability. For example, data on truck volumes and climatic conditions are more readily available now, making it possible to develop models that account for these deterioration factors. These challenges and opportunities combined indicate that the time is ripe to develop new models to address the current modeling needs of INDOT bridge managers.

Deterioration models are typically developed separately for the wearing course, deck, superstructure, and substructure. For the wearing course, INDOT recently developed deterioration curves; however, the decades-old models continue to be used for the remaining components. INDOT therefore commissioned the present study to update the deterioration models for the remaining components.

1.2 Study Objectives and Scope

Objectives: The following objectives were established to address the motivation and problem statement:

a. Develop a set of bridge condition deterioration curves on the basis of the physical and operational characteristics, climate, and truck traffic. It is expected that separate models would be developed for the deck, superstructure, and substructure, from both deterministic and probabilistic perspectives.
b. Identify the factors that influence bridge component deterioration, and measure the direction and strength of the influence of each factor.

Scope: This study was directed to address only the bridges located on the state highway system (Interstates, U.S. roads, and state roads). These bridges were placed into "families" based on their material type, functional class, and administrative/climatic region, and were calibrated for each family. Bridges on local routes were excluded.

1.3 Organization of the Report

The entire report is presented in two parts. Part I (this part) is the main report, which summarizes the study and presents a synthesis of the literature, the study methodologies, and results. Part II provides details on the study's components (i.e., literature review, methodology, and results).

2. SYNTHESIS OF RELEVANT LITERATURE

A number of past research efforts related to bridge deterioration modeling are reviewed and discussed in this chapter. The discussion covers briefly the model functional form, the response variables, and the independent variables.

2.1 Modeling Techniques

The methodologies applied in past bridge deterioration studies were examined, starting with the regression-based models. In most such studies, the only explanatory variable considered was the bridge age. The regression approach, as used in previous studies, had a number of limitations, which included inadequate accounting for uncertainty and the influence of unobserved variables, lack of consideration of the historical condition of the bridge components, and absence of any accounting for past maintenance. However, these limitations relate more to the manner of application in past studies than in the inherent structure of regression models.

Another approach used in past bridge deterioration modeling is the Markov chain, a specific expression of stochastic processes. Its inherent assumption that the future condition is independent of the historical condition may lead to inconsistent prediction. The Markov process assumes, in theory, a programmed and fixed inspection interval for bridges occurs, but in practice, bridges can be inspected less or more frequently than programmed for reasons such as financial limitations and technical challenges. The Markov chain has its merits, such as accounting for the stochastic nature of deterioration, facilitation of the condition characterization of large bridge networks and its computational efficiency and simplicity.

The literature also contains a number of count data modeling techniques that were used in the past to develop bridge deterioration models. Of these, the two most commonly-used are the Poisson and negative binomial regression approaches. Unlike the Poisson approach, the negative binomial is flexible and relaxes the assumption of the mean being equal to the variance. Although count data techniques have been used in the past, the developed models were considered rather limited in their application to real practice because the model structure does not facilitate a direct linkage between the bridge condition and multiple explanatory factors. Furthermore, the models do not account for the ordinal scale of bridge condition ratings. To address these limitations, logit/probit models were considered in some of the past studies; however, these models fail to account for heterogeneity and the state dependence present in panel-structured bridge data. Another count model specification, the binary probit random effects model, was identified in other past studies as a promising technique that could incorporate state dependence and heterogeneity in the modeling framework.

Another bridge modeling approach discussed in the literature is the Bayesian technique, in which the uncertainty associated with estimation of the parameters is merged with the inherent variability of a random variable. In order to use the Bayesian technique, subjective judgments from experience can be analytically combined with the observed data to arrive at consistent and unbiased estimation. In past studies in Indiana, the Bayesian technique and binary probit random effects model both were used to predict the bridge condition states of bridge components and were duly validated.

The literature review also introduced a few other emerging approaches for bridge deterioration modeling, which include the Weibull-based probability density and artificial intelligence. Under the Weibull-based probability density approach, the length of time a bridge element stays at a specific condition or state is modeled as a random variable. Artificial intelligence modeling is another emerging technique being used for developing bridge deterioration, which is based on computer-based algorithms that mimic past patterns of bridge deterioration trends or behavior.

2.2 Response Variables

2.2.1 Condition Rating

Consistent with past literature, the response variable used in this study for modeling bridge deterioration is the National Bridge Inventory (NBI) component condition rating, which describes the overall physical condition of the bridge component. Condition ratings are discrete numbers that take values from 0 to 9. In the probabilistic models for each of the three component types, the response variable is the transition probability (i.e., the percentage of bridge components that transition from a higher condition state to a lower one).

2.3 Independent Variables

The following independent variables were considered in the present study.

2.3.1 Bridge Age

Past studies in the literature determined that bridge component age is the main factor of deterioration. Age is computed as the difference between the year of inspection and the year built or year of reconstruction. Intuitively, a higher age is generally associated with a more deteriorated condition.

2.3.2 Highway Functional Class

NBI Item 104 (highway system of the inventory route) of the "Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges" identifies the functional classes of bridges (National Highway System (NHS) or otherwise). It was observed in the past literature that the rate of deterioration is directly linked to the highway system or class of bridges on which they are located. In the literature, the effect of highway functional class was captured either by including that factor as an independent variable or by developing models separately for the NHS bridges and the non-NHS bridges.

2.3.3 Service under the Bridge

The service under the bridge indicates the facility or feature over which the bridge traverses. This feature may be a highway, railroad, pedestrian-bicycle routes, waterway, or other feature. In past studies, bridge deterioration was linked to the type of service under the bridge, namely, that bridges located over waterways tend to deteriorate faster than bridges traversing other features.

2.3.4 Number of Freeze-Thaw Cycles

Freeze-thaw cycles influence the deterioration patterns of bridges due to the pressures caused by the cyclic contraction and expansion of materials under temperature extremes.

2.3.5 Freeze Index

Past studies demonstrated that bridges located in cold climates exhibit deterioration patterns different from those in warmer climates. The freeze index, which is an expression of the severity and length of freezing conditions, is associated with volumetric changes that can lead to accelerated deterioration.

2.3.6 Average Daily Truck Traffic (ADTT)

Bridges exposed to high levels of truck traffic loading generally deteriorate faster than bridges with lower truck traffic volumes.

2.3.7 Number of Spans in Main Unit

Generally, a higher number of spans may be linked to poor condition.

2.3.8 Degrees Skew

Bridge skew describes the twist (in degrees) of the main span from the approach roadway in degrees. Bridges with higher degrees of skew are believed to generally deteriorate faster compared to bridges with little or no skew.

2.3.9 Bridge Length

As bridge length increases, the rate of deterioration also increases because longer bridges are associated with higher tensile forces in comparison to their shorter counterparts.

In summary, the lessons learned from the literature review were applied to the present study. Both stochastic and deterministic models were developed in the present study; and the findings of past research were used as a platform to identify the potential factors of deterioration, to guide the data collection process, and to establish a-priori expectations of the model outcomes. The next chapter discusses the methodology used for the present study.

3. DATA

3.1 Data Collection

The primary source of data for developing the bridge deterioration models in this study was the NBI database. The NBI data has a panel structure and includes bridge information spanning 1992 to 2014. Bridge components were inspected every two years and condition ratings were assigned to the components. The bridge data obtained from the NBI database included bridge geometric characteristics (bridge length, total deck width, degrees skew, and vertical clearance), functional class, highway system, type of material, type of construction design. Referencing data indicate the spatial position of the bridge with respect to the highway type, county, or milepost, highway district, and longitude and latitude. Other information collected included environmental data obtained from the National Oceanic and Atmospheric Administration (NOAA). The climate data are specific to each county in Indiana. Traffic data, which were obtained from the NBI database, include traffic volumes and percentage of trucks in the traffic stream. The maintenance data included the year of construction, last year of repair, and type of repair undertaken. The term “bridges with prior repair” refers to bridges that had received at least one rehabilitation activity since the original construction or reconstruction; and “bridges without prior repair” refers to those that had received no such activity.

3.2 Data Collation

3.2.1 Preliminary Checks on Data

The major limitation of the NBI data is that it represents the visual and subjective scores assigned by bridge inspectors. The technical knowhow and experience of the inspectors cannot be doubted. However, as with all subjective assessments that are also visual, there is often more potential for human error. Secondly, not all parts of the bridge component may be accessible for inspection. Thirdly, there may be some propensity for inspectors to assign specific ratings more on the basis of the bridge age and less on the bridge condition. Such “play it safe” rating assignment behavior may be more pronounced for bridges in their middle ages. Inspections of the same bridge by different inspectors potentially can result in different ratings being assigned to the same bridge component. Also, in certain cases, newly-constructed bridge components, contrary to expectations, do not have a condition rating of 8 or 9 in the NBI database. Due to these and several other limitations, certain researchers have argued that the use of the NBI condition ratings must be based on the assumption that the observed condition ratings are randomly distributed about their “true” values. Overall, the subjective and visual nature of bridge inspections could be introducing serious bias to the rating assignments. In spite of these challenges, the NBI database still represents the best dataset available for bridge deterioration analysis.

3.2.2 Data Preparation

Data filtering was carried out on the inspection data obtained from the NBI database in order to obtain a reliable dataset for developing the deterioration models. The filtering framework is as follows: (i) The models were developed for only state highways; thus, the data for local roads and other agencies (Tribal Governments, U.S. Forest Service, City or Municipal Highways) were filtered out. (ii) Data Coded N and 0 and this type of data constituted about 0.19% of the state highway observation data. (iii) Bridges >20 ft. in length were also filtered. The bridge length as defined in the “Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation’s Bridges” is the length of the bridge measured back to back of the back walls of abutments from paving notch to paving notch. In this specific regard, 29 observations corresponding to 0.03% of state highway data were deleted.

3.2.3 Maximum and Minimum Age Restriction Development

The NBI database indicated that there were a number of bridges whose components had been repaired or reconstructed at certain years, as evidenced in sudden sharp increases in their condition ratings. However, the dates of these activities were not recorded. Bridge components that had been replaced are considered new and therefore should have been assigned ages to match the "excellent" condition rating assigned to them. However, an individual component replacement may not necessarily mean the entire bridge has been replaced and the bridge age may only reflect the age of the entire bridge, rather than its component. Bridge age is calculated based on the year built or reconstructed. In the absence of work history data, bridge ages are calculated using the original built year, which consequently yields misleading and erroneous results corresponding to the component condition ratings. For example, a 50-year-old bridge deck is not expected to have a condition rating of 9; neither is a relatively new deck expected to have a condition rating of 2 or 3. Also, the NBI database has instances where there is a record of a work history which shows there was a component replacement but the records do not show a commensurate increase in condition rating of the component. These anomalous data values were found to be rather pervasive in the NBI database, unfortunately.

In order to address this issue, a limit was developed and imposed on the minimum and maximum ages a bridge begins and remains at a particular condition rating. Bridges that had undergone no prior repair were extracted in order to link bridge deterioration unaffected by major repairs and replacement with the development of the age restrictions. Bridges with no prior repair were found to represent approximately 30% of all the bridges.

3.2.4 Criterion for Outlier Identification

For each condition rating, the maximum and minimum ages at that rating were extracted from the database, which was done for each bridge components (deck, superstructure, and substructure). The ages at the different condition ratings were analyzed and the identified outliers were removed. For both the minimum and maximum ages, the data points that were at least one standard deviation from the mean were considered as outliers and were deleted. Volume II of this report presents the results of the data restriction and outlier deletion process for each of the three bridge components.

4. METHODOLOGY

4.1 Methodology for the Deterministic Models

As discussed in the literature review, the basic concept of a regression model is that it expresses a statistical relationship between a predictor and a response variable. This relationship is based on the tendency of the response variable to vary with the predictor in a systematic manner and a scattering of the points around the curve of the statistical relationship. In bridge deterioration modeling, regression analysis is used to derive parameter estimates or coefficients of independent variables, including climate, traffic loading characteristics, and age, which relate to the dependent variable (condition rating). The present study focuses on the deck, superstructure, and substructure components of Indiana's state highway bridges. The criteria for developing the bridge model families and the deterministic model structure are discussed in Sections 4.2 and 4.3 below.

4.2 Criteria for Developing the Bridge Model Families for the Deterministic Model

In order to develop reliable deterioration models that take into account unique bridge conditions and environmental factors, it was necessary to classify the data into homogeneous and consistent families. Another reason was to avoid including these factors as independent variables in the deterioration model because of confounding and interactions between the independent variables that would introduce bias and thus impair the models' predictive ability. The following categories of variables were used.

4.2.1 Highway Districts

INDOT has six highway districts which correspond to Indiana's three distinct climate regions: LaPorte and Fort Wayne are the northern districts, Crawfordsville and Greenfield are the central districts, and Vincennes and Seymour are the southern districts.

4.2.2 Highway Functional Class

Bridges were classified according to the highway system on which they are located. These classifications were based on whether the bridges are located on NHS or non-NHS roads.

4.2.3 Bridge Material Type

The superstructure material defines the bridge material type classification. On Indiana's state highways, the dominant material type is concrete, and is approximately evenly split between pre-stressed and cast-in-place concrete. The next dominant bridge superstructure material is steel. There are very few masonry and timber bridges on state highways and therefore these bridge types were excluded from the modeling process.

4.2.4 Superstructure Design Type

For each superstructure material type, models were developed for the predominant design types: stringer, box beam multiple and single, slab and arch deck.

4.3 Deterministic Model Structure

In developing the deterioration models, the functional forms that were investigated include:

a. Polynomial:

$$Y = \beta_o + \sum_{i=1}^{n} \beta_i x^i$$

If n = 1, then linear; If n = 2, then quadratic; If n = 3, then cubic.

b. Exponential /Logistic:

$$Y = \left(\beta_O + \sum_{i=1}^{n} \alpha_i \beta_i^{xi}\right)^k;$$

If k = 1, then Exponential' If k = -1, then Logistic.

c. Gompertz:

$$Y = \sum_{i=1}^{n} c_i \alpha_i^{\beta_i^{xi}}$$

Where Y represents a dependable variable, c_i, α_i and β_i represent estimable parameters, and x_i represents an independent variable.

The variables used for the deterministic modeling are shown in Table 4.1.

4.4 Methodology for Probit Models

As discussed in the literature review, the most common approaches for probabilistic modeling include the Markov chain, ordered probit, and the binary probit models. The estimation of ordered probit models using panel data is time consuming and rather cumbersome. Studies using panel data have discovered many problems, such as state dependence and heterogeneity, particularly in other disciplines and areas such as labor, economics, and highway safety where this modeling technique has been applied to model human behavior. The binary probit model was selected in the present study because the complexity associated with the estimation procedure could be simplified using binary probit models. The dependent variable is a 0/1 indicator variable for condition switching state. The developed binary probit models considered the discreteness of the condition states.

4.4.1 Dependent and Independent Variables

The choice of variables for the deck/superstructure/substructure deterioration modeling was guided by previous theoretical and empirical work on bridge deterioration analysis, intuitive arguments regarding the effects of exogenous variables, and data availability considerations. The dependent variable is a 0/1 indicator variable for the condition-switching state. If the deck/superstructure/substructure condition drops from one state to another in a single inspection interval, the switching state indicator is 1; if the condition state stays the same; the switching state indicator is 0. The condition state is a discrete number ranging from 0 to 9 as described previously. As a measure of performance, the NBI ratings were used instead of the sufficiency rating due to the need for consistency with existing practice at most highway agencies.

The independent variables included bridge age, truck traffic on the bridge (calculated as the product of the AADT and percent truck traffic), bridge superstructure material type, highway functional class, service under the bridge and climate effects (measured in terms of a regional variable that was determined by the highway district, freeze-thaw cycles, and number of cold days). This study also considered the bridge condition (measured in terms of the current condition rating and the switching state in the last inspection period), and rehabilitation history (measured in terms of the number of years from the last major work year to the current year). Table 4.2 presents the variables considered for the binary probit models.

TABLE 4.1
Model Variables

Variable		**Code**
Response Variables	Deck Condition Rating	*DCR*
	Superstructure Condition Rating	*SUPCR*
	Substructure Condition Rating	*SUBCR*
Independent Variables	Component Age (years)	*AGE*
	Skew	*SKEW*
	Type of Service Under Bridge	*SERVUNDER*
	Number of Spans in Main Unit	*SPANNO*
	Freeze Index (1000's of degree-days)	*FRZINDX*
	Number of Freeze-Thaw Cycles	*NRFTC*
	Average Daily Truck Traffic (in 1000s)	*ADTT*
	Interstate (1 if located on Interstate, 0 otherwise)	*INT*
	Deck Protection (1 if deck is protected, 0 otherwise)	*DECKPROT*
	Bridge Length	*LENGTH*

TABLE 4.2
Variables for Probabilistic Modeling

	Symbol	Description
Response Variables	*Z* (*i*, *t*)	Transition indicator in current year or the analysis year. If the condition drops from one state to another, $Z(i,t) = 1$, if the condition stays in the same state, $Z(i,t) = 0$;
Independent Variables	*Z* (*i*, *t*–1)	Transition indicator in previous inspection period. If condition dropped from one state to another, then $Z(i,t–1) = 1$; if the condition stayed in the same state, then $Z(i,t–1) = 0$;
	AGE	The primary age of bridge (years since construction or replacement)
	DIST	Dummy variable for highway district location of the bridge (1- Crawfordsville, 2-Fort Wayne, 3-Greenfield, 4- LaPorte, 5-Seymour, 6-Vincennes)
	SOUTH	Dummy variable for bridges located in Indiana's southern districts (1 if located in districts 5 or 6, 0 otherwise)
	IFSTEEL	Dummy variable for superstructure material type (1 if steel, 0 otherwise)
	YRTOTRAN	Number of years from the last year of transition to the current year
	RATING	Component condition rating at last inspection year (1 if condition 1-8, 0 otherwise)
	IFSTEEL	Dummy variable for bridges that have steel superstructure
	NHS	Dummy variable for bridges located on NHS route (1 if yes, 0 otherwise)
	URBAN	Dummy variable for bridges at urban location (1 if yes, 0 otherwise)
	SERVUNDER	Dummy variable for bridges under which the type of service is waterway
	WS	Type of wearing surface (1 surface has protective system, 0 otherwise)
	IFEXBI	Dummy variable for bridges with epoxy overlay or bituminous wearing surface
	COLDDAYS	Average of cold days ($<32°$F) per year
	NRFTC	Average number of freeze-thaw cycles per year
	HNRFTC	Dummy variable for bridges in the counties with NRFTC >60
	ADT	Average Daily Traffic
	ADTT	Average Daily Truck Traffic
	DECKIMPROV	Dummy variable for bridges whose deck ratings improved within the most recent five inspection periods (1 if yes, 0 otherwise)
	SUPIMPROV	Dummy variable for bridges whose superstructure ratings improved within the most recent five inspection periods (1 if yes, 0 otherwise)
	SUBIMPROV	Dummy variable for bridges whose substructure ratings improved within the most recent five inspection periods (1 if yes, 0 otherwise)

4.4.2 Model Specification

This study also developed binary probit models that involved the use of discrete response variables (specifically, the condition transition indicator, which is binary). The binary probit specification is as follows:

$$\Pr[Z(i,t)=1]=\Phi[\beta X+\varepsilon]$$

$$U(i,t)=\beta X+\varepsilon$$

Where: $Pr[Z(i,t) = 1]$ represent the probability that the component will transition to the next lower condition state. X = a vector of variables that influence the probability of condition transition for observation; β = a vector of estimable parameters; ε = is a random disturbance.

Of the several binary probit models that were developed, the best model form was selected on the basis of the goodness of fit and the engineering intuitiveness of the signs and the magnitudes of the parameters. For the binary probit models, the most common statistical measure to check the goodness of fit is the chi-squared statistic.

5. RESULTS

In this section, we discuss the results of the deterministic and probabilistic models. Table 5.1 presents the best functional form and the number of observations in each family of models or the deterministic models. In Table 5.2, the significant variables are presented for the probabilistic model.

5.1 Introduction

Six deterioration models were built for the bridge decks. The best models were either exponential or polynomial of the second or third order. Tables 5.1–5.3 present the detailed modeling results for bridge decks, superstructure, and substructure. The influential variables were found to be as follows: deck age in years (AGE), Interstate location (1 if located on Interstate, 0 Otherwise) (INT), angle of skew (SKEW), bridge length (LENGTH), type of service under bridge (SERVUNDER), number of spans in main unit (SPANNO), freeze index in 1,000s of degree-days (FRZINDX), average annual number of freeze-thaw cycles (NRFTC), ADTT in 1000s, deck protection = 1 with protective system, 0 otherwise, (DECKPROT). For the other bridge component types, similarly, the best functional forms were the exponential or polynomial of the second or third order, and the influential variables were those related to the bridge functional class, design features, traffic loading, and climate.

5.2 Results for the Probabilistic Deterioration Modeling

The results of the deterioration models were developed using the binary probit approach and calibrated on a LIMDEP platform. The statistical significance of the variables were assessed using a hypothesis test at a 5% significance level ($\alpha = 0.05$). The estimated models are presented as Equations 5.1, 5.2, and 5.3. Table 5.4 presents the significant explanatory variables in the probabilistic model.

Deck.

$$Pr[Z(i,t)=1]=\Phi[-2.041-0.699\cdot Z(i,t-1)+0.043\cdot YRTOTRAN+0.024\cdot ADTT-0.113\cdot SOUTH+0.005\cdot COLDDAY+0.136\cdot HNRFTC-0.275\cdot IFEPBI+0.149\cdot URBAN+0.075\cdot WATERWAY-0.006\cdot AGE-0.047\cdot RATING+0.561\cdot DECKIMPROV] \quad (5.1)$$

Superstructure.

$$Pr[Z(i,t)=1]=\Phi[-1.382-0.282\cdot Z(i,t-1)+0.028\cdot YRTOTRAN-0.186\cdot SOUTH+0.217\cdot HNRFTC-0.397\cdot IFSTEEL+0.102\cdot URBAN+0.096\cdot SERVUNDER-0.006\cdot AGE-0.0124\cdot RATING+0.263\cdot SUPERIMPROV] \quad (5.2)$$

TABLE 5.1
Summary of the Deterministic Models for Bridge Deck Deterioration

Bridge Component	Districts	Functional Class	Deterioration Model
Deck	Northern	NHS	$DCR = 8.55637 - 0.24129{\bullet}AGE + 0.0096{\bullet}AGE^2 - 0.0001667{\bullet}AGE^3 - 0.04301{\bullet}SERVUNDER - 0.01218{\bullet}SPANNO + 0.51375{\bullet}DECKPROT - 0.05182{\bullet}FRZINDX - 0.01872{\bullet}ADTT$
		Non-NHS	$DCR = 9.22454 - 0.24998{\bullet}AGE + 0.01158{\bullet}AGE^2 - 0.00021831{\bullet}AGE^3 - 0.00136{\bullet}SKEW - 0.01023{\bullet}SPANNO + 0.39602{\bullet}DECKPROT - 0.03037{\bullet}FRZINDX - 0.01397{\bullet}NRFTC - 0.08597{\bullet}ADTT$
	Central	NHS	$DCR = 8.1961 - 0.16459{\bullet}AGE + 0.0068\,{\bullet}AGE^2 - 0.0001442{\bullet}AGE^3 - 0.06213{\bullet}INT - 0.04249{\bullet}SERVUNDER - 0.0005587{\bullet}LENGTH + 0.50755{\bullet}DECKPROT - 0.00769{\bullet}NRFTC$
		Non-NHS	$DCR = 7.6959 - 0.09989{\bullet}AGE + 0.00234\,{\bullet}AGE^2 - 0.00005094{\bullet}AGE^3 - 0.06901{\bullet}SERVUNDER - 0.00119{\bullet}LENGTH + 0.33696{\bullet}DECKPROT - 0.03016{\bullet}ADTT$
	Southern	NHS	$DCR = 8.58845 - 0.09752{\bullet}AGE + 0.00341\,{\bullet}AGE^2 - 0.0000855{\bullet}AGE^3 - 0.00186{\bullet}SKEW - 0.00041603{\bullet}LENGTH + 0.53671{\bullet}DECKPROT - 0.06989{\bullet}FRZINDX - 0.04431{\bullet}ADTT$
		Non-NHS	$DCR = 8.05846 - 0.14617{\bullet}AGE + 0.00663\,{\bullet}AGE^2 - 0.00015219{\bullet}AGE^3 - 0.00098333{\bullet}LENGTH + 0.43363{\bullet}DECKPROT - 0.01421{\bullet}NRFTC - 0.06043{\bullet}FRZINDX - 0.14681{\bullet}ADTT$

TABLE 5.2
Summary of the Deterministic Models for Bridge Superstructure Deterioration

Bridge Component	District	Functional Class	Deterioration Model
Cast-in-Place Concrete Arch Deck	Northern	NHS	$SUPCR = EXP\ (2.28405 - 0.00731 \cdot AGE - 0.01578 \cdot SPANNO - 0.36788 \cdot FRZINDX)$
		Non-NHS	$SUPCR = EXP\ (2.1644 - 0.00673 \cdot AGE - 0.03545 \cdot SPANNO - 0.16104 \cdot FRZINDX - 0.03782 \cdot ADTT)$
	Central	NHS	$SUPCR = EXP\ (2.02476 - 0.00799 \cdot AGE - 0.0122 \cdot LENGTH)$
		Non-NHS	$SUPCR = EXP\ (2.03724 - 0.00798 \cdot AGE - 0.00106 \cdot SKEW - 0.0006104 \cdot LENGTH - 0.02451 \cdot ADTT)$
	Southern	NHS	$SUPCR = EXP\ (2.19722 - 0.00633 \cdot AGE + 0.18559 \cdot INT - 0.19154 \cdot SERVUNDER - 0.0005814 \cdot LENGTH)$
		Non-NHS	$SUPCR = EXP\ (2.05829 - 0.00734 \cdot AGE - 0.02018 \cdot SPANNO)$
Cast-in-Place Concrete Slab	Northern	NHS	$SUPCR = 9.5820 - 0.27195 \cdot AGE + 0.00874 \cdot AGE^2 - 0.0000933 \cdot AGE^3 - 0.1991 \cdot INT - 0.17981 \cdot SERVUNDER - 0.71169 \cdot FRZINDX$
		Non-NHS	$SUPCR = 8.85183 - 0.22032 \cdot AGE + 0.00598 \cdot AGE^2 - 0.00005627 \cdot AGE^3 - 0.11229 \cdot ADTT$
	Central	NHS	$SUPCR = EXP\ (2.10113 - 0.01135 \cdot AGE - 0.01968 \cdot INT - 0.01845 \cdot SPANNO)$
		Non-NHS	$SUPCR = EXP\ (2.13095 - 0.01255 \cdot AGE - 0.00027854 \cdot SKEW - 0.01169 \cdot SPANNO - 0.0933 \cdot ADTT)$
	Southern	NHS	$SUPCR = 8.1804 - 0.02287 \cdot AGE - 0.00058022 \cdot AGE^2 - 0.06369 \cdot SPANNO - 0.00942 \cdot LENGTH - 0.74059 \cdot FRZINDX - 0.29919 \cdot ADTT$
		Non-NHS	$SUPCR = 9.00 - 0.09891 \cdot AGE + 0.00108 \cdot AGE^2 - 0.00000876 \cdot AGE^3 - 0.00458 \cdot SKEW - 0.11453 \cdot SPANNO - 1.01643 \cdot FRZINDX - 0.21873 \cdot ADTT$
Cast-in-Place Concrete Stringer	Northern	NHS	$SUPCR = 9.62497 - 0.19661 \cdot AGE + 0.00646 \cdot AGE^2 - 0.00007503 \cdot AGE^3 + 0.18145 \cdot INT - 0.00288 \cdot SKEW - 0.02567 \cdot NRFTC$
		Non-NHS	$SUPCR = 9.00 - 0.14006 \cdot AGE + 0.00332 \cdot AGE^2 - 0.00003153 \cdot AGE^3 - 0.1991 \cdot SERVUNDER - 0.04507 \cdot SPANNO - 0.94618 \cdot FRZINDX$
	Central	NHS	$SUPCR = 9.00 - 0.0709 \cdot AGE + 0.0015 \cdot AGE^2 - 0.00002415 \cdot AGE^3 + 0.1544 \cdot INT - 0.12283 \cdot SERVUNDER - 0.02661 \cdot NRFTC$
		Non-NHS	$SUPCR = 9.00 - 0.09665 \cdot AGE + 0.00143 \cdot AGE^2 - 0.00001223 \cdot AGE^3 - 0.2726 \cdot SERVUNDER - 0.0154 \cdot NRFTC - 0.22006 \cdot ADTT$
	Southern	NHS	$SUPCR = 9.00 - 0.13354 \cdot AGE + 0.00495 \cdot AGE^2 - 0.00007504 \cdot AGE^3 - 0.00866 \cdot SKEW - 0.01625 \cdot NRFTC - 0.04244 \cdot ADTT$
		Non-NHS	$SUPCR = EXP(2.19722 - 0.00866 \cdot AGE - 0.07182 \cdot SERVUNDER - 0.06813 \cdot FRZINDX - 0.00161 \cdot NRFTC - 0.01764 \cdot ADTT)$
Prestressed Concrete Box Beam Multiple	Northern	NHS	$SUPCR = EXP(2.52216 - 0.01574 \cdot AGE - 0.21057 \cdot INT - 0.00629 \cdot NRFTC)$
		Non-NHS	$SUPCR = 9.88923 - 0.21844 \cdot AGE + 0.00939 \cdot AGE^2 - 0.00016916 \cdot AGE^3 - 0.04952 \cdot SPANNO - 0.02252 \cdot NRFTC$
	Central	NHS	$SUPCR = 7.86526 - 0.00146 \cdot AGE^2 + 0.89263 \cdot INT - 0.02073 \cdot SKEW - 1.08296 \cdot FRZINDX$
		Non-NHS	$SUPCR = 8.85961 - 0.00163 \cdot AGE^2 - 0.00583 \cdot SKEW - 0.32021 \cdot SERVUNDER - 0.10322 \cdot SPANNO - 0.02203 \cdot NRFTC$
	Southern	NHS	$SUPCR = 9.00 - 0.33126 \cdot AGE + 0.01619 \cdot AGE^2 - 0.00029693 \cdot AGE^3$
		Non-NHS	$SUPCR = 9.00 - 0.00085258 \cdot AGE^2 - 0.51398 \cdot FRXINDX - 0.03316 \cdot NRFTC$

(Continued)

TABLE 5.2
(Continued)

Bridge Component	District	Functional Class	Deterioration Model
Prestressed Concrete Box Beam Single	Northern	NHS	$SUPCR$ = 10.60812 – 0.00194•AGE^2 + 0.51923•INT – 0.20284•$SPANNO$ – 1.47489•$FRZINDX$ – 0.02781•$NRFTC$
		Non-NHS	$SUPCR$ = 9.00 – 0.16164•AGE + 0.00651•AGE^2 – 0.00011437•AGE^3 – 0.20539•$SERVUNDER$ – 0.0047•$LENGTH$ – 0.1666•$ADTT$
	Southern	NHS	$SUPCR$ = 9.00 – 0.00221•AGE^2 – 0.17157•INT – 0.00568•$LENGTH$ – 2.97178•$FRZINDX$
		Non-NHS	$SUPCR$ = 9.00 – 0.162•AGE + 0.00904•AGE^2 – 0.00020555•AGE^3 – 0.00996•$NRFTC$
Prestressed Concrete Stringer	Northern	NHS	$SUPCR$ = 9.67048 – 0.03572•AGE – 0.00076366•AGE^2 + 0.12316•INT – 0.00089223•$LENGTH$ – 0.66583•$FRZINDX$ – 0.0178•$NRFTC$
		Non-NHS	$SUPCR$ = 9.00 – 0.11174•AGE + 0.00366•AGE^2 – 0.00006889•AGE^3 – 0.00399•$SKEW$ – 0.05439•$SPANNO$ – 0.53304•$FRZINDX$
	Central	NHS	$SUPCR$ = 10.51217 – 0.00208•AGE^2 – 0.06621•$SPANNO$ – 0.0421•$NRFTC$
		Non-NHS	$SUPCR$ = 8.9232 – 0.00177•AGE^2 – 0.00465•$SKEW$ – 0.00153•$LENGTH$ – 0.01915•$NRFTC$
	Southern	NHS	$SUPCR$ = 8.50758 – 0.02473•AGE – 0.00101•AGE^2 – 0.00481•$LENGTH$ – 0.15089•$ADTT$
		Non-NHS	$SUPCR$ = 9.00 – 0.05674•AGE + 0.00123•AGE^2 – 0.00003815•AGE^3 – 0.43769•$SERVUNDER$ – 0.00319•$LENGTH$ – 0.00402•$NRFTC$
Steel Stringer	Northern	NHS	$SUPCR$ = 9.46753 – 0.19653•AGE + 0.00892•AGE^2 – 0.00016286•AGE^3 – 0.02808•$AVGPPN$
		Non-NHS	$SUPCR$ = 8.08791 – 0.10604•AGE + 0.00274•AGE^2 – 0.00003634•AGE^3 – 0.10482•$ADTT$
	Central	NHS	$SUPCR$ = 7.86936 – 0.09765•AGE + 0.00415•AGE^2 – 0.00008244•AGE^3 – 0.05396•INT – 0.02771•$SERVUNDER$ – 0.00027153•$LENGTH$ – 0.00362•$NRFTC$
		Non-NHS	$SUPCR$ = 8.27835 – 0.07275•AGE + 0.00104•AGE^2 – 0.00001068•AGE^3 – 0.00138•$SKEW$ – 0.00882•$NRFTC$
	Southern	NHS	$SUPCR$ = 9.00 – 0.10947•AGE + 0.00533•AGE^2 – 0.00009904•AGE^3 – 0.00297•$SKEW$ – 0.0148•$AVGPPN$ – 0.87639•$FRZINDX$ – 0.00786•$NRFTC$ – 0.0204•$ADTT$
		Non-NHS	$SUPCR$ = 8.05118 – 0.1127•AGE + 0.00444•AGE^2 – 0.00007786•AGE^3 – 0.10251•$SERVUNDER$ – 0.14818•$ADTT$
Steel Truss Thru	Northern	Non-NHS	$SUPCR$ = 9.00 – 0.14679•AGE + 0.00354•AGE^2 – 0.00004253•AGE^3 – 0.03021•$AVGPPN$
	Southern	Non-NHS	$SUPCR$ = EXP(2.19722 – 0.01288•AGE – 0.00249•$SKEW$ – 0.00259•$AVGPPN$ – 0.27557•$FRZINDX$)

Substructure.

$$Pr[Z(i,t)=1]=\Phi[-1.582–0.285\cdot Z(i,t–1)+0.023 \cdot YRTOTRAN-0.190\cdot SOUTH+0.228\cdot HNRFTC +0.056\cdot URBAN+0.292 \cdot SERVUNDER–0.007\cdot AGE–0.0126\cdot RATING+0.257 \cdot SUBIMPROV] \quad (5.3)$$

where $\Phi(.)$ is the standard normal cumulative distribution function.

The results of the probabilistic modeling suggest that age, current condition rating, transition in last inspection period, and number of years to last transition are the most significant factors that influence the likelihood that a bridge component will transition to a lower condition state. Also, in the models for each of the three components, the variables representing functional class, region, freeze-thaw cycles, and rehabilitation status were found to be influential predictors of the transition probability to a lower state. ADTT, type of wearing surface, and number of cold days were found to be significant only in the deck deterioration model, and superstructure material type was found to be a significant explanatory variable only in the superstructure deterioration model. In addition, the service under bridge (waterway) was found to be more significant statistically in the substructure deterioration model than it was in the deck and superstructure models. Furthermore, it was observed that the

TABLE 5.3
Summary of the Deterministic Models for Bridge Substructure Deterioration

Bridge Component	Districts	Functional Class	Deterioration Model
Substructure	Northern	NHS	$SUBCR = 8.15937 - 0.1233 \cdot AGE + 0.00314 \cdot AGE^2 - 0.00003179 \cdot AGE^3 - 0.01163 \cdot SPANNO - 0.00775 \cdot ADTT$
		Non-NHS	$SUBCR = 8.43932 - 0.1565 \cdot AGE + 0.00386 \cdot AGE^2 - 0.00003454 \cdot AGE^3 - 0.05085 \cdot ADTT$
		Combined	$SUBCR = \mathrm{EXP}\,(2.07773 - 0.00662 \cdot AGE - 0.02842 \cdot SERVUNDER - 0.0609 \cdot FRZINDX - 0.01056 \cdot ADTT)$
	Central	NHS	$SUBCR = 8.25023 - 0.10552 \cdot AGE + 0.00274 \cdot AGE^2 - 0.00002766 \cdot AGE^3 - 0.03816 \cdot INT - 0.08212 \cdot SERVUNDER - 0.00045568 \cdot LENGTH - 0.00648 \cdot NRFTC$
		Non-NHS	$SUBCR = 8.48942 - 0.13866 \cdot AGE + 0.00312 \cdot AGE^2 - 0.00002722 \cdot AGE^3 - 0.09838 \cdot SERVUNDER - 0.00054403 \cdot LENGTH - 0.00255 \cdot NRFTC - 0.0933 \cdot ADTT$
		Combined	$SUBCR = \mathrm{EXP}\,(2.19722 - 0.00688 \cdot AGE - 0.0127 \cdot INT - 0.0172 \cdot SERVUNDER - 0.00006274 \cdot LENGTH - 0.00275 \cdot NRFTC)$
	Southern	NHS	$SUBCR = 8.96898 - 0.07394 \cdot AGE + 0.00161 \cdot AGE^2 - 0.00001654 \cdot AGE^3 - 0.00199 \cdot SKEW - 0.09562 \cdot SERVUNDER - 0.01205 \cdot SPANNO - 0.72823 \cdot FRZINDX - 0.01557 \cdot NRFTC - 0.06789 \cdot ADTT$
		Non-NHS	$SUBCR = 8.5448 - 0.12212 \cdot \mathrm{AGE} + 0.00255 \cdot AGE^2 - 0.00002126 \cdot AGE^3 - 0.29416 \cdot SERVUNDER - 0.0407 \cdot ADTT$
		Combined	$SUBCR = \mathrm{EXP}\,(2.19722 - 0.00713 \cdot AGE - 0.00006455 \cdot LENGTH - 0.06336 \cdot FRZINDX - 0.00187 \cdot NRFTC)$

TABLE 5.4
Significant Explanatory Variables in the Probabilistic Model

Component	Significant Variables
Deck	Primary age Transition status in the last inspection period Number of years to last transition Type of wearing surface Functional classification of inventory route Daily truck traffic Number of cold days per year Number of freeze-thaw cycles Service under bridge structure Deck rating found in current inspection period Rehabilitation history (if there was any rating improvement in the past five periods)
Superstructure	Primary age Transition status in the last inspection period Number of years to last transition Type of superstructure material Functional classification of inventory route Number of cold days per year Number of freeze-thaw cycles Service under bridge structure Superstructure rating found in current inspection period Rehabilitation history (if there was any rating improvement in the past five periods)
Substructure	Primary age Transition status in the last inspection period Number of years to last transition Functional classification of inventory route Rehabilitation history (if there was any rating improvement in the past five periods)

coefficients of ADTT, service under bridge (if waterway), number of cold days, and freeze-thaw cycle (if larger than 60) had positive signs whereas region (if south) and superstructure material type (if steel) had negative signs. A positive sign of the coefficient means an increase in the variable will increase the probability of transitioning to a lower condition state whereas a negative coefficient implies that increases in that variable will lead to a decrease in the transition probability.

Consistent with intuition, in the current time period (t), a bridge was found to be less likely to deteriorate to a lower condition state if it had deteriorated to a lower state in the previous time period (t–1). The number of years to last transition had a positive sign, which is intuitive because the longer the duration to the last transition, the higher the probability that the transition will occur in the current period. It is expected that bridges with poor condition ratings deteriorate faster than those in good condition. However, in this model, when the factors of the condition rating and the number of years to last transition were considered together, age was found to have a negative sign, which means that for bridges with the same condition rating and similar time elapsed to the previous transition, the older bridge had a lower transition probability compared to the newer bridge.

The variable representing the status of recent rehabilitation (if there was any improvement of 2 or more within the recent five inspection periods) was found to have a positive sign. This indicates that if there was a recent condition improvement, the transition probability is higher. Other results of the model indicated that bridges in colder climates, such as northern Indiana, generally can be expected to deteriorate faster compared to those in milder climates such as southern Indiana, partly due to the effects of the deicing salts applied to road surfaces during the winter months. It was determined that the factors representing the number of cold days and freeze-thaw cycles each had positive signs, which supports the hypothesis that bridges located in more severe climates generally have a greater propensity to transition to a lower condition state. Also, bridges with high truck traffic volumes are expected to deteriorate at a faster rate, which again was consistent with the model outcome. The coefficient of the superstructure material type was negative, indicating that the probability of transitioning to a lower condition state was higher for bridges with concrete superstructure compared to their steel counterparts. The coefficient for the service type variable (water under bridge or otherwise) was positive for all three components, which indicates that waterway service features are associated with higher deterioration rates. The location variable had a positive sign, which indicated that bridges located in urban areas generally had higher deterioration rates.

For each bridge component, different physical, operational, and environmental conditions served as inputs into the model equations using the MATLAB program for each individual bridge on Indiana's state roads in the NBI database. The bridge component deterioration was simulated by running the program 10,000 times and calculating the average rating at each year. Also, the average number of years a bridge component stays in each condition rating was determined, and this result was used to track the trend of the movement of the component rating from the higher condition states to the lower states over time. A user interface was developed in MATLAB to visualize the bridge component deterioration process (Figures 5.1 and 5.2).

5.3 Sample Condition Prediction Using Model Equations

To demonstrate the application of the developed models, consider Bridge 0030 of the NBI database. It is sought to predict the superstructure condition of this bridge at year 2020, using the deterministic and probabilistic models developed. The bridge had the following parameters as of 2014:

- Bridge type: Concrete
- Design type: Arch deck
- Year Built: 1932
- Year Reconstructed: 1984
- Bridge location: Southern district
- Highway system: non-NHS
- Number of spans = 1
- Transition in last inspection period: none [therefore, Z(i,t-1) = 0]
- Number of years to transition: No transition since 1992 therefore, YRTOTRAN = 0 years)
- ADTT = 320
- District: Southern Districts (therefore, SOUTH = 1)
- Average number of cold days in a year = 60 days
- Average number of freeze-thaw cycles in a year (NFTC) = 56
- Therefore, HNFTC indicator = 0
- Wearing surface type = Bituminous (therefore, IFEPBI=0)
- Service under Bridge = Waterway (therefore, WATERWAY = 1)
- Superstructure Condition Rating in 2014 = 7 (therefore, RATING = 1)
- Superstructure Improvement: No superstructure improvement within the most recent five inspection periods (therefore, SUPERIMPROV = 0)
- Location: Bridge located in rural area (therefore, URBAN=0)

5.3.1 Deterministic Method

The deterministic equation for concrete arch deck superstructures in the southern districts is:

$$SUPCR = Exp(2.05829 - 0.00734.AGE - 0.02018.SPANNO)$$

In 2020, the age of the bridge since major repair will be 36 years, this gives:

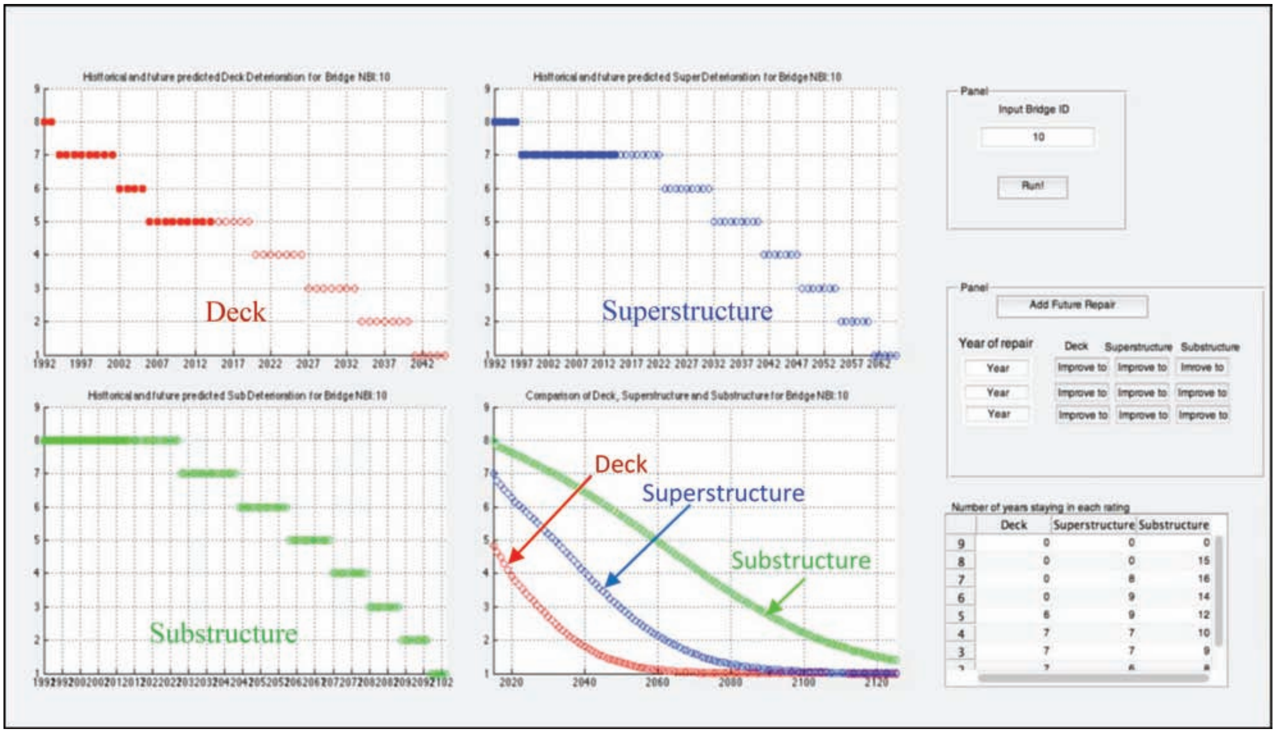

Figure 5.1 User interface presenting modeling results for Bridge #0010 after 10,000 simulations.

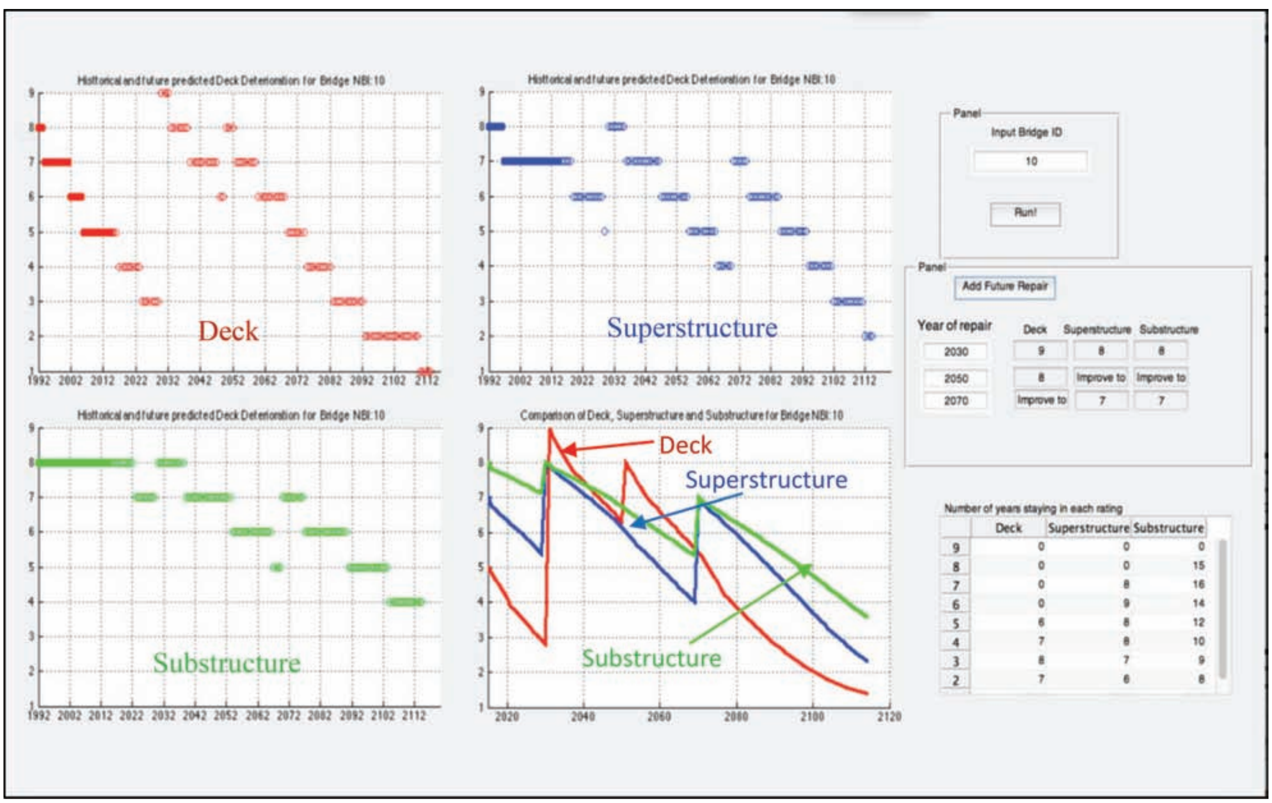

Figure 5.2 Simulation example of updating the deterioration model to reflect future repair.

$$\text{SUPCR} = Exp[2.05829 - 0.00734(36)$$

$$- 0.02018(1)] = 5.89 \approx 6$$

Using the deterministic model, the superstructure condition rating in 2020 will be 6.

5.3.2 Probabilistic Method

The probabilistic equation for superstructures is:

$Pr[Z(i,\ t) = 1] = \Phi[-1.382 + 0.282 \cdot Z(i,\ t - 1) + 0.028 \cdot YRTOTRAN - 0.186 \cdot SOUTH + 0.217 \cdot HNRFTC - 0.397 \cdot IFSTEEL + 0.102 \cdot URBAN + 0.096 \cdot WATERWAY - 0.006 \cdot AGE - 0.0124 \cdot RATING + 0.263 \cdot SUPERIMPROV]$

where, $\Phi(.)$ is the standard normal cumulative distribution function.

The primary age of the superstructure in 2020 was 77 years, which gives:

$$Pr[Z(i,t) = 1]$$

$$Pr[Z(i,t) = 1] = \Phi[-1.382 + 0.282(0) + 0.028(0)$$

$$- 0.186(1) + 0.217(0) - 0.397(0) + 0.102(0)$$

$$- 0.397(0) + 0.102(0) + 0.096(1) - 0.006(88)$$

$$- 0.0124(1) + 0.263(0)]$$

$$Pr[Z(i,t) = 1] = \Phi[-2.0124)] = 0.022$$

$$Pr[Z(i,t) = 0] = 1 - Pr[Z(i,t) = 1] = Pr[Z(i,t) = 0] = 1$$

$$- 0.022 = 0.978$$

The probability of transitioning to a lower state is low. Therefore, the bridge is likely to remain in the current condition rating of 7 at year 2020. Therefore, it can be seen that the deterministic and probabilistic models do not always produce the same answer.

6. SUMMARY AND CONCLUSIONS

6.1 Summary

The Indiana BMS bridge deterioration models currently in use were developed over two decades ago. In the ensuing years, significant changes have taken place in construction techniques and technologies, materials, condition inspection methods, and loading patterns. At the same time, several important advancements in statistical techniques for data analysis and model building have emerged and the data resources have increased exponentially in terms of the volume of data, the variety of data items, and the integrity of the data. For example, the data on truck volumes and climatic conditions are more readily available at the current time, making it possible to develop models that account for these deterioration factors. With these challenges and opportunities, the time is ripe for the development of updated models to address the bridge management needs of INDOT's bridge managers.

In addressing this research need, this study developed families of curves representing deterioration models for bridge decks, superstructures, and substructures. Data from the NBI database and the NOAA online datasets were used for this purpose, and the models utilized the NBI condition ratings as the response variable. The model families were categorized by administrative region, functional class, and superstructure material type. The explanatory factors included variables related to traffic volume, truck traffic, design type, climatic conditions, and design features. The results indicate that traffic loading and environmental (climate) variables can play a significant role in bridge deterioration. The latter include the freeze index, number of freeze-thaw cycles, and average precipitation.

6.2 Future Research

It became apparent during this study that additional research areas could be investigated that would benefit the Indiana BMS. As data become available, deterioration modeling studies could go beyond the present study's three components to develop individual models for each bridge element as defined in PONTIS. Also, in order to reduce the number of models, future studies could incorporate certain grouping criteria, such as the bridge design type, as explanatory variables in the model. However, due caution should be exercised in the model formulation and specification to avoid any interaction effects between the explanatory variables. Lastly, further studies could carry out comprehensive validation of each component of the deterministic and probabilistic models, using recent bridge condition data, and thereby establish calibration factors as needed for either one of these models if it is found to be relatively less powerful in its predictive capability.

PART II CONTENTS

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1. INTRODUCTION

1.1 Study Background and Problem Statement

The need to carefully monitor bridge condition was first addressed explicitly in the late 1960s when the Federal Highway Act of 1968 created the National Bridge Inspection Program (NBIP) that required state agencies to catalogue and track the condition of principal highway bridges. The Surface Transportation Assistance Act of 1978 expanded the NBIP to include bridges on all public roads, and the Highway Bridge Replacement and Rehabilitation Program (HBRRP) was established to provide funding for bridge rehabilitation and replacement projects (Czepiel, 1995). A subsequent legislative impetus for bridge condition monitoring, the 1991 Intermodal Surface Transportation Efficiency Act, was geared towards protecting investments in the nation's existing and future bridges by providing information for making optimal decisions on bridge program expenditures under financial constraints (Adams & Sianipar, 1995).

The need for data-driven bridge management is more apparent at the current time than ever before, as state highway agencies continue to grapple with ongoing challenges, which include aging structures, increased demand and loading, higher user expectations, renewed emphasis on vulnerability issues, and uncertainty of sustained funding for reconstruction and preservation (Labi, 2014). An integral aspect of cost-effective bridge management is regular monitoring of the condition of the three bridge components, namely, the deck, superstructure, and substructure.

A typical bridge management system (BMS) is comprised of four basic components: data management, deterioration models, cost models, and program development models. BMS deterioration models are used to track trends in bridge element deterioration so that appropriate bridge interventions may be applied at the appropriate time. As such, information on the current state and future condition of bridges and estimation techniques of bridge performance are key tools for devising the most cost-effective strategies for the maintenance, rehabilitation, and replacement (MR&R) of bridges.

The bridge deterioration models currently in use in the Indiana BMS were developed over two decades ago (Sinha, Saito, Jiang, Murthy, Tee, & Bowman, 1988a,b). Since then, there have been significant changes in construction techniques and technologies, materials, condition inspection methods, and loading patterns. The past few decades also have seen advancements in statistical techniques for data analysis and model building. In addition, the availability of data in terms of the volume of data and the different data items as well as the integrity of the data. For example, data on truck volumes and climatic conditions are more readily available now, making it possible to develop models that account for these deterioration factors. Generally, bridge deterioration models are developed separately for wearing course, deck, superstructure, and substructure. The Indiana Department of Transportation (INDOT) recently developed deterioration curves for the wearing course; however, for the remaining components, the decades-old models continue to be used. In light of these challenges and opportunities, INDOT commissioned SPR-3828 in 2013, to develop deterioration models for the remaining components for use in their BMS.

A BMS that is equipped with reliable deterioration models is expected to assist bridge engineers in their tasks associated with effectiveness assessment (Labi, Thompson, Shirolé, & Sinha, 2011), long-term programming, planning, and needs assessment at both the project and network levels. At the project level, they help engineers track the physical condition of the bridge deck, superstructure, and substructure, and therefore provide guidance in predicting when rehabilitation and replacement should be carried out. At the network level, they help bridge engineers accumulate the needs of individual bridge components and thereby assist in the task of determining the system-wide needs over a specified future time horizon (Labi, Rodriguez, & Sinha, 2006). Deterioration models also play important roles in other asset management business processes, such as bridge cost allocation and asset valuation.

1.2 Study Objectives and Scope

In addressing the study motivation and problem statement, the present study carried out the following:

- Developed a family of bridge condition deterioration curves on the basis of physical and operational characteristics, climate, and truck traffic for decks, superstructures, and substructures.
- Identified the factors that influence the physical condition of the bridge elements and measure the strength of the influence of each factor.

The study was carried out for bridges that are located on the state highway system (Interstates, U.S. roads, and state roads). The bridges were placed into "families" based on their material and design type, functional class, and administrative/climatic region. Using the data provided, deterioration models were calibrated for each family, using a variety of alternative specifications and functional forms.

1.3 Organization of the Report

This report is presented in two parts. Part I is the main report that summarizes the study, and Part II provides details on the study components (i.e., literature review, methodology, and results. In this part of the report, (Part II), the full details of the study are presented. In Part II, Chapter 2 reviews the existing literature on the methodologies that have been used in past studies for bridge deterioration modeling as well as the merits and demerits of the different methodologies. Chapter 3 identifies the methodology adopted for the present study, provides justification for the selection, and explains the details of the selected methodologies.

Chapters 4 and 5 present the results of the deterministic and probabilistic deterioration modeling; and Chapter 6 summarizes and concludes the report. Part II's Appendix A contains further details of the literature review on modeling techniques, deterioration models (with and without prior repair) and the establishment of age restrictions for the purposes of data filtering.

2. LITERATURE REVIEW

2.1 Introduction

Deterioration models describe the slow degradation and change in the strength of a material and are used to predict the change in structural as well as functional parameters in response to future accumulations of structural loading, environmental stresses, and maintenance practices (Godart & Vassie, 2001). Several models were developed in past studies to assist decision-makers in predicting the future condition of a specific bridge (project-level analysis) or the health of an entire bridge network (network-level analysis). One way of categorizing bridge deterioration models is as follows: deterministic models, stochastic models, and artificial intelligence models. These are discussed in the following sections.

2.2 Deterministic Models

Deterministic models estimate the predicted conditions with the assumption of perfect knowledge of the variables and therefore do not account for any random error in prediction (Adams & Sianipar, 1995; Morcous, Rivard, & Hanna, 2002). Most deterministic models have used the regression technique, for which a wide range of mathematical forms have been used, including exponential decay functions (Sanders & Zhang, 1994) and polynomial functions (Jiang, Saito, & Sinha, 1988). Chase, Small, and Nutakor (2000) carried out a study that modeled the bridge superstructure condition and used different functional forms (linear, nonlinear, nonparametric, and non-linear parametric) for their regression models.

2.3 Stochastic Models

Stochastic models are used to account duly for the inherent uncertainty, random occurrence, and variation associated with deterioration factors (Godart & Vassie, 2001; Morcous et al., 2002). The most common of these are Markov chain models, which have been used extensively in modeling the deterioration of infrastructure facilities.

2.3.1 Markov Chain

A Markov model is a type of discrete probabilistic model where events are structured into stages spaced uniformly over time. The underlying assumption in these models is that the state of the system at a given time depends only on the state at the previous time and intervening actions between the previous and the given time. Deterioration models using the Markovian Decision Process (MDP) are based on the concept of defining the states of facility conditions and obtaining the probabilities of facility condition transition from one state to another during one inspection period (Jiang et al., 1988; Scherer & Glagola, 1994). The transitions are probabilistic because bridge deterioration cannot be predicted with certainty due to the effect of unobserved independent variables, the presence of measurement errors, and the underlying stochastic nature of the deterioration process.

The Markov chain approach has been used in developing bridge deterioration models because it facilitates the concept of defining the state of each discrete bridge condition rating on the basis of a stochastic process. Bridge condition ratings are determined by bridge inspections at assumed regular intervals. Bridge condition ratings range from 0 to 9; 9 being the superior desirable bridge condition, and the Markov process defines the ratings as condition states. For example, state 1 is condition rating 9, state 2 is condition rating 8, and these states are defined in the Markov chain to follow the concept that, without repair of an existing bridge, the condition will continue to deteriorate in the future.

Various approaches have been used to estimate Markovian transition probabilities for bridge condition including the expected value method approach (Jiang et al., 1988), and econometric methods such as ordered probit techniques (Lee & Chang, 2003; Madanat, Mishalani, & Ibrahim, 1995), random-effects probit models (Bulusu, 1996; Madanat, Karlaftis, & McCarthy, 1997), and count data models, Poison and negative binomial regression models (Madanat & Ibrahim, 1995). The most commonly-used approach is the regression-based method (Carnahan, Davis, Shahin, Keane, & Wu, 1987; Jiang & Sinha, 1989a; Kong & Frangopol, 2003; Saydam, Bocchini, & Frangopol, 2013). However, a number of studies (Frangopol & Bocchini, 2012; Jiang & Sinha, 1992) found that such an approach may intro-
duce bias in the prediction of the condition states using a Markov chain.

Zhang, Sun, and Wang (2003) generated Markov matrices for bridge component deterioration, using Louisiana's National Bridge Inventory data and an empirical formula through a trial-and-error process and interviews with local bridge inspectors (Zhang et al., 2003). The Markovian models currently implemented in existing PONTIS and BRIDGIT BMS software packages assume that the future bridge condition depends only on the current condition and not on the condition history—an assumption that was identified as being unrealistic (Madanat et al., 1995) but was subsequently overcome by including a lagged indicator independent variable (Bulusu, 1996).

While a Markov chain appears to be an enhanced approach compared to regression-based analysis, the assumption of ignoring the previous states of a bridge condition could lead to inconsistent prediction. Ignoring the previous state would have a significant effect on the future bridge condition state because the time elapsed in the initial state would affect the transition probability to the future state. The assumption of state independence, which suggests that the conditional probability of a future event, given the present and past condition states, depends only on the present state, should be thoroughly examined prior to using Markov chains for predicting the future condition states of bridge elements (Wirahadikusumah, Abraham, & Iseley, 2001).

In order to ensure an accurate sequence analysis of data, inspection data for at least three successive condition states are required. These states should be the previous, present, and future condition states. In the analysis, two possible transition sequences with the same future and present conditions, but with varied past conditions, are compared. The comparison is accomplished using either inference analysis or frequency analysis. In order to ensure that the state independence is valid, the statistical tests should show that the difference between sequence occurrences is statistically insignificant (Scherer & Glagola, 1994). However, due to the unavailability of an adequate amount of data and successive condition states data for the past, present, and future without any maintenance activity, this investigation becomes difficult to conduct.

The Markov process assumes a programmed and fixed inspection interval for bridges. But most often in practice, bridges can be inspected less or more frequently than programmed due to financial, technical, and many other factors. Therefore, if there is significant variation in inspection intervals and the Markov chain models are developed or updated with these unequally spaced condition data, inaccurate Markov chain estimates can be the result.

Additional limitations of stochastic models were identified by Morcous (2006). Markov chains facilitate the concept of defining the state of each discrete bridge condition rating on the basis of a stochastic process. Markov chains appear to represent an enhanced approach compared to the regression-based analysis, but the assumption of ignoring the previous states of a bridge condition could lead to inconsistent prediction. The Markov process assumes a programmed and fixed inspection interval for bridges. But most often, in practice, bridges can be inspected less or more frequently than programmed for reasons including financial, technical, and so on. The Markov chain has some merits including accounting for the stochastic nature of bridge deterioration, using the present bridge element condition to predict the future condition, and the computational efficiency and simplicity make it possible to estimate the conditions of large numbers of bridges in a network.

Another merit of the Markov chain in developing or updating bridge deterioration models is that it is a stochastic approach and can reflect the uncertainty in the conditions of bridges coupled with the uncertainty in the loads applied and the latent uncertainty of the deterioration process (Lounis & Mirza, 2001). Secondly, the Markov chain heavily depends on the present bridge condition in order to predict the future condition. Thus, this incremental method of analysis accounts for the present condition when predicting the future bridge condition state (Madanat & Ibrahim, 1995). Thirdly, due to the computational efficiency and simplicity provided by the Markov chain, the approach can be used to easily estimate the conditions of an enormous number of bridges in a network (Morcous, 2006). In order to model large quantities of bridges and make this model more reasonable for use, bridges can be categorized into many different small groups. The component in each small group is considered to have the same or similar characteristics and dimensions, on the assumption that all bridges in a certain group will have similar performance or deterioration characteristics, given the same maintenance actions. Bayesian techniques also can be applied to correlate different variables. If elements A and B are corrected during a deteriorating process, for example, the change in variable B would affect the changing rate of variable A. therefore A must have a nonstationary Markovian transition matrix (Cesare, Santamarina, Turkstra, & Vanmarcke, 1992). In Appendix A, we provide additional details of Markov chain techniques.

2.3.2 Count Data Modeling Techniques

Of the count data modeling techniques that were used in the past to develop bridge deterioration models, the two most commonly-used include the Poisson and negative binomial regression approaches. Unlike the Poisson approach, the negative binomial approach is flexible and relaxes the assumption of the mean being equal to the variance. Although count data techniques have been used in the past, the developed models were considered to be rather limited in their application to the practice because the model structure does not facilitate overt linkage between the bridge condition and the independent variables; moreover, the models do not account for the ordinal scale of bridge condition ratings. To address this, and to link the deterioration to the independent variables, discrete modeling techniques, the traditional logit/probit models, have also been used. However, these econometric logit/probit models fail to account for the heterogeneity and state dependence present in bridge data which has a panel structure. The binary probit random effects model, nevertheless, remains a promising technique that could incorporate state dependence and heterogeneity in the modeling framework. In Appendix A to this report, we provide additional details on the count data modeling techniques.

2.3.3 The Bayesian Technique

Another approach is the Bayesian technique, where the uncertainty associated with the estimation of the parameters is merged with the inherent variability of a random variable. In order to use the Bayesian technique, subjective judgments from experience can be analytically combined with observed data to arrive at consistent and unbiased estimation. In past studies in Indiana, the Bayesian technique and a binary probit random effects model have been used to predict the bridge condition states of bridge components, and the results were not significantly different from observed conditions. The precision of facility condition forecasting directly influences the quality of maintenance and rehabilitation decision- making. One way to improve the precision of forecasting is by successive updating of the deterioration model parameters with the use of Bayesian modeling techniques (Enright & Frangopol, 1999; Hudson, Haas, & Uddin, 1997; Lu & Madanat, 1994).

The literature review also revealed emerging approaches for bridge deterioration modeling exist, which include Weibull-based probability density and artificial intelligence (AI). Under the Weibull-based probability density approach, the duration for which a bridge element stays at a specific condition or state, can be considered and modeled as a random variable. In Appendix A to this report, we provide additional details on Bayesian techniques.

2.4 Artificial Intelligence (AI) Models

In automating intelligent behaviors such as expert systems, artificial neural networks (ANN), and case-based reasoning (CBR), AI models exploit the benefits of computerization such as high processing speeds. The use of ANN in modeling bridge deterioration is quite recent and involves parallel computational models for knowledge representation and information processing. A review of the literature determined that there are three common types of neural network models: conditional average estimator (CAE), algorithm inductive decision tree (ID3), and back propagation neural network model (BPNN) (Godart & Vassie, 2001). Sobanjo (1997) utilized a multilayer ANN to relate the bridge age (in years) to the bridge superstructure condition rating. A more detailed investigation by Tokdemir, Ayvalik, and Mohammadi (2000) predicted bridge sufficiency rating on the basis of age, traffic, geometry, and structural attributes. ANN shares the problems of the deterministic models (Morcous et al., 2002). Case-based reasoning (CBR) is an AI technique that looks for previous cases that are similar to the current problem and re-uses them to solve the problem. The use of CBR in modeling bridge deterioration is based on the assumption that two bridges that have similar physical features, environmental and operational conditions, and inspection and maintenance history will provide similar performance. The performance of the CBR model for modeling infrastructure deterioration of concrete bridge decks, using data obtained from the Canadian Province of Quebec, showed that the CBR approach could overcome some of the shortcomings of current models; however, further research is required to further enhance this approach, verify its compatibility with other BMS modules, and validate its performance in a real-world environment (Morcous et al., 2002).

2.5 Summary of the Literature Review

This chapter presented and discussed the literature review related to bridge deterioration models, as well as the main methodologies applied in past studies. The regression-based models were first discussed. It was found that the sole independent variable considered in most of the past studies is the component age. The regression approach was found to have a number of challenges, including inadequate accounting for the uncertainty and possible influence of the unobserved variables associated with bridge deterioration and its use of a continuous response variable. These limitations may result in a bridge deterioration model that could be unreliable.

The second approach discussed was the Markov chain. A special form of the stochastic process, the Markov chain is used in developing bridge deterioration models because it facilitates the concept of defining the state of each discrete bridge condition rating based on that stochastic process. While the Markov chain appears to be an enhanced approach compared to the regression-based analysis, its assumption of ignoring the previous states of a bridge condition could lead to inconsistent prediction. The Markov process assumes programmed and fixed inspection intervals for bridges, but most often in practice bridges are inspected less or more frequently than programmed due to financial, technical, and other factors. However, the Markov chain has a number of merits including accounting for the stochastic nature of bridge deterioration and providing superior computational efficiency and simplicity to easily estimate the conditions of a large number of bridges in a network.

Also, a number of count-data modeling techniques have been used in the past to develop bridge deterioration models. The two most commonly-used techniques include Poisson and negative binomial regression. While the Poisson approach may be viable for developing bridge deterioration models, it has several limitations. The Poisson restricts the mean of the random variable to be equal to the variance; if not, the data can be said to be either over-dispersed or under-dispersed, and consequently, the estimated parameters will be biased. In order to overcome the dispersion restrictions, negative binominal regression can be considered. Negative binomial regression is flexible and relaxes the assumption of the mean being equal to the variance. Although count data techniques have been used in the past, the developed models were limited in use because bridge condition deterioration was not overtly linked to the independent variables, and the models did not account for the ordinal scale of bridge condition ratings. In order to capture the ordinal nature of condition states and to link deterioration to independent variables, discrete modeling techniques, the traditional logit/probit models, also were considered. Nonetheless, the traditional logit/probit model fails to account for the heterogeneity and state dependence present in panel. However, the binary probit random effects model is another technique appropriate for incorporating state dependence and heterogeneity in the modeling framework.

Another approach discussed in this chapter is the Bayesian technique. Using Bayes Theorem, the uncertainty associated with the estimation of the parameters is merged with the inherent variability of a random variable. In order to use the Bayesian technique, subjective judgments from experience can be analytically combined with the observed data to arrive at consistent and unbiased estimation. In Indiana, the Bayesian technique and binary probit random effects model have been used in past studies to predict condition states of bridge components, and after validation, found the predicted conditions to be significantly same as the observed conditions.

There are other emerging approaches for bridge deterioration, which include Weibull-based probability density and artificial intelligence. Under the Weibull-based probability density approach, the duration for which a bridge element stays at a specific condition or state can be considered and modeled as a random variable. Another emerging area used for developing bridge deterioration is the artificial intelligence model. The artificial intelligence modeling framework is developed on the basis of computer procedures that mimic and automate intelligent behaviors.

In this study, helpful modeling information was drawn from the literature review in order to develop both stochastic and deterministic models, and the findings of past research were used as a platform to identify the potential factors of deterioration and to collect data on these and other factors. In summary, it was concluded that bridge deterioration can be realistically modeled with a combination of stochastic and deterministic models. In the next chapter, the methodology for the present study is discussed.

3. STUDY METHODOLOGY

3.1 Methodology for Regression Model

The regression approach was used to investigate the relationships between bridge component condition rating and various independent variables. The basic concept of a regression model is that it expresses a statistical relationship between a predictor and a response variable, which is based on the tendency of the response variable to vary with the predictor in a systematic way and a scattering of the points around the curve of the statistical relationship (Kutner, Nachtsheim, Neter, & Li, 2005). Regression models are commonly used by most highway agencies due to their ease of computation and application (Ford et al., 2012). Also, regression models are calibrated rather easily with available software. In bridge deterioration modeling, regression analysis is used to derive parameter estimates or coefficients of independent variables such as climate, traffic loading characteristics and age, which relate to a dependent variable such as condition rating.

3.1.1 Response and Independent Variables

In this study, consistent with past literature (Bolukbasi, Mohammadi, & Arditi, 2004; Tolliver & Lu, 2011; Veshosky, Beidleman, Buetow, & Demir, 1994), the response variable for modeling deterioration is the bridge component condition rating, which describes the overall physical condition of the component. As noted previously, condition ratings are discrete numbers that take values from 0 to 9 and provide an overall description of the general condition of the entire component being rated (FHWA, 1995).

The independent variables considered in the study were as follows.

Bridge Age. Past literature indicates that age is the main factor for bridge deterioration (Busa, Cassella, Gazadia, & Horn, 1985; Jiang & Sinha, 1989b). Bridge age is computed as the difference between the year of inspection and the year built or year reconstructed. Intuitively, an increase in age means there will be a decrease in condition rating. Bridge component deterioration tends to follow approximately a polynomial functional form over the long term (Tolliver & Lu, 2011).

Highway Functional Class. Highway functional class was included as a variable in this study to indicate the class on which the bridge route is located. Item 104 (highway system of the inventory route) of the coding guide specifies the routes as being on the National Highway System (NHS) or otherwise. It has been observed in past literature that the rate of deterioration is directly linked to the highway class. Jiang and Sinha (1989b) noted that bridges on different classes of roads deteriorated differently and thus factored the effects of highway systems by developing models separately for bridges on Interstate and non-Interstate highways.

Service Feature. The service feature, or the service under the bridge, indicates the facility or feature over which the bridge traverses. This feature may be a highway, railroad, pedestrian-bicycle way, or other features. Bridge deterioration has been linked to the service under the bridge (Agrawal & Kawaguchi, 2009; Rodriguez, 2004); bridges located over waterways tend to deteriorate faster than bridges traversing other obstacles. This is because any open cracks on bridge components exposed to water may allow water laden with salt or other pollutants to infiltrate the cracks and reaching reinforcement bars and prestressing steel resulting in delamination, corrosion of steel and spalling of concrete (Strategic Highway Research Program [SHRP] 2, 2015).

Number of Freeze-Thaw Cycles. A freeze thaw-cycle is defined as the cumulative number of degree-days when the air temperatures are below and above 0°C (Liao & Labi, 2013; Zhang, 1998). Freeze-thaw cycles influence deterioration, especially in concrete bridges, by causing scaling of the concrete due to the pressure caused by the volumetric changes of water in the concrete (SHRP 2, 2015).

Freeze Index. Bridges in cold areas exhibit different deterioration patterns than bridges in warmer climates. The freeze index, which measures the total number of days of freezing for a given winter, can result in volume changes that may lead to accelerated deterioration. The climate data for each county in Indiana is shown in Appendix D.

Average Daily Truck Traffic (ADTT). ADTT affects the rate of bridge component deterioration. Bridges exposed to high traffic loading, such as decks on major Interstates, deteriorate faster than bridges on other functional classes of roads which carry lower volumes of traffic (Kim & Yoon, 2010). ADTT is calculated by multiplying the percentage of truck traffic by the average daily traffic (ADT).

Number of Spans in Main Unit. All other factors remaining the same, a higher number of spans was associated with a higher rate of deterioration in the past literature. For multiple span bridges, bearings are required at the end and beginning of each span leading to multiple points to maintain on a single bridge (Tonias, 1995).

Skew. Bridge skew refers to the angle between the centerline of a pier and a line normal to the roadway centerline (FHWA, 1995). Bridges with higher degrees of skew generally deteriorate faster than bridges with little or no skew (Busa et al., 1985).

Deck protection is = 1 if the bridge deck has any of the following protection technologies: some coated reinforcement, galvanized reinforcement, cathodic protection, polymer integration, or internal sealant, as defined in item 108C of the FHWA NVI Coding Guide; and is = 0 if it does not.

Other Factors. Salt application levels tend to play an important role in deck deterioration; however, due to the lack of specific data on salt application rates, this variable was implicitly considered in the present study by using qualitative regional variables and climate variables as proxies.

3.2 Modeling Steps

Kutner et al. (2005) defined the regression-based approach in the following four main steps with smaller subsets of tasks: (i) data collection and preparation; (ii) preliminary model investigation (reduction in the number of independent variables); (iii) model refinement and selection; and (iv) model validation (Figure 3.1).

(a) Data Collection. The primary source of data for the bridge deterioration modeling in this study was the National Bridge Inventory (NBI) database. The NBI data is cross-sectional and includes bridge information spanning 1992 to 2014. Bridge components generally are inspected every two years and condition ratings are assigned to the components. The bridge data obtained from the NBI database included bridge geometric characteristics (bridge length, total deck width, degrees skew, vertical clearance, etc.), functional class, highway system, type of material, type of construction design.

Reference data included the spatial position of the bridge in association with the highway type and the county or milepost which provided highway district, longitude and latitude, etc. Other collected data included environmental data obtained from the National Oceanic and Atmospheric Administration (NOAA) (Table 3.1) and is specific to individual counties in the state of Indiana. Traffic data were obtained from the NBI database, which included traffic volumes and percent truck traffic. Missing ADT and percent truck traffic data were observed in the database, which were accounted for using simple mathematical techniques and simple linear extrapolation of data between the known values. Maintenance data included the year of construction, last year of repair, and the kind of repair undertaken. Repaired bridges refers to bridges that had received at least one rehabilitation activity since their construction or reconstruction.

(b) Preliminary Checks on Data. The major limitation of the NBI data is that inspector subjectivity can introduce serious bias to the ratings assigned. Inspections of the same bridge by different inspectors could potentially result in different ratings being assigned to the same bridge component. Unfortunately, in the NBI database, a number of newly-constructed bridge components are not assigned a condition rating of 9 as expected. Due to these and several other limitations, the NBI data must be used with circumspection and with recognition that there exists marked variability and uncertainty in the data. In spite of these challenges, the NBI database currently remains the most comprehensive data source for bridge deterioration modeling.

(c) Data Preparation. To ensure that reliable data were used for developing the deterioration models, an extensive data filtering effort was carried out for the inspection data obtained from the NBI database. The filtering process was as follows. (i) The models were developed for only state highways. Data from local roads and other agencies (Tribal Governments, U.S. Forest Service, City or Municipal Highways, etc.) were filtered out. (ii) Data Coded N and 0 constituted about 0.19% of the state highway observation data. (iii) Bridges >20 feet in length were excluded. The

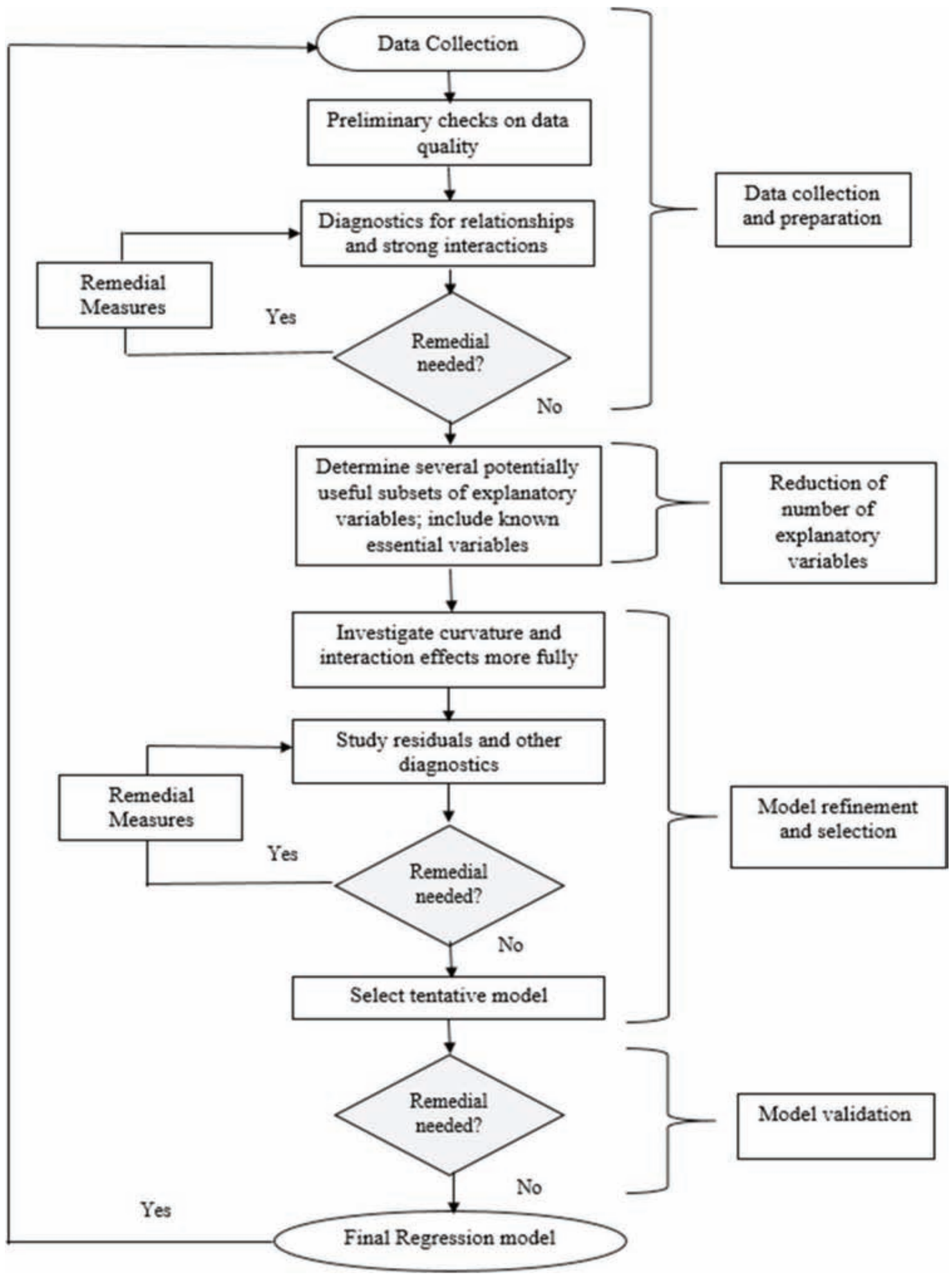


Figure 3.1 Steps in regression modeling (Kutner et al., 2005).

bridge length is defined in the "Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges" as that length of the bridge measured back to back of the back walls of abutments from paving notch to paving notch.

(d) Maximum and Minimum Age Restriction Development. When bridge components (often decks) are replaced, they are new and should have zero age to match the condition ratings assigned them at that time. An individual component replacement may not necessarily mean the entire bridge has been replaced, and the bridge age may only reflect the age of the entire bridge. In certain cases, the component bridge age is not updated to match the replaced component. The ages of the bridges are calculated based on the year built or reconstructed, and in the absence of the work history data, bridge ages computed using the original built year yield misleading and erroneous results for the component condition rating. For instance, a 50-year-old bridge deck is not expected to have a condition rating of 9 nor is a relatively new deck (e.g., age 2 years) expected to have a condition rating of 2 or 3. Unfortunately, the NBI database has records where there is a

TABLE 3.1
Climate Variables

Variable	Variable Code
Average Precipitation	AVG PPN
Wet Days	WETDAYS
Average Temperature	AVG TEMP
Average Winter Temperature	AVG WINTEMP
Average Summer Temperature	AVG SUMTEMP
Hot Days	HOT DAYS
Warm Days	WARM DAYS
Cold Days	COLD DAYS
Freeze Index	FRZ NDX
Number of Freeze-Thaw Cycles	NRFTC
Number of Freeze Thaw Transitions	NRFTT
Spring-Fall Freeze Interval	SF FZINT
Maximum Temperature	MAX TEMP
Minimum Temperature	MIN TEMP
Freeze Modulus	FRZ MOD
Relative Weather Severity Level	WSL

work history that shows there was a component replacement but no increase in the condition rating of that component is recorded.

In a bid to address this issue, at least partially, a limit was developed and imposed on the minimum and maximum ages that a bridge remains in a particular condition rating. Bridges that have undergone no prior repair were extracted in order to link bridge deterioration unaffected by major repairs and replacement with the development of the age restrictions. In the NBI database, Indiana's state highway bridges with no prior repair constitute approximately 30% of all state highway bridges in Indiana.

Morcous and Hatami (2011) developed age restrictions for condition ratings. Their restrictions were based primarily on observations of scatter plots of bridge data and expert opinion. Agrawal and Kawachi (2009) addressed this problem for bridge decks by developing age restrictions using Markov chains and Weibull- based methods. Their study concluded that bridge decks can remain up to 35 years in condition rating 7 and up to 50 years in condition rating 6.

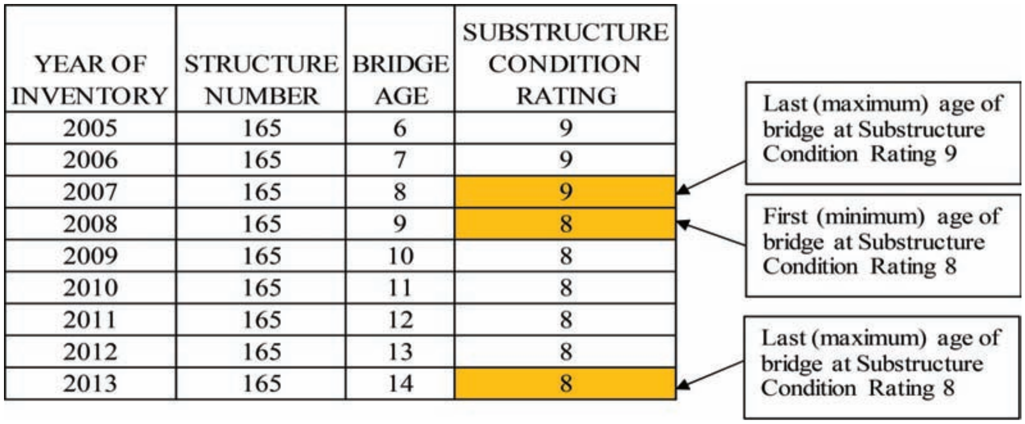
(e) Methodology for Developing Restrictions. The last (maximum) age at a condition rating and the first (minimum) age at the same condition rating for each bridge without prior repair were determined from the database for all the components and their condition ratings, which is shown for substructure condition ratings (Figure 3.2). The ages at the different condition ratings were analyzed and outliers were removed. For both minimum and maximum ages, the data points located at least one standard deviation from the mean were considered outliers and deleted. An envelope consistent with the results of past studies was produced.

For all the components, the extreme values for the maximum and minimum ages at the different condition ratings were plotted after deleting the outliers. Curves and lines were then fitted to the plotted points, and the best functions that gave intuitive results for the points, were retained as the envelope boundaries. Most of the boundary equations were polynomial functions. The equations through the plotted points were used to predict the expected minimum and maximum ages at each condition rating. These predicted restrictions were then approximated to the nearest fives or tens. Some engineering judgment was used for the approximations. For example, using a polynomial function, the minimum age at which bridge superstructures reach condition ratings 2 and 1 were calculated as 48.11 and 52.23 years, respectively (Table B.2). Both ages may be approximated to 50; however, a bridge component deteriorates to condition 2 before reaching condition 1. This implies that the age at which the superstructure reaches condition rating 1 must not also be approximated to 50 years; therefore, the minimum age restriction at condition rating 1 was approximated to 60 years instead of 50 years. Tables for the detailed analysis are provided in Appendix C. For bridges without prior repair, approximately 33%, 28%, and 28% of the deck, superstructure and substructure observations, respectively, were deleted as outliers. For bridges with prior repairs, 10%, 20%, and 11% of the deck, superstructure, and substructure observations were identified as outliers using the age restrictions developed and deleted. The developed minimum and maximum age restrictions corresponding to the ratings of the deck, superstructure, and substructure, are provided in Tables 3.2–3.4 and Figures 3.3–3.5.

3.2.1 Criteria for Developing the Bridge Families

In order to develop good deterioration models that take into account unique bridge conditions and environmental factors, it was necessary to group the data into homogeneous families, and the following factors were used: bridges with and without prior repair, highway districts, highway functional class, bridge (superstructure) material and design type. In the main report (Volume 1), the deterioration models are presented without separating bridges without prior repair and those with prior repair. In this part of the report (Volume 2), the deterioration models are presented separately for bridges without prior repair and those with prior repair (the detailed results are presented in Appendix B).

(a) Bridges without Prior Repair and Repaired Bridges. In the database, bridges without prior repair refers to those bridges whose components have not been replaced or undergone any major maintenance activity. Conversely, bridges with prior repair are those that have received some major repair or rehabilitation since construction. From the 1992 to 2014 NBI database for Indiana's state highway bridges, approximately 30% of the approximately 5,500 bridges have not had any major repairs or replacement of their components since the year of construction. Models for bridges without prior repair and with repair are presented in Appendix B.



YEAR OF INVENTORY	STRUCTURE NUMBER	BRIDGE AGE	SUBSTRUCTURE CONDITION RATING
2005	165	6	9
2006	165	7	9
2007	165	8	9
2008	165	9	8
2009	165	10	8
2010	165	11	8
2011	165	12	8
2012	165	13	8
2013	165	14	8

Figure 3.2 A sample of extracted data from the NBI database.

TABLE 3.2
Minimum and Maximum Age Restrictions for Deck Condition Rating

Condition Rating	Minimum Age	Maximum Age
9	0	10
8	0	15
7	0	25
6	5	30
5	10	35
4	20	40
3	30	50
2	40	60
1	50	70

TABLE 3.3
Minimum and Maximum Age Restrictions for Superstructure Condition Rating

Condition Rating	Minimum Age	Maximum Age
9	0	10
8	0	20
7	5	30
6	10	45
5	20	50
4	30	60
3	40	65
2	50	70
1	60	75

(b) Highway Districts. Indiana has six highway districts which correspond to the state's three distinct climatic regions (Northern, Central and Southern). LaPorte and Fort Wayne are the Northern districts, Crawfordsville and Greenfield are the Central districts, and Vincennes and Seymour are the Southern districts (Figure 3.6). Deterioration models were developed for each district as a first step. However, the results were generally not very good because for certain bridge families, there was inadequate number of observations. The six districts were therefore combined to form three regions, and the deterioration models were developed for these regions. The Central and Southern regions have approximately the same number of state highway bridges; and the Northern region has fewer bridges compared to the Central and Southern regions (Figure 3.7).

TABLE 3.4
Minimum and Maximum Age Restrictions for Substructure Condition Rating

Condition Rating	Minimum Age	Maximum Age
9	0	10
8	0	20
7	5	35
6	10	50
5	20	60
4	30	65
3	40	70
2	45	80
1	50	90

(c) Highway Functional Class. Bridges were classified according to the highway system on which they are located. These classifications were based on whether the bridges were located on the NHS or non-NHS. Figure 3.8 shows the distribution of bridges across the two functional classes.

(d) Bridge (Superstructure) Material Type. The superstructure material defines the type of bridge classification. On Indiana's state highways, the dominant material type is concrete, of which approximately 50% are pre-stressed and the other 50% are cast-in-place reinforced concrete. The next dominant bridge material is steel bridges. There are very few masonry and timber bridges on state highways and deterioration models therefore were not developed for these superstructure types. The distribution of bridges by superstructure material types is shown in Figure 3.9.

(e) Bridge (Superstructure) Design Type. Another criteria for classifying the bridges were based on the superstructure design type. Models were developed for the predominant design types. These included stringer, box beam multiple, box beam single, slab, and arch

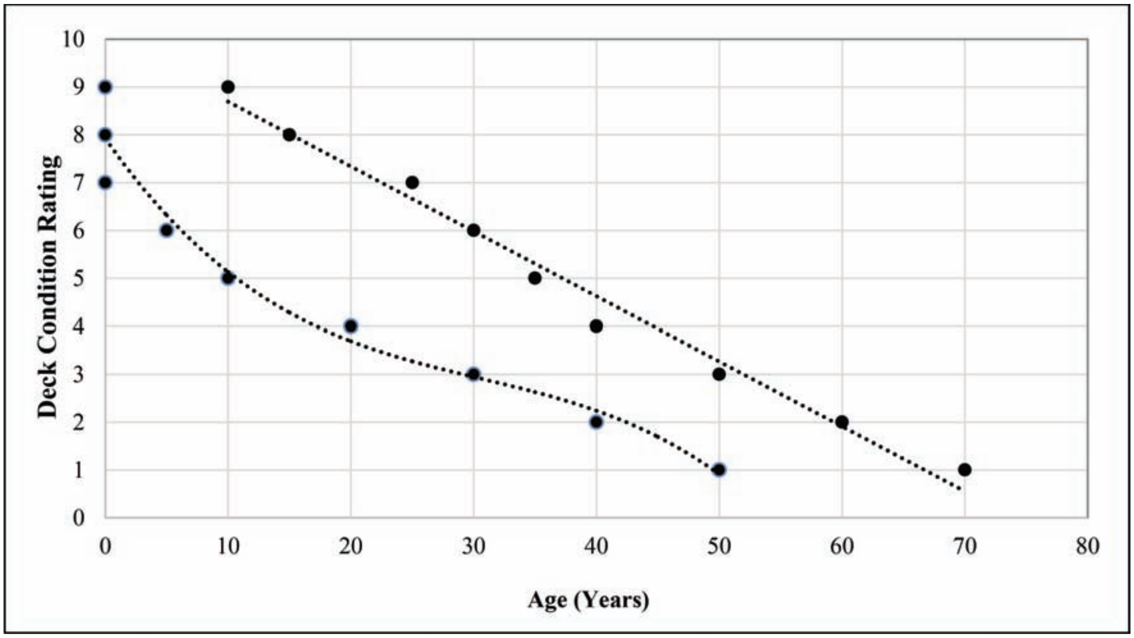


Figure 3.3 Minimum and maximum age restriction envelope for deck.

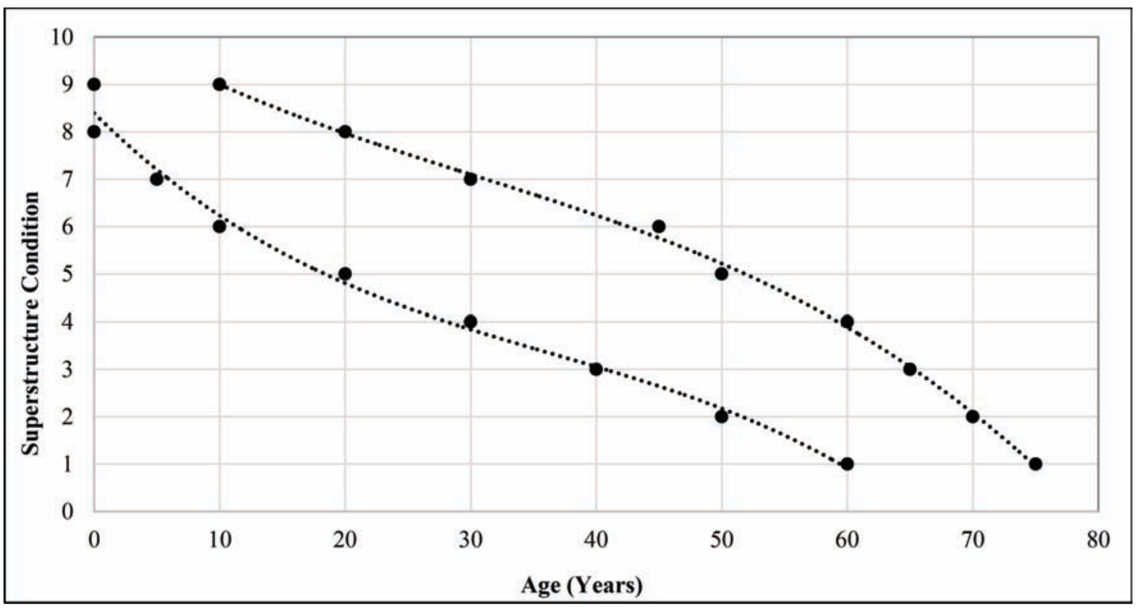


Figure 3.4 Minimum and maximum age restriction envelope for superstructure.

deck superstructures. The distribution is shown in Figure 3.10.

3.2.2 Preliminary Model Investigation

In this study, the functional forms considered for the regression models are the following.

Polynomial:

$$Y = \beta_o + \sum_{i=1}^{n} \beta_i x^i$$

If n = 1, then linear; if n = 2, then quadratic; if n = 3, then cubic.

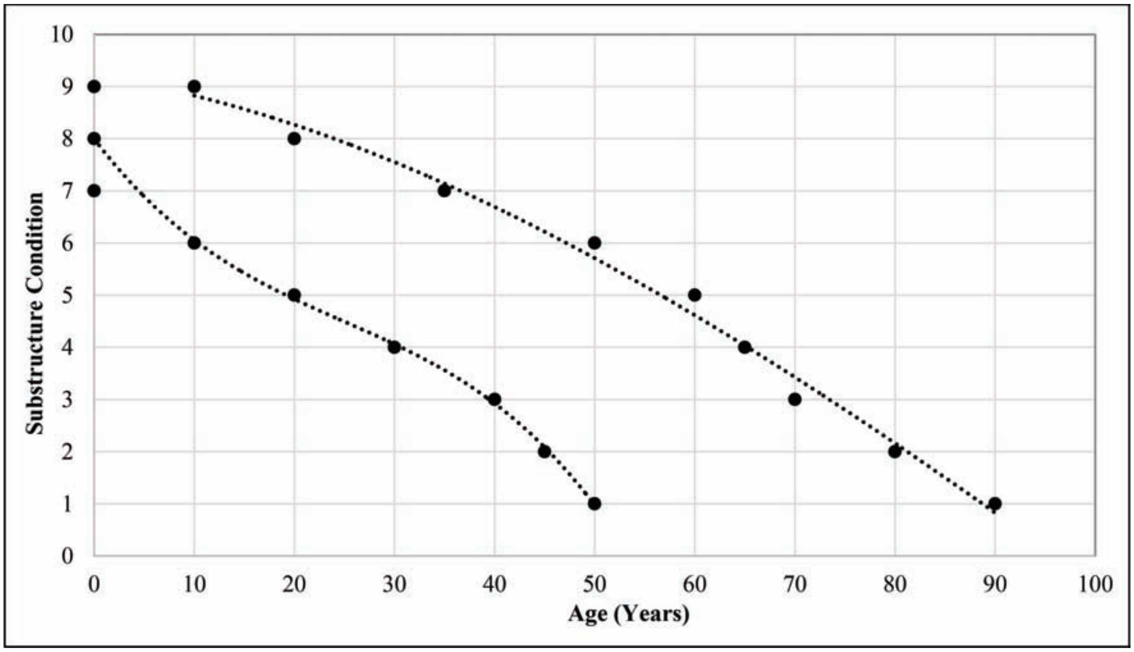


Figure 3.5 Minimum and maximum age restriction envelope for substructure.

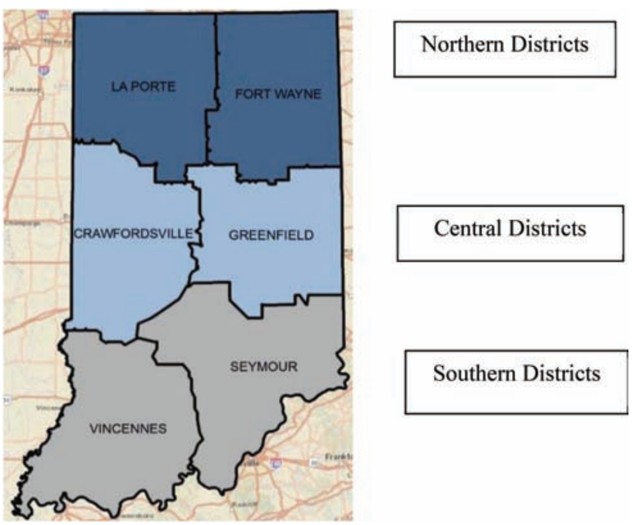


Figure 3.6 Indiana's highway administrative districts.

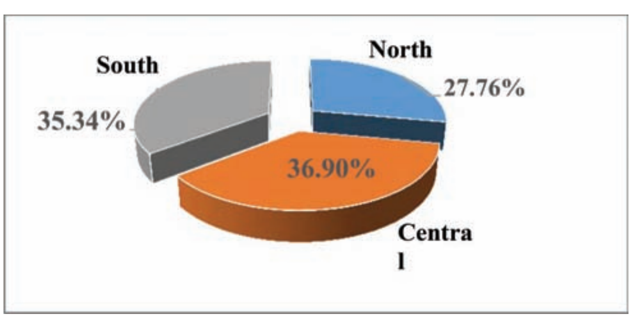


Figure 3.7 Bridge distribution by highway district.

Exponential/Logistic:

$$Y = \left(\beta_O + \sum_{i=1}^{n} \alpha_i \beta_i^{xi}\right)^k$$

For k = -1 or 1
If k = 1, then Exponential; if k = –1, then Logistic.

Gompertz:

$$Y = \sum_{i=1}^{n} c_i \alpha_i^{\beta_i^{xi}}$$

Where Y represents a dependable variable, c_i, α_i and β_i represent the estimable parameters and x_i represents an individual variable.

Past studies on bridge deterioration modeling fitted polynomial functional forms to the data (Agrawal & Kawaguchi, 2009; Bolukbasi et al., 2004; Jiang & Sinha, 1989b) and concluded that the polynomial functional form adequately describes the deterioration pattern of bridge components in the long term. Some past studies considered only age as an independent variable in their models and other independent variables such as climate and traffic were used as classification factors. This study included other independent variables besides the bridge component age: the functional class, service feature (service under the bridge), freeze index, ADTT, number of freeze-thaw cycles, average precipitation, and number of spans in main unit of the bridge. The functional class, service feature, and highway functional class were treated as indicator variables. A variety of functional forms, including the polynomial and exponential functional forms, were investigated for use in this study to establish the relationship between the component condition ratings and the independent variables.

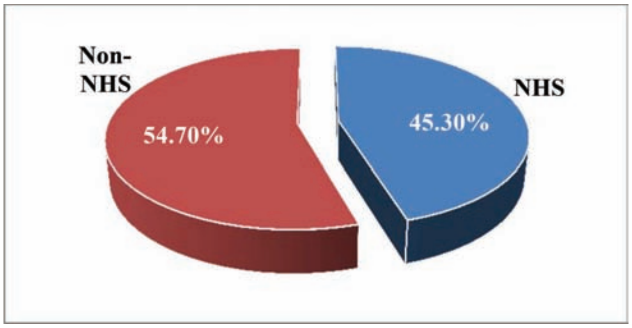


Figure 3.8 Bridge distribution by highway functional class.

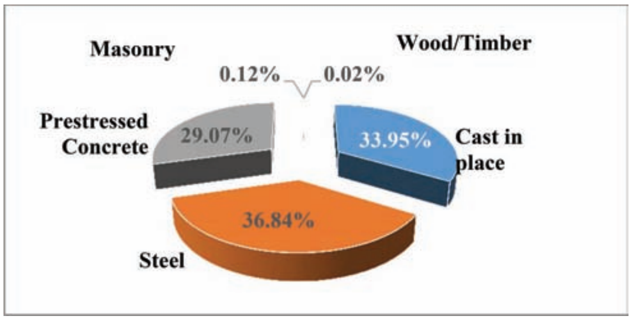


Figure 3.9 Bridge distribution by material type.

3.2.3 Model Calibration

The deterministic models were calibrated using SAS 9.4 statistical software package (SAS Institute, Cary NC). The component condition ratings were regressed against the various explanatory variables. Independent variables that were determined to be insignificant were dropped from the model. In the modeling process, the intercept was not constrained at 9.0 (the maximum rating which is associated with newly built components). Instead, the model was allowed to establish this value according to the data values. As such, it can be seen that the starting point for most models were often different than 9.0. The detailed results of the analysis are presented and discussed in Chapter 4.

3.2.4 Model Validation

Model validation is important as this step tests the stability and reasonableness of the regression coefficients, the usability of the model, and the ability to generally apply inferences drawn from the regression analysis (Kutner et al., 2005). The validation of the models was carried out using the root mean square error method (RMSE). The RMSE measures the dispersion of data around a regression line. Implicitly, this is a typical measure of the typical size of residuals (Barreto & Howland, 2006). The procedure involves squaring the residuals and summing them up. The mean of the squared residuals is found and the square root computed. The RMSE is computed by:

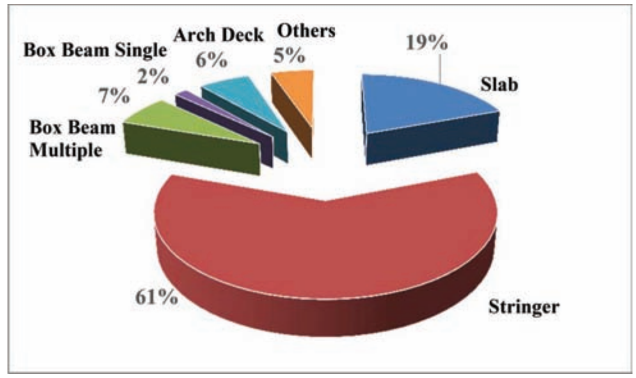


Figure 3.10 Bridge distribution by superstructure design type.

$$RMSE = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{3.1}$$

Where n is the number of observations; $\hat{y}_i$ is the estimated response variable using the developed model; and y_i is the actual response variable.

It is usually preferable to split the data sets into two equal parts; estimation and prediction or validation data sets (Snee, 1977). The drawback to this technique is that reliable models may not be developed if the prediction dataset is not sufficiently large. Kutner et al. (2005) indicated that the number of observations in the validation set should be at least 6 to 10 times the number of variables in the pool of predictor variables. Taking into account the trade-off between having a dataset large enough to develop reliable deterioration models and having an acceptable variable to observation ratio, ten percent of the data was set aside for validating the models developed in this study.

3.3 Methodology for the Probabilistic Models

The NBI bridge condition ratings are discrete in nature. As such, modeling that uses discrete techniques for the response variables, can be considered most appropriate for modeling such data. Discrete modeling techniques tend to be associated with probabilistic outcomes. The most common techniques are the Markov chain, ordered probit model, and binary probit model. Estimation of ordered probit models using panel data can be time consuming and cumbersome, and several studies that used panel data discovered problems related to state dependence and heterogeneity, particularly in the area where behavior modeling is undertaken, such as labor economics (Davies, Crouchley, & Pickles, 1982; Heckman, 1981; Heckman & Wills, 1977) and highway safety (Bates & Neyman, 1951). The binary probit model was selected in this study because it can be used to address the complexity associated with the estimation procedure (Bulusu & Sinha, 1997). The dependent variable is a 0/1 indicator variable for the

TABLE 3.5
Variables Selected for Probit Model Analysis

	Symbol	Description
Response Variable	$Z\ (i,t)$	Transition indicator in current inspection period that indicates whether the condition drops from one state to another, $Z(i,t)=1$, if the condition stays in the same state, $Z(i,t) = 0$ if the condition does not stay in the same state
Independent Variables	$Z\ (i,t–1)$	Transition indicator in last inspection period that indicates whether the condition dropped from one state to another, $Z(i,t–1) = 1$ if the condition stayed in the same state, $Z(i,t–1) = 0$ if the condition did not stay in the same state
	AGE	Primary age of bridges, that is, since construction or reconstruction
	DIST	Indiana highway agency districts from 1 to 6 (1=LaPorte; 2= Fort Wayne; 3=Crawfordsville; 4=Greenfield; 5=Vincennes; 6=Seymour)
	SOUTH	Dummy variable for bridges located in Indiana's Southern districts (1 if located in district 5 or 6; 0 otherwise)
	SUPERTYPE	Type of superstructure (XXX)
	YRTOTRAN	Number of years to transition
	RATING	Component condition rating (1 if conditions 1–7, 0 otherwise)
	IFSTEEL	Dummy variable for superstructure material type (1 if steel; 0 otherwise)
	NHS	Dummy variable for NHS location (1 if NHS; 0 otherwise)
	URBAN	Dummy variable for urban location (1 if urban; 0 otherwise)
	WATERWAY	Dummy variable for service type (1 if waterway; 0 otherwise)
	WS	Dummy variable for wearing surface (1 if protective system, 0 otherwise)
	IFEXBI	Dummy variable for protection type (1 if epoxy overlay or bituminous wearing surface; 0 otherwise)
	COLDDAYS	Number of cold days per year
	NRFTC	Number of freeze-thaw cycles
	HNRFTC	Dummy variable for location at areas with high freeze-thaw cycles (NRFTC >60)
	ADT	Average Daily Traffic
	ADTT	Average Daily Truck Traffic
	DECKIMPROV	Dummy variable for bridges that have been improved in terms of deck rating within the most recent five inspection periods
	SUPIMPROV	Dummy variable for bridges that have been improved in terms of superstructure rating within the most recent five inspection periods
	SUBIMPROV	Dummy variable for bridges that have been improved in terms of substructure rating within the most recent five inspection periods

condition switching state. The developed binary probit models in this study considered the discreteness of the condition states and explicitly linked the deterioration to the relevant independent variables.

3.3.1 Dependent and Independent Variables

The choice of variables for the probabilistic deterioration modeling was guided by previous academic and practical work on bridge deterioration analysis and data availability considerations. The dependent variable is a 0/1 indicator variable for condition switching state. If the deck, superstructure, or substructure condition drops from one state to another in a single inspection interval, the switching state indicator is 1; if the condition state stays the same, the switching state indicator is 0. As a measure of performance, the NBI rating was used instead of the bridge sufficiency rating due to the need for consistency with existing practices at most highway agencies. Similar to the deterministic models, the independent variables included the bridge age, truck traffic on the bridge (calculated as the product of the average daily traffic volume and the truck percentage), bridge superstructure material type, highway functional class, service under the bridge, and climatic effects (measured in terms of a regional variable that was determined according to the highway district, freeze-thaw cycles, and number of cold days). Salt application levels tend to play an important role in deck deterioration. However, due to lack of specific data on salt application rates, this variable was implicitly considered by using qualitative regional variables and climate variables as proxies. The study also considered the bridge condition (measured in terms of the current condition rating and the switching state in the last inspection period), and the rehabilitation history (measured in terms of the number of years from the last reconstruction year to the current year). A full description of the selected variables used for the present analysis is presented in Table 3.5.

3.3.2 Model Specification

As discussed in the introduction to Section 3.2 above, the bridge deck NBI condition rating is discrete in nature, and traditional project-level deterioration models have used regression techniques to model deck variables. However, it is a truism that regression modeling is more appropriate for continuous variables and not for discrete variables. To investigate the hypothesis that more conceptually appropriate specifications of the response variable (i.e., discrete formulations) could yield superior deterioration models, an alternative specification was considered. Binary Probit (BP) models that involve the use of discrete binary response variables (in this case, whether the condition rating of a bridge component transitions to the next lower rating, or otherwise) were developed as part of the present study.

Furthermore, Binary Probit models allow for capturing the effects of latent factors of infrastructure deterioration by defining a latent variable that represents unobserved or unobservable factors. The Binary Probit specification is as follows:

$$\Pr[Z(i,t)=1]=\Phi[\beta X+\varepsilon] \tag{3.2}$$

$$U(\mathrm{i,t})=\beta X+\varepsilon \tag{3.3}$$

where: X = a vector of variables determining the condition transition statue for observation n; β = a vector of estimable parameters; ε = is a random disturbance.

Of the several BP models that were developed, the best was selected on the basis of goodness of fit and engineering intuitiveness of the model outcomes. For BP models, the most common measure of overall model fit is the ρ^2 statistic.

4. RESULTS

4.1 Combined Deterministic Models

In this study, deterioration models were developed for the three main bridge components (deck, superstructure and substructure). For the purpose of simplicity and ease of use, combined (combined data for components with and without prior repairs) models were built. The combined data also meant there were adequate observations to develop superstructure deterioration models by material and design type. Fifty four deterioration models were built: twelve models for the deck and substructure, and forty-two models for the superstructure. A summary of the combined deterministic models is shown in the Tables 4.2 and 4.3. Also, models for bridge components with and without prior repairs were built separately; these are presented in Appendix B.

4.2 Deterministic Deck Deterioration Models

Six deterioration models were built using the combined data for bridge decks based on the classification parameters identified in Chapter 3. Two main functional forms were investigated for the best fit: exponential and polynomial. Second- and third-order polynomial functional forms were considered for building the best models in this study. The variables used for the deck deterioration models are shown in Table 4.1. Table 4.4 shows the detailed modeling results for bridge decks. The influential variables are found to be the following: deck condition rating (DCR), deck age (Years) (AGE), Interstate (1 if located on Interstate, 0 Otherwise), INT, angle of skew (SKEW), bridge length (LENGTH), type of service under bridge (SERVUNDER), number of spans in main unit (SPANNO), freeze index in 1000s of degree-days (FRZINDX), number of freeze-thaw cycles (NRFTC), average daily truck traffic in 1000s (ADTT), deck protection = 1 with protective system, 0 otherwise, (DECKPROT).

4.2.1 Models for Bridge Decks

4.2.1.1 Models for Bridge Decks, Northern Districts. The results of the deterioration modeling (Table 4.4) suggest that age is the most significant variable in bridge deck deterioration in the Northern districts. For bridges on the NHS, age, service under the bridge, the number of spans in the main unit, deck protection, freeze index, and ADTT were found to be significant at 95% confidence. Age, service under the bridge, the number of spans in the main unit, deck protection and freeze index, the number of freeze-thaw cycles and ADTT were significant for bridge decks on the non-NHS. The models accounted for 49% and 44% of the variability in deck condition rating, respectively, for decks on the NHS and non-NHS. The polynomial functional form was found to fit both models with a RMSE of 0.74. Figures 4.1 and 4.2 present the trends in the deck condition rating as a function of the deck age, plotted

TABLE 4.1
Summary of the Deterministic Models for Bridge Deck Deterioration

Bridge Component	Region	Functional Class	Deterioration Model
Deck	Northern	NHS	$DCR = 8.55637 - 0.24129 \cdot AGE + 0.0096 \cdot AGE^2 - 0.0001667 \cdot AGE^3 - 0.04301 \cdot SERVUNDER - 0.01218 \cdot SPANNO + 0.51375 \cdot DECKPROT - 0.05182 \cdot FRZINDX - 0.01872 \cdot ADTT$
		Non-NHS	$DCR = 9.22454 - 0.24998 \cdot AGE + 0.01158 \cdot AGE^2 - 0.00021831 \cdot AGE^3 - 0.00136 \cdot SKEW - 0.01023 \cdot SPANNO + 0.39602 \cdot DECKPROT - 0.03037 \cdot FRZINDX - 0.01397 \cdot NRFTC - 0.08597 \cdot ADTT$
	Central	NHS	$DCR = 8.1961 - 0.16459 \cdot AGE + 0.0068 \cdot AGE^2 - 0.0001442 \cdot AGE^3 - 0.06213 \cdot \mathrm{INT} - 0.04249 \cdot SERVUNDER - 0.0005587 \cdot LENGTH + 0.50755 \cdot DECKPROT - 0.00769 \cdot NRFTC$
		Non-NHS	$DCR = 7.6959 - 0.09989 \cdot AGE + 0.00234 \cdot AGE^2 - 0.00005094 \cdot AGE^3 - 0.06901 \cdot SERVUNDER - 0.00119 \cdot LENGTH + 0.33696 \cdot DECKPROT - 0.03016 \cdot ADTT$
	Southern	NHS	$DCR = 8.58845 - 0.09752 \cdot AGE + 0.00341 \cdot AGE^2 - 0.0000855 \cdot AGE^3 - 0.00186 \cdot SKEW - 0.00041603 \cdot LENGTH + 0.53671 \cdot DECKPROT - 0.06989 \cdot FRZINDX - 0.01421 \cdot NRFTC - 0.04431 \cdot ADTT$
		Non-NHS	$DCR = 8.05846 - 0.14617 \cdot AGE + 0.00663 \cdot AGE^2 - 0.00015219 \cdot AGE^3 - 0.00098333 \cdot LENGTH + 0.43363 \cdot DECKPROT - 0.06043 \cdot FRZINDX - 0.14681 \cdot ADTT$

using specific values of the independent variables (as shown in the upper right box) of the general model (shown in the lower left box).

4.2.1.2 Models for Bridge Decks, Central Districts. For the Central districts, age, functional class, service under the bridge, bridge length, deck protection and the number of freeze-thaw cycles were found to be influential in NHS bridge deck deterioration. With regard to their non-NHS counterparts, service under the bridge, bridge length, deck protection and truck traffic (ADTT) affected deck deterioration. The models explained 48% and 53%, respectively, of the variation in deck condition rating for bridge decks on the NHS and non-NHS in the Central districts. The predictive efficiency of the models as determined by the RMSE were 0.65 and 0.66, respectively, for the NHS and non-NHS. Figures 4.3 and 4.4 illustrate the relationship between the deck condition rating and deck age; this was plotted using specific values of the independent variables (as shown in the upper right box) of the general model shown in the lower left box.

4.2.1.3 Models for Bridge Decks, Southern Districts. For NHS bridge decks in the Southern districts, the condition rating was found to be explained by the following design, climatic, and operational factors: deck age, skew, bridge length, deck protection, freeze index, the number of freeze-thaw cycles and truck traffic (ADTT) were found to be significant at 95% confidence. Variables that were found to be significant in the non-NHS model were age, bridge length, deck protection, freeze index, and ADTT. The models explained approximately 48% and 53%, respectively of the variation in the condition rating of NHS and non-NHS bridge decks. The polynomial curve was found to be the best fit for the data and the RSME for the NHS and non-NHS models were 0.59 and 0.65, respectively. In Figures 4.5 and 4.6, the plotted curves represent the deck condition rating as a function of the deck age corresponding to specific hypothetical values of the independent variables (the upper right box) of the general model (shown in the lower left box).

4.3 Deterministic Superstructure Deterioration Models

A total of 42 deterministic superstructure deterioration models were developed. The classification of superstructures was based on the bridge (superstructure) material and design type, the highway district, and the highway functional class. Table 4.5 shows the variables used for the superstructure deterioration models.

4.3.1 Deterministic Models for Cast-in-Place Concrete Superstructures

Figure 4.7 shows the distribution of the different bridge superstructures by design types for cast-in-place concrete. The distribution suggests that slabs, stringers, and arch decks are the predominant design types for cast-in-place concrete. Deterioration models were developed for these three design types only. Figure 4.8 and Figure 4.9 present photo illustrations of bridges with "cast-in-place concrete arch deck" and "cast-in-place concrete slab" superstructures, respectively.

TABLE 4.2
Summary of the Deterministic Models for Bridge Superstructure Deterioration

Bridge Component	Region	Functional Class	Deterioration Model
Cast-in-Place Concrete Arch Deck	Northern	NHS	$SUPCR = \text{EXP}\,(2.28405 - 0.00731 \cdot AGE - 0.01578 \cdot SPANNO - 0.36788 \cdot FRZINDX)$
		Non-NHS	$SUPCR = \text{EXP}\,(2.1644 - 0.00673 \cdot AGE - 0.03545 \cdot SPANNO - 0.16104 \cdot FRZINDX - 0.03782 \cdot ADTT)$
	Central	NHS	$SUPCR = \text{EXP}\,(2.02476 - 0.00799 \cdot AGE - 0.0122 \cdot LENGTH)$
		Non-NHS	$SUPCR = \text{EXP}\,(2.03724 - 0.00798 \cdot AGE - 0.00106 \cdot SKEW - 0.0006104 \cdot LENGTH - 0.02451 \cdot ADTT)$
	Southern	NHS	$SUPCR = \text{EXP}\,(2.19722 - 0.00633 \cdot AGE + 0.18559 \cdot INT - 0.19154 \cdot SERVUNDER - 0.0005814 \cdot LENGTH)$
		Non-NHS	$SUPCR = \text{EXP}\,(2.05829 - 0.00734 \cdot AGE - 0.02018 \cdot SPANNO)$
Cast-in-Place Concrete Slab	Northern	NHS	$SUPCR = 9.5820 - 0.27195 \cdot AGE + 0.00874 \cdot AGE^2 - 0.0000933 \cdot AGE^3 - 0.1991 \cdot INT - 0.17981 \cdot SERVUNDER - 0.71169 \cdot FRZINDX$
		Non-NHS	$SUPCR = 8.85183 - 0.22032 \cdot AGE + 0.00598 \cdot AGE^2 - 0.00005627 \cdot AGE^3 - 0.11229 \cdot ADTT$
	Central	NHS	$SUPCR = \text{EXP}\,(2.10131 - 0.01135 \cdot AGE - 0.01968 \cdot INT - 0.01845 \cdot SPANNO)$
		Non-NHS	$SUPCR = \text{EXP}\,(2.13095 - 0.01255 \cdot AGE - 0.00027854 \cdot SKEW - 0.01169 \cdot SPANNO - 0.0933 \cdot ADTT)$
	Southern	NHS	$SUPCR = 8.1804 - 0.02287 \cdot AGE - 0.00058022 \cdot AGE^2 - 0.06369 \cdot SPANNO - 0.00942 \cdot LENGTH - 0.74059 \cdot FRZINDX - 0.29919 \cdot ADTT$
		Non-NHS	$SUPCR = 9.00 - 0.09891 \cdot AGE + 0.00108 \cdot AGE^2 - 0.00000876 \cdot AGE^3 - 0.00458 \cdot SKEW - 0.11453 \cdot SPANNO - 1.01643 \cdot FRZINDX - 0.21873 \cdot ADTT$
Cast-in-Place Concrete Stringer	Northern	NHS	$SUPCR = 9.62497 - 0.19661 \cdot AGE + 0.00646 \cdot AGE^2 - 0.00007503 \cdot AGE^3 + 0.18145 \cdot INT - 0.00288 \cdot SKEW - 0.02567 \cdot NRFTC$
		Non-NHS	$SUPCR = 9.00 - 0.14006 \cdot AGE + 0.00332 \cdot AGE^2 - 0.00003153 \cdot AGE^3 - 0.1991 \cdot SERVUNDER - 0.04507 \cdot SPANNO - 0.94618 \cdot FRZINDX$
	Central	NHS	$SUPCR = 9.00 - 0.0709 \cdot AGE + 0.0015 \cdot AGE^2 - 0.00002415 \cdot AGE^3 + 0.1544 \cdot INT - 0.12283 \cdot SERVUNDER - 0.02661 \cdot NRFTC$
		Non-NHS	$SUPCR = 9.00 - 0.09665 \cdot AGE + 0.00143 \cdot AGE^2 - 0.00001223 \cdot AGE^3 - 0.2726 \cdot SERVUNDER - 0.0154 \cdot NRFTC - 0.22006 \cdot ADTT$
	Southern	NHS	$SUPCR = 9.00 - 0.13354 \cdot AGE + 0.00495 \cdot AGE^2 - 0.00007504 \cdot AGE^3 - 0.00866 \cdot SKEW - 0.01625 \cdot NRFTC - 0.04244 \cdot ADTT$
		Non-NHS	$SUPCR = \text{EXP}(2.19722 - 0.00866 \cdot AGE - 0.07182 \cdot SERVUNDER - 0.06813 \cdot FRZINDX - 0.00161 \cdot NRFTC - 0.01764 \cdot ADTT)$
Prestressed Concrete Box Beam Multiple	Northern	NHS	$SUPCR = \text{EXP}(2.52216 - 0.01574 \cdot AGE - 0.21057 \cdot INT - 0.00629 \cdot NRFTC)$
		Non-NHS	$SUPCR = 9.88923 - 0.21844 \cdot AGE + 0.00939 \cdot AGE^2 - 0.00016916 \cdot AGE^3 - 0.04952 \cdot SPANNO - 0.02252 \cdot NRFTC$
	Central	NHS	$SUPCR = 7.86526 - 0.00146 \cdot AGE^2 + 0.89263 \cdot INT - 0.02073 \cdot SKEW - 1.08296 \cdot FRZINDX$
		Non-NHS	$SUPCR = 8.85961 - 0.00163 \cdot AGE^2 - 0.00583 \cdot SKEW - 0.32021 \cdot SERVUNDER - 0.10322 \cdot SPANNO - 0.02203 \cdot NRFTC$
	Southern	NHS	$SUPCR = 9.00 - 0.33126 \cdot AGE + 0.01619 \cdot AGE^2 - 0.00029693 \cdot AGE^3$
		Non-NHS	$SUPCR = 9.00 - 0.00085258 \cdot AGE^2 - 0.51398 \cdot FRXINDX - 0.03316 \cdot NRFTC$

(Continued)

TABLE 4.2
(Continued)

Bridge Component	Region	Functional Class	Deterioration Model
Prestressed Concrete Box Beam Single	Northern	NHS	$SUPCR = 10.60812 - 0.00194 \cdot AGE^2 + 0.51923 \cdot INT - 0.20284 \cdot SPANNO - 1.47489 \cdot FRZINDX - 0.02781 \cdot NRFTC$
		Non-NHS	$SUPCR = 9.00 - 0.16164 \cdot AGE + 0.00651 \cdot AGE^2 - 0.00011437 \cdot AGE^3 - 0.20539 \cdot SERVUNDER - 0.0047 \cdot LENGTH - 0.1666 \cdot ADTT$
	Southern	NHS	$SUPCR = 9.00 - 0.00221 \cdot AGE^2 - 0.17157 \cdot INT - 0.00568 \cdot LENGTH - 2.97178 \cdot FRZINDX$
		Non-NHS	$SUPCR = 9.00 - 0.162 \cdot AGE + 0.00904 \cdot AGE^2 - 0.00020555 \cdot AGE^3 - 0.00996 \cdot NRFTC$
Prestressed Concrete Stringer	Northern	NHS	$SUPCR = 9.67048 - 0.03572 \cdot AGE - 0.00076366 \cdot AGE^2 + 0.12316 \cdot INT - 0.00089223 \cdot LENGTH - 0.66583 \cdot FRZINDX - 0.0178 \cdot NRFTC$
		Non-NHS	$SUPCR = 9.00 - 0.11174 \cdot AGE + 0.00366 \cdot AGE^2 - 0.00006889 \cdot AGE^3 - 0.00399 \cdot SKEW - 0.05439 \cdot SPANNO - 0.53304 \cdot FRZINDX$
	Central	NHS	$SUPCR = 10.51217 - 0.00208 \cdot AGE^2 - 0.06621 \cdot SPANNO - 0.0421 \cdot NRFTC$
		Non-NHS	$SUPCR = 8.9232 - 0.00177 \cdot AGE^2 - 0.00465 \cdot SKEW - 0.00153 \cdot LENGTH - 0.01915 \cdot NRFTC$
	Southern	NHS	$SUPCR = 8.50758 - 0.02473 \cdot AGE - 0.00101 \cdot AGE^2 - 0.00481 \cdot LENGTH - 0.15089 \cdot ADTT$
		Non-NHS	$SUPCR = 9.00 - 0.05674 \cdot AGE + 0.00123 \cdot AGE^2 - 0.00003815 \cdot AGE^3 - 0.43769 \cdot SERVUNDER - 0.00319 \cdot LENGTH - 0.00402 \cdot NRFTC$
Steel Stringer	Northern	NHS	$SUPCR = 9.46753 - 0.19653 \cdot AGE + 0.00892 \cdot AGE^2 - 0.00016286 \cdot AGE^3 - 0.02808 \cdot AVGPPN$
		Non-NHS	$SUPCR = 8.08791 - 0.10604 \cdot AGE + 0.00274 \cdot AGE^2 - 0.00003634 \cdot AGE^3 - 0.10482 \cdot ADTT$
	Central	NHS	$SUPCR = 7.86936 - 0.09765 \cdot AGE + 0.00415 \cdot AGE^2 - 0.00008244 \cdot AGE^3 - 0.05396 \cdot INT - 0.02771 \cdot SERVUNDER - 0.00027153 \cdot LENGTH - 0.00362 \cdot NRFTC$
		Non-NHS	$SUPCR = 8.27835 - 0.07275 \cdot AGE + 0.00104 \cdot AGE^2 - 0.00001068 \cdot AGE^3 - 0.00138 \cdot SKEW - 0.00882 \cdot NRFTC$
	Southern	NHS	$SUPCR = 9.00 - 0.10947 \cdot AGE + 0.00533 \cdot AGE^2 - 0.00009904 \cdot AGE^3 - 0.00297 \cdot SKEW - 0.0148 \cdot AVGPPN - 0.87639 \cdot FRZINDX - 0.00786 \cdot NRFTC - 0.0204 \cdot ADTT$
		Non-NHS	$SUPCR = 8.05118 - 0.1127 \cdot AGE + 0.00444 \cdot AGE^2 - 0.00007786 \cdot AGE^3 - 0.10251 \cdot SERVUNDER - 0.14818 \cdot ADTT$
Steel Truss Thru	Northern	Non-NHS	$SUPCR = 9.00 - 0.14679 \cdot AGE + 0.00354 \cdot AGE^2 - 0.00004253 \cdot AGE^3 - 0.03021 \cdot AVGPPN$
	Southern	Non-NHS	$SUPCR = \mathrm{EXP}(2.19722 - 0.01288 \cdot AGE - 0.00249 \cdot SKEW - 0.00259 \cdot AVGPPN - 0.27557 \cdot FRZINDX)$

4.3.1.1 Models for Cast-in-Place Concrete Arch Deck Superstructures, Northern Districts. The model results for NHS bridges (Table 4.6) in this family suggest that age, number of spans and freeze index are the significant factors of the superstructure condition rating. This implies that there is rather little variation in the values of the other factors. For arch deck superstructures on the non-NHS, age, the number of spans in the main unit, freeze index, and truck traffic (ADTT) were found to be significant at 95% confidence. Both models explained 45% of the variation in the superstructure condition rating. The predictive efficiencies of the models as determined by the RMSE were 0.67 and 0.66 for the NHS and non-NHS models, respectively. The deterioration curves are shown in Figures 4.10 and 4.11.

4.3.1.2 Models for Cast-in-Place Concrete Arch Deck Superstructures, Central Districts. For the NHS bridge superstructures in this family (Table 4.6), the model suggested that the superstructure age and length are the only significant factors of deterioration and the exponential function explains 55% of the variation in the superstructure condition rating. The model had a RMSE of 0.71. For the non-NHS bridge superstructures in this model, the superstructure age, bridge skew, the bridge length, and truck traffic were significant at 95% confidence. The function explained 48% of the variation in superstructure condition rating and the predictive competence of the model in terms of RMSE was 0.54. In Figures 4.12 and 4.13, the relationship between the superstructure condition rating and age is illustrated. The plot was prepared using specific values

TABLE 4.3
Summary of the Deterministic Models for Bridge Substructure Deterioration

Bridge Component	Districts	Functional Class	Deterioration Model
Substructure	Northern	NHS	$SUBCR = 8.15937 - 0.1233{\bullet}AGE + 0.00314{\bullet}AGE^2 - 0.00015219{\bullet}AGE^3 - 0.01163{\bullet}SPANNO - 0.00775{\bullet}ADTT$
		Non-NHS	$SUBCR = 8.43932 - 0.1565{\bullet}AGE + 0.00386{\bullet}AGE^2 - 0.00003454{\bullet}AGE^3 - 0.05085{\bullet}ADTT$
	Central	NHS	$SUBCR = 8.25023 - 0.10552{\bullet}AGE + 0.00274\ {\bullet}AGE^2 - 0.00002766{\bullet}AGE^3 - 0.03816{\bullet}INT - 0.008212{\bullet}SERVUNDER - 0.00045568{\bullet}LENGTH - 0.00648{\bullet}NRFTC$
		Non-NHS	$SUBCR = 8.48942 - 0.13866{\bullet}AGE + 0.00312\ {\bullet}AGE^2 - 0.00002722{\bullet}AGE^3 - 0.09838{\bullet}SERVUNDER - 0.00054403{\bullet}LENGTH - 0.00255{\bullet}NRFTC - 0.0933{\bullet}ADTT$
	Southern	NHS	$SUBCR = 8.96898 - 0.07394{\bullet}AGE + 0.00161{\bullet}AGE^2 - 0.00001654{\bullet}AGE^3 - 0.00199{\bullet}\mathrm{SKEW} - 0.09562{\bullet}SERVUNDER - 0.01205{\bullet}SPANNO - 0.72823{\bullet}FRZINDX - 0.01557{\bullet}NRFTC - 0.06789{\bullet}ADTT$
		Non-NHS	$SUBCR = 8.5448 - 0.12212{\bullet}AGE + 0.00255\ {\bullet}AGE^2 - 0.00002126{\bullet}AGE^3 - 0.29416{\bullet}SERVUNDER - 0.0407{\bullet}ADTT$

of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.3.1.3 Models for Cast-in-Place Concrete Arch Deck Superstructures, Southern Districts. The model result for this family of bridges (cast-in-place concrete arch deck) suggested that the superstructure age, the functional class of the route on which the bridge is located, service under the bridge, and bridge length significantly affected the condition of arch decks of NHS bridges in the Southern district. For the non-NHS arch deck superstructures (Table 4.6), the variables found to be significant were the superstructure age and the number of spans in the main unit. The models explained 36% and 40% of the variation in superstructure condition rating of NHS and non-NHS, respectively. The predictive efficiency of the models (determined by the RMSE) were 0.52 and 0.60 for models on the NHS and non-NHS, respectively. Figures 4.14 and 4.15 show the plotted curves representing the superstructure condition rating as a function of superstructure age corresponding to specific values of the independent variables (upper right box) of the general model represented in the lower left box.

4.3.1.4 Models for Cast-in-Place Concrete Slab Superstructures, Northern Districts. The results of the analysis (Table 4.7) showed that age, functional class, service under the bridge and freeze index were significant factors of the deterioration of cast-in-place concrete slab superstructure bridges on the NHS in the Northern districts. For their non-NHS counterparts, age and truck traffic (ADTT) were found to be significant factors of deterioration of this superstructure type. The direction of the signs of these variables in both models suggest that higher levels of the variables are associated with lower condition ratings of this superstructure type. A third-order polynomial curve was found to be the most appropriate functional form to fit the data for both models and accounted for about 55% and 37% of the variation in superstructure condition rating for the NHS and non-NHS models, respectively. The RMSE was calculated as 0.55 and 0.71 for the models representing the NHS and non-NHS slab superstructures, respectively. In Figures 4.16 and 4.17 below, the plotted curves represent the superstructure condition rating corresponding to specific values of the independent variables (upper right box) of the general model presented in the lower left box.

4.3.1.5 Models for Cast-in-Place Concrete Slab Superstructures, Central Districts. For cast-in-place concrete slab superstructures on the NHS (Table 4.7), the data analysis suggested that the significant variables were the superstructure age, the functional class of the route on which the bridge is located and the number of spans in the main unit of the bridge. The exponential model accounted for 45% of the variation in superstructure condition rating and had a RMSE of 0.55. For the non-NHS concrete slab superstructures (Table 4.7), age, bridge skew, the number of spans in main unit, and ADTT were significant at 95% confidence. The exponential model explained 55% of the variation in superstructure condition rating with a RMSE of 0.68. The parameter signs for both models were intuitive and adequately explained the models presented herein. In Figures 4.18 and 4.19 below, the plotted curves represent the superstructure condition rating plotted against age using specific values of the independent variables (upper right box) of the general model presented in the lower left box.

TABLE 4.4
Deck Deterioration Models (Deterministic)

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	8.55637	103.2	9.22454	64.39	8.1961	101.24	7.6959	248.73	8.58845	72.16	8.05846	236.6
Design Factors												
Age	-0.24129	-30.58	-0.24998	-26.00	-0.16459	-27.98	-0.09989	-19.73	-0.09752	-14.2	-0.14617	-20.59
Age-Squared	0.0096	16.50	0.01158	17.69	0.0068	15.43	0.00234	8.22	0.00341	6.71	0.00663	14.25
Age-Cubed	0.00016673	-13.33	-0.00021831	-16.62	-0.0001442	-15.14	-0.00005094	-10.74	-0.0000855	-7.86	-0.00015219	-17.01
Interstate (1 if on the Interstate, 0 otherwise)	–	–	–	–	-0.06213	-4.92	–	–	–	–	–	–
Skew	–	–	-0.00136	-2.74	–	–	–	–	-0.00186	-5.8	–	–
Service Under (1 if waterway, 0 otherwise)	-0.04301	-2.99	–	–	-0.04249	-3.96	-0.06901	-4.87	–	–	–	–
Number of Spans in Main Unit	-0.01218	-4.12	-0.01023	-1.95	–	–	–	–	–	–	–	–
Length	–	–	–	–	-0.000587	-8.55	-0.00119	-7.65	-0.00041503	-5.54	-0.00098333	-9.36
Deck Protection (1 if protected, 0, otherwise)	0.51375	35.88	0.39602	24.05	0.50755	46.78	0.33696	26.66	0.53671	40.5	0.43363	33.33
Climate Factors												
Freeze Index (1000)	-0.05182	-5.15	-0.03037	-3.14	–	–	–	–	-0.06989	-13.95	-0.06043	-11.18
Number of Freeze-Thaw Cycles	–	–	-0.01397	-6.52	-0.00769	-5.89	–	–	-0.01421	-6.67	–	–
Operational Factors												
ADTT(1000)	-0.01872	-8.79	-0.08597	-5.81	–	–	-0.03016	-2.32	-0.04431	-11.97	-0.14681	-10.08
Model Fit Statistics												
Observations	11224		8705		16101		11988		9562		10180	
R-Squared	0.4917		0.435		0.4838		0.534		0.4817		0.526	

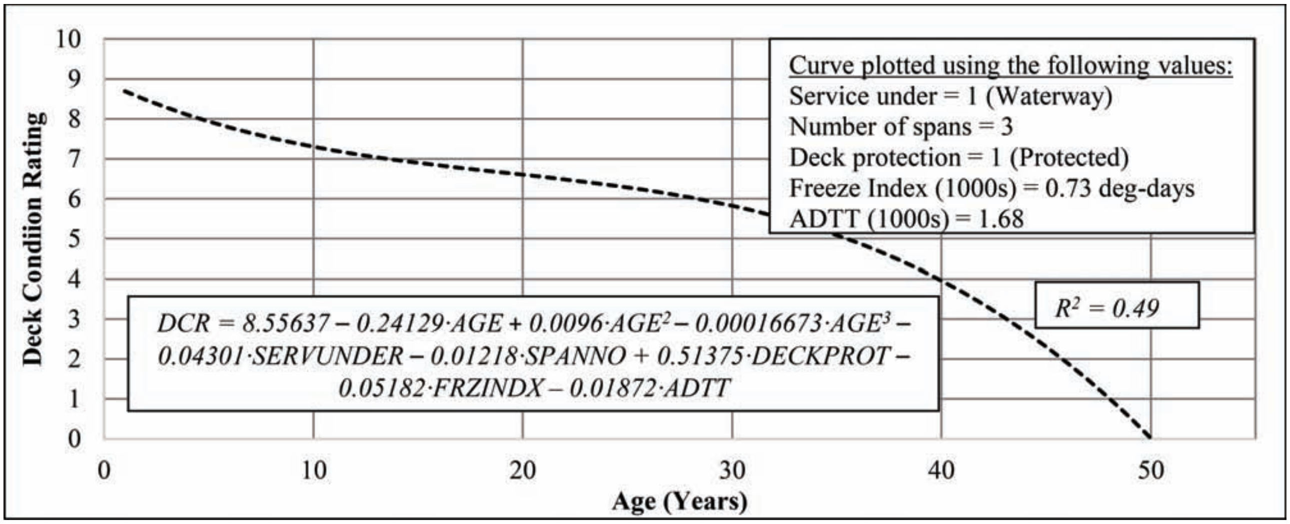


Figure 4.1 Example plot of the bridge deck deterioration model—Northern districts, NHS.

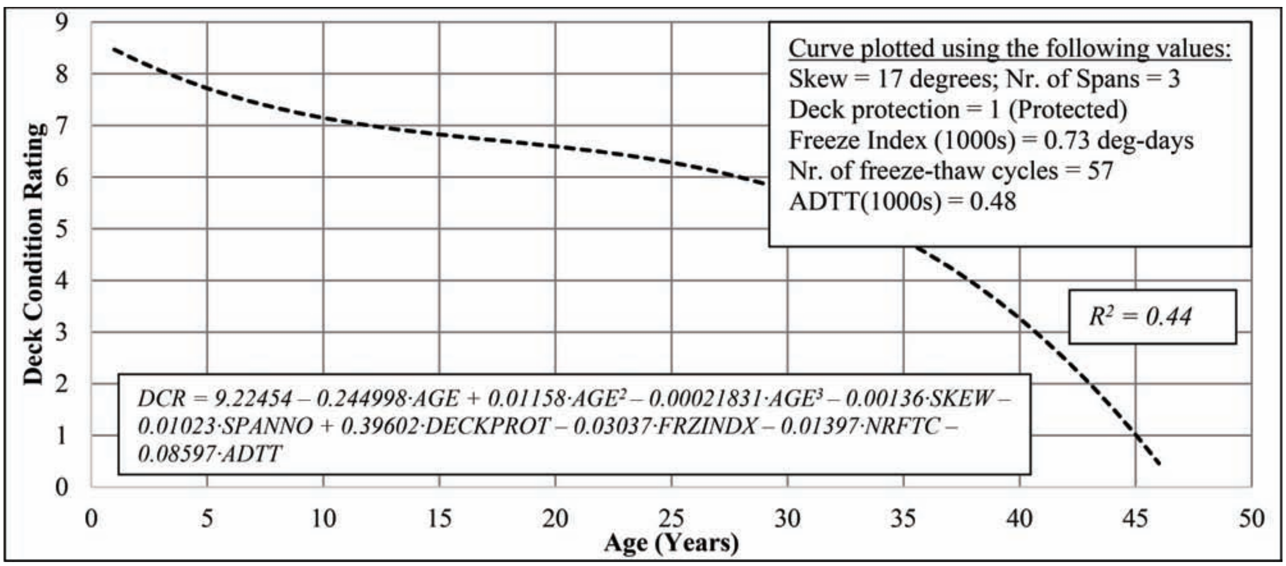


Figure 4.2 Example plot of the bridge deck deterioration model—Northern districts, non-NHS.

4.3.1.6 Models for Cast-in-Place Concrete Slab Superstructures, Southern Districts. The model results (Table 4.7) suggest that for Indiana's Southern district bridges with cast-in-place concrete superstructures on the NHS, the superstructure age, the number of spans in the main unit, bridge length, freeze index, and ADTT significantly affected the superstructure condition rating. The polynomial functional form explained about 44% of the variation in the superstructure condition rating. For the non-NHS deterioration model (Table 4.7), the variables found to be significant were superstructure age, bridge skew, the number of spans in the main unit, freeze index, and ADTT. The model accounted for a relatively high value of 56% of the variation in superstructure condition rating. The predictive adequacy as determined by the RMSE were 0.50 and 0.64 for the models on the NHS and non-NHS, respectively. In Figures 4.20 and 4.21 below, the plotted curves represent the superstructure condition rating as a function of the superstructure age corresponding to specific values of the independent variables (upper right box) of the general model presented in the lower left box.

4.3.1.7 Models for Cast-in-Place Concrete Stringer Superstructures, Northern Districts. The superstructure condition rating for cast-in-place concrete stringer on the NHS was explained by four variables: age, functional class, bridge skew, and the number of freeze-thaw cycles (Table 4.8). This suggests that, for this family of bridges, the design and climate variables are the main factors of superstructure deterioration. The model accounted for 55% of the variation in superstructure condition

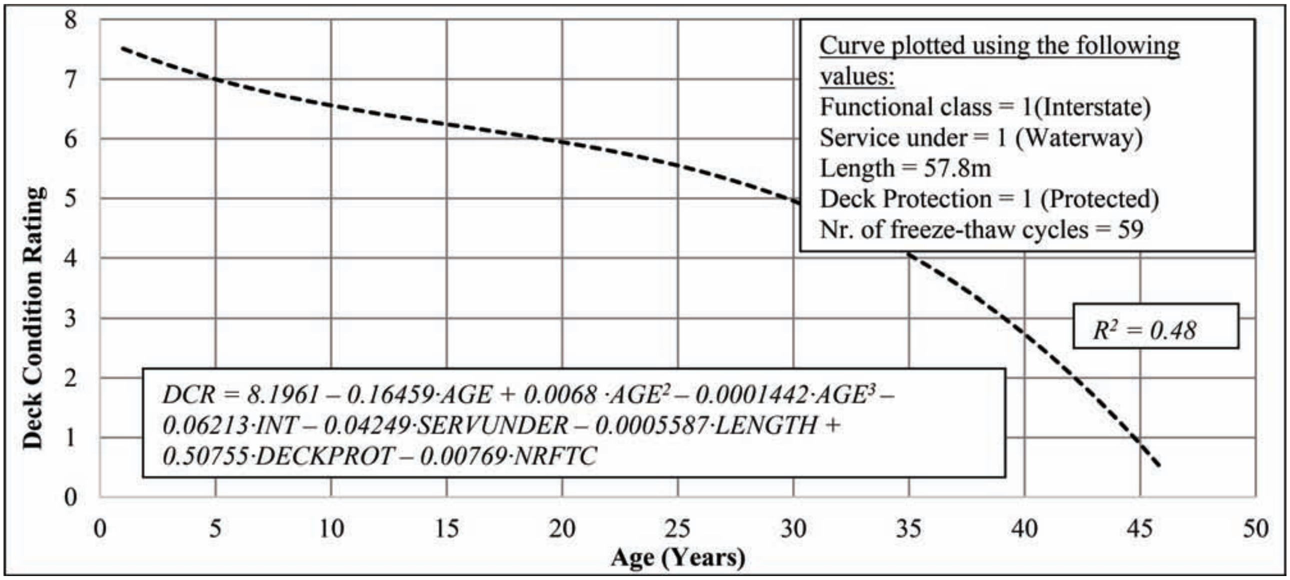


Figure 4.3 Example plot of the bridge deck deterioration model—Central districts, NHS.

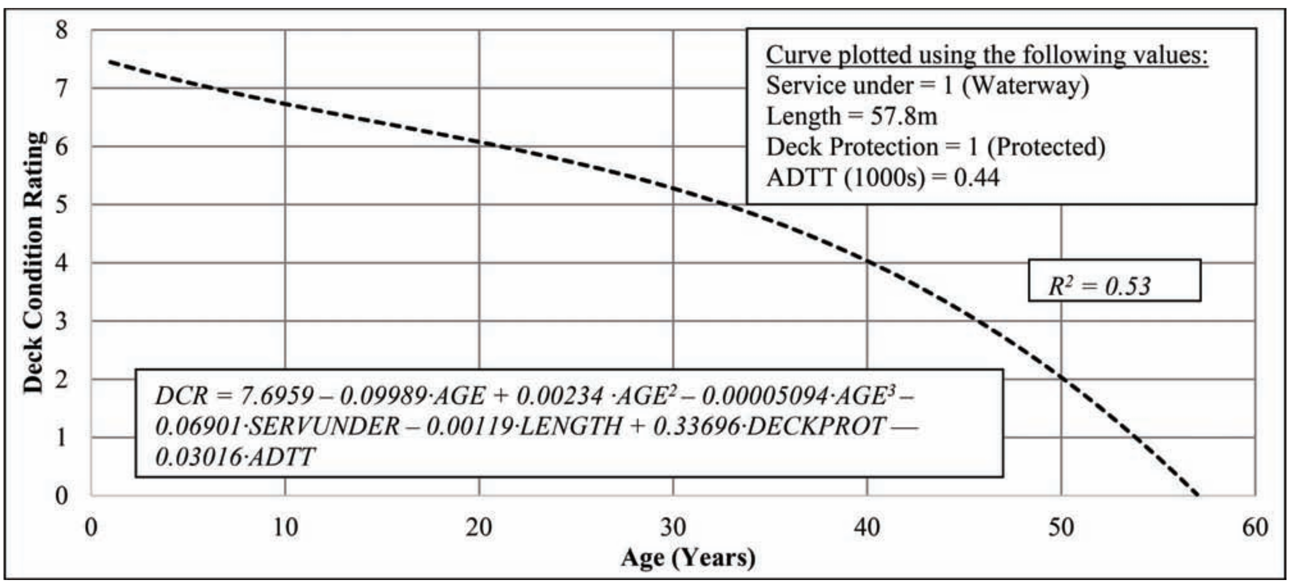


Figure 4.4 Example plot of the bridge deck deterioration model—Central districts, non-NHS.

rating. For their non-NHS counterparts (Table 4.8), the age, service under the bridge, the number of spans in the main unit, and freeze index were found to be significant at 95% confidence. The model explained about 44% of the variation in superstructure condition rating. The predictive adequacy of both models as determined by the RMSE were 0.51 and 0.56 for the models on the NHS and non-NHS, respectively. The curves in Figures 4.22 and 4.23 representing the deterioration curves of concrete stringers in the Northern districts were plotted for the superstructure condition rating versus age using specific values of the independent variables (upper right box) of the general model presented in the lower left box.

4.3.1.8 Models for Cast-in-Place Concrete Stringer Superstructures, Central Districts. A detailed analysis of the cast-in-place concrete stringer deterioration model on the NHS in the Central districts showed that age, functional class, service under the bridge, and the number of freeze-thaw cycles were significant at 95% confidence (Table 4.8). The third order polynomial functional form chosen for the deterioration model accounted for approximately 44% of the variation in the superstructure condition rating for this bridge family. For the non-NHS bridges in this family (Table 4.8), the model suggested that the superstructure age, service under the bridge, the number of freeze-thaw cycles, and ADTT were significant factors. The model explained about 57%

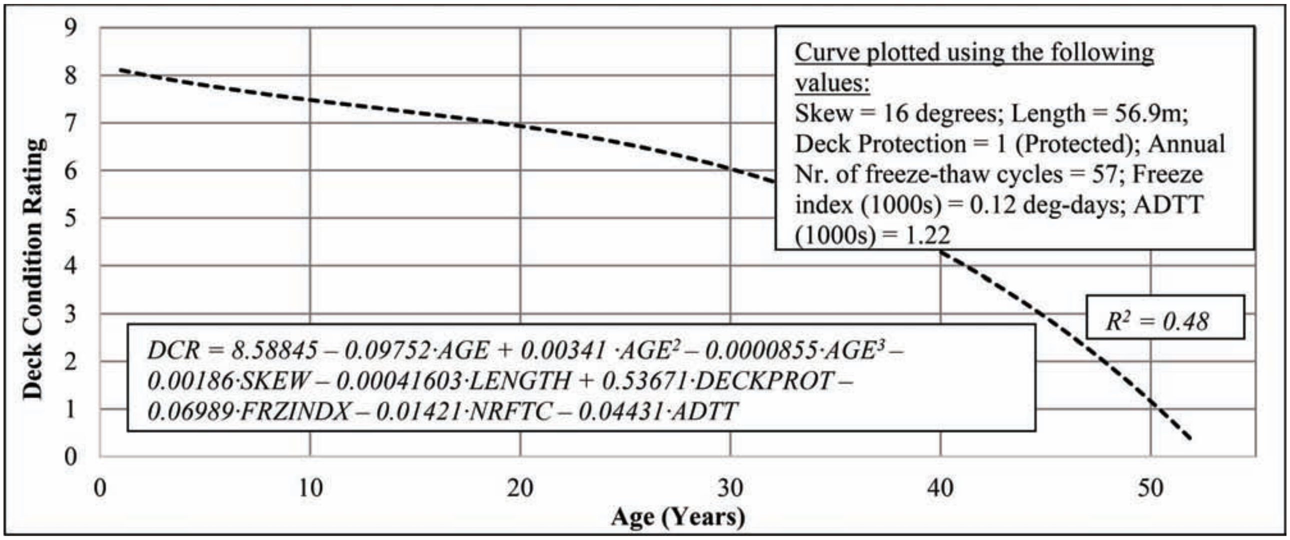


Figure 4.5 Example plot of the bridge deck deterioration model—Southern districts, NHS.

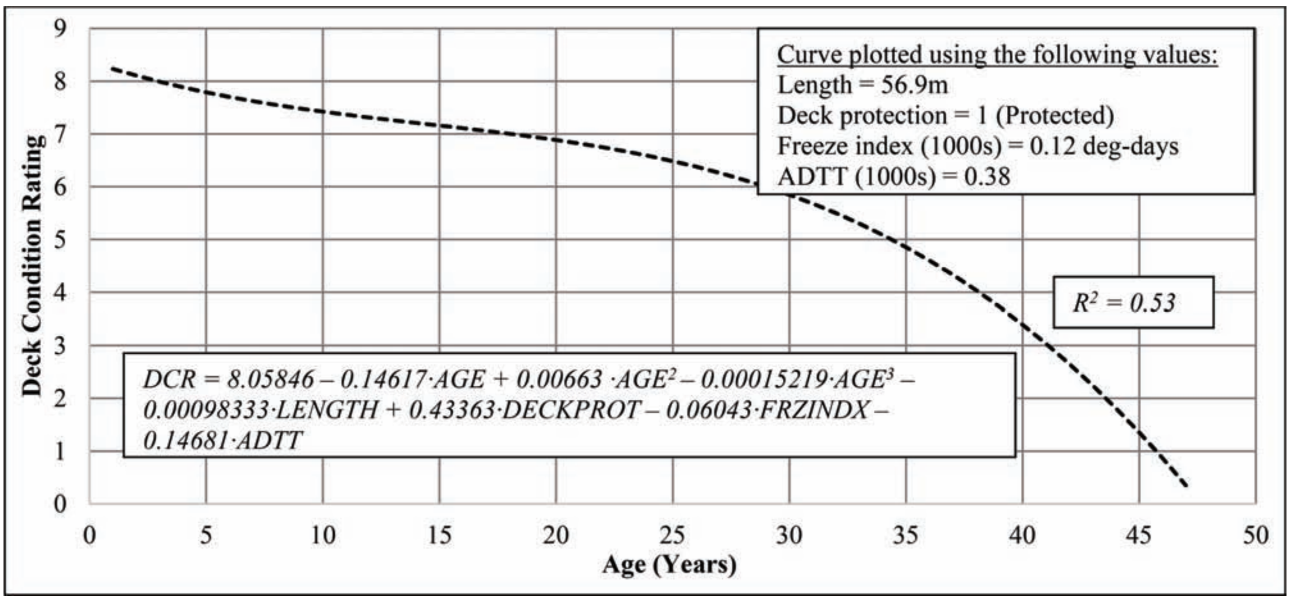


Figure 4.6 Example plot of the bridge deck deterioration model—Southern districts, non-NHS.

of the variation in superstructure condition rating. The predictive efficiency of the models determined by the RMSE were 0.23 and 0.60 for the models on the NHS and non-NHS, respectively. In Figures 4.24 and 4.25 below, the plotted curves represent the superstructure condition rating versus the bridge age corresponding to specific values of the independent variables (the upper right box) of the general model presented in the lower left box.

4.3.1.9 Models for Cast-in-Place Concrete Stringer Superstructures, Southern Districts. The results show that superstructure age, bridge skew, the number of freeze-thaw cycles, and ADTT were significant for concrete stringer superstructures on the NHS (Table 4.8). The polynomial functional form (Figure 4.26), which was ascertained to be the best model, explained 32% of the variation in the superstructure condition rating. For the non-NHS model, superstructure age, service under the bridge, freeze index, the number of freeze-thaw cycles, and ADTT were significant at 95% confidence. The exponential functional form shown in Figure 4.27 was found to fit the data and accounted for 46% of the variation in the superstructure condition rating. The models for superstructures on the NHS and non-NHS had RMSE values of 0.61 and 0.73, respectively.

4.3.2 Deterministic Models for Prestressed Concrete Superstructures

Figure 4.28 shows the distribution of the superstructure design types for prestressed concrete bridges. The distribution suggests that stringer, box beam

TABLE 4.5
Variables for Deterministic Superstructure Deterioration Models

Variable	Code
Superstructure Condition Rating	*SUPCR*
Superstructure Age (years)	*AGE*
Interstate (1 if located on Interstate, 0 Otherwise)	*INT*
Bridge skew	*SKEW*
Bridge length	*LENGTH*
Type of Service Under Bridge	*SERVUNDER*
Number of spans in main unit of the bridge	*SPANNO*
Freeze Index (1000's of degree-days)	*FRZINDX*
Number of freeze-thaw cycles	*NRFTC*
Average precipitation	*AVGPPN*
Average daily truck traffic (in 1000's)	*ADTT*

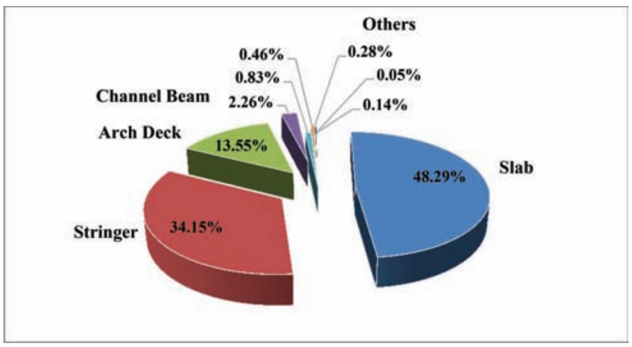


Figure 4.7 Bridges distribution of cast-in-place concrete superstructure design types.

Figure 4.8 Example of bridge with "cast-in-place concrete arch deck" superstructure. (Source: www.oscoconstruction-group.com.)

Figure 4.9 Example of bridge with "cast-in-place concrete slab" superstructure. (Source: www.flickr.com.)

multiple and single, and Tee-beam are the predominant superstructure design types for prestressed concrete. Deterioration models were developed for the design types mentioned above apart from the tee-beam. Even though the distribution shows there is a significant number of bridges with the tee-beam design, there were not enough observations per individual bridge and in total to develop deterioration models for the districts or for the different highway functional classes. Figure 4.29 presents a photo illustration of a bridge with "prestressed concrete box beam single" superstructure. Also, Figure 4.30 and Figure 4.31 present photo illustrations of bridges with "prestressed concrete box beam multiple" and "prestressed concrete stringer superstructures, respectively.

4.3.2.1 Models for Prestressed Concrete Box Beam Multiple Superstructures, Northern Districts. The results of the analysis (Table 4.9) indicates that three variables affected prestressed concrete box beam multiple superstructure deterioration on the NHS: age, functional class, and the number of freeze-thaw cycles. The exponential functional form was found to provide the best fit for the data and explained about 61% of the variation in the superstructure condition rating. For the non-NHS model (Table 4.9), the superstructure age, the number of spans in the main unit, skew, and the number of freeze-thaw cycles were found to be significant at 95% confidence. The predictive efficiency of the models determined by the RMSE method for both models were 0.66 and 0.70 for the NHS and non-NHS, respectively. In Figures 4.32 and 4.33, the plotted curves represent the superstructure condition rating plotted against the superstructure age corresponding to specific values of the independent variables (shown in the upper right box) of the general model presented in the lower left box.

4.3.2.2 Models for Prestressed Concrete Box Beam Multiple Superstructures, Central Districts. For this family of bridges (Table 4.9), superstructure age, functional class, bridge skew, and freeze index were significant at 95% confidence for box beam multiple superstructures on the NHS. The selected second order polynomial functional form explained 55% of the variation in the superstructure condition rating. For the non-NHS counterpart, the significant variables affecting superstructure condition rating were age, bridge skew, service under the bridge, the number of spans in the main unit, and the number of freeze-thaw cycles (Table 4.9). The model explained about 40% of the variation in the superstructure condition rating. The negative signs of the coefficients of the significant variables for both models indicated that an increase in these variables decreased the superstructure rating. The RMSE for the models were 0.46 and 0.61 for the NHS and non-NHS models,

TABLE 4.6
"Cast-in-Place Concrete Arch Deck" Superstructure Deterioration Models (Deterministic, Exponential)

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	2.28405	30.13	2.1644	52.53	2.02476	142.99	2.03724	180.62	2.19722	–	2.05829	140.10
Design Factors												
Age	-0.00731	-11.71	-0.00673	-17.71	-0.00799	-14.97	-0.00798	-24.75	-0.00633	-11.64	-0.00734	-21.13
Age-Squared	–	–	–	–	–	–	–	–	–	–	–	–
Age-Cubed	–	–	–	–	–	–	–	–	–	–	–	–
Interstate (1 if on the Interstate, 0 otherwise)	–	–	–	–	–	–	–	–	0.18559	4.09	–	–
Skew	–	–	–	–	–	–	-0.00106	-3.04	–	–	–	–
Service Under (1 if waterway, 0 otherwise)	–	–	–	–	–	–	–	–	-0.191540	-8.34	–	–
Number of Spans in Main Unit	-0.01578	-2.62	-0.03545	-8.13	–	–	–	–	–	–	-0.02018	-4.68
Length	–	–	–	–	–	–	–	–	-0.00336	-2.42	–	–
Climate Factors												
Freeze Index (1000)	-0.36788	-3.91	-0.16104	-2.97	–	–	–	–	–	–	–	–
Number of Freeze-Thaw Cycles	–	–	–	–	–	–	–	–	–	–	–	–
Operational Factors												
ADTT(1000s)	–	–	-0.03782	-2.54	–	–	-0.02451	-2.39	–	–	–	–
Model Fit Statistics												
Observations	266		407		242		734		262		657	
R-Squared	0.4505		0.4548		0.5508		0.4921		0.3304		0.4044	

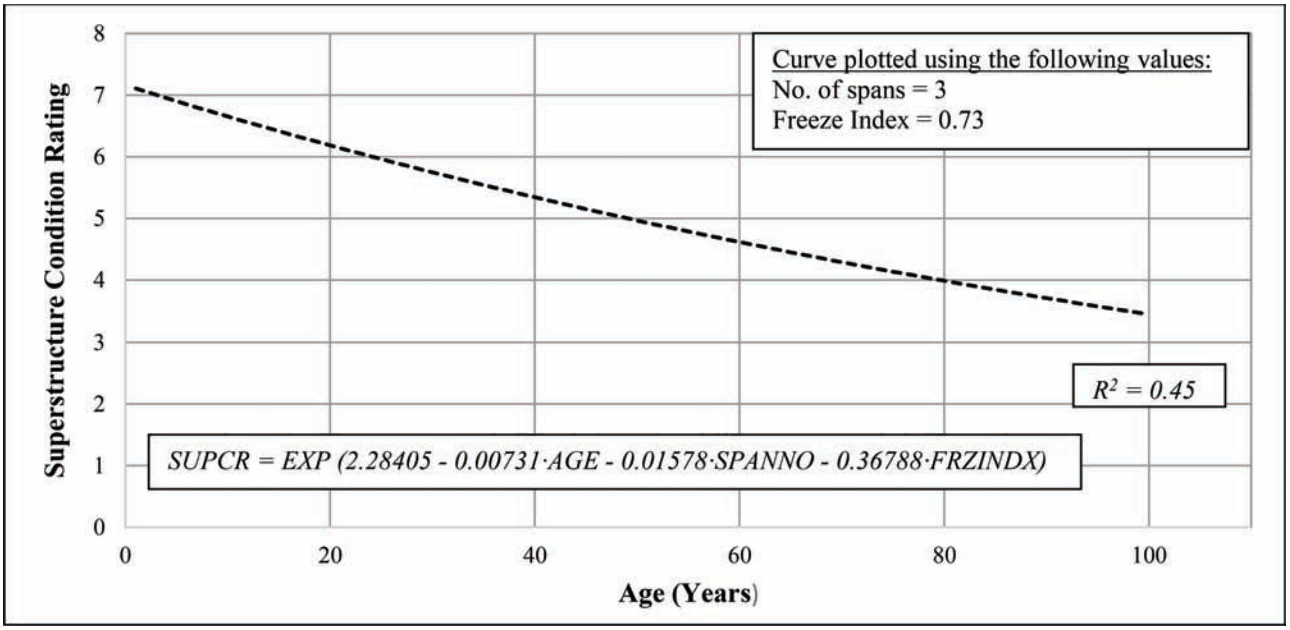


Figure 4.10 Example plot of the "cast-in-place concrete arch deck" superstructure deterioration model—Northern districts, NHS.

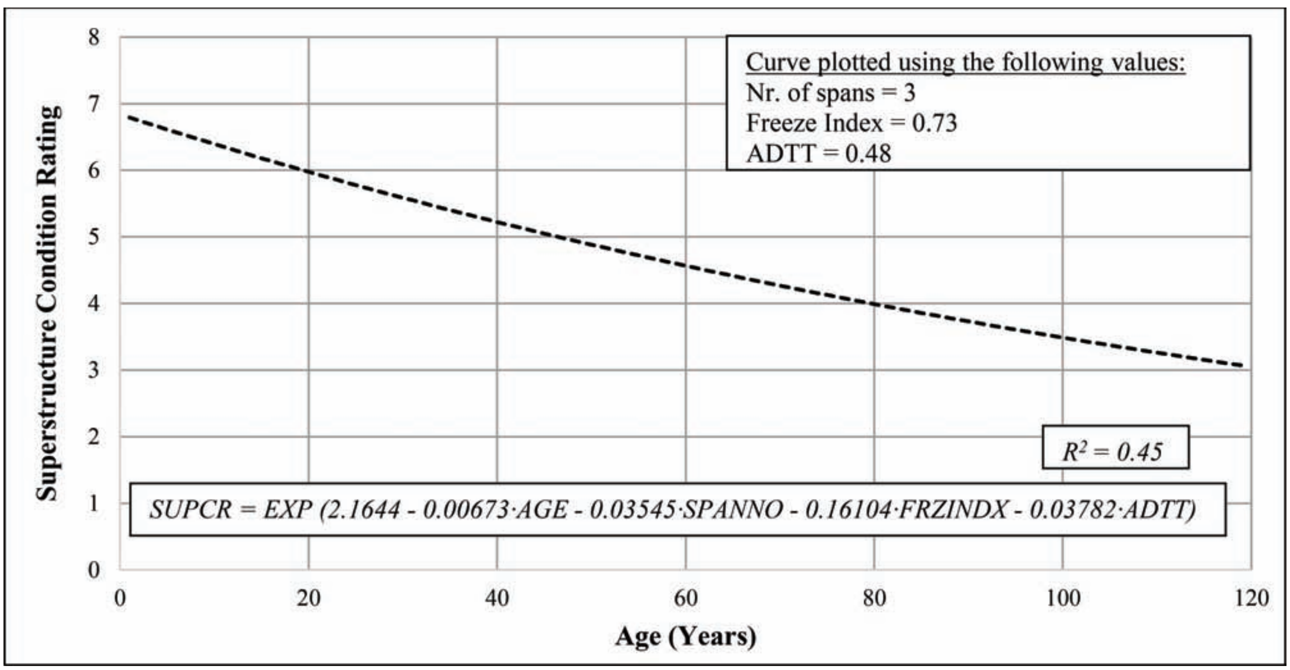


Figure 4.11 Example plot of the "cast-in-place concrete arch deck" superstructure deterioration model—Northern districts, non-NHS.

respectively. In Figures 4.34 and 4.35, the plotted curves represent the superstructure condition rating versus age corresponding to specific values of the independent variables (shown in the upper right box) of the general model presented in the lower left box.

4.3.2.3 Models for Prestressed Concrete Box Beam Multiple Superstructures, Southern Districts. For prestressed concrete box beam multiple superstructures of NHS bridges in Indiana's Southern districts, the model results suggest that superstructure age is the only significant variable at 95% confidence (Table 4.9). The variation observed in the values of the other variables related to design, climatic, and operational variables to make them significant. This does not mean however that the other variables are not influential determinants of NHS bridge box beam multiple superstructure deterioration. The polynomial functional form (Figure 4.36) was the best fit for the data and explained 52% of the variation in the superstructure condition rating. The model had a RMSE of 0.70. For the non-NHS prestressed concrete superstructures in the Southern districts (Table 4.9),

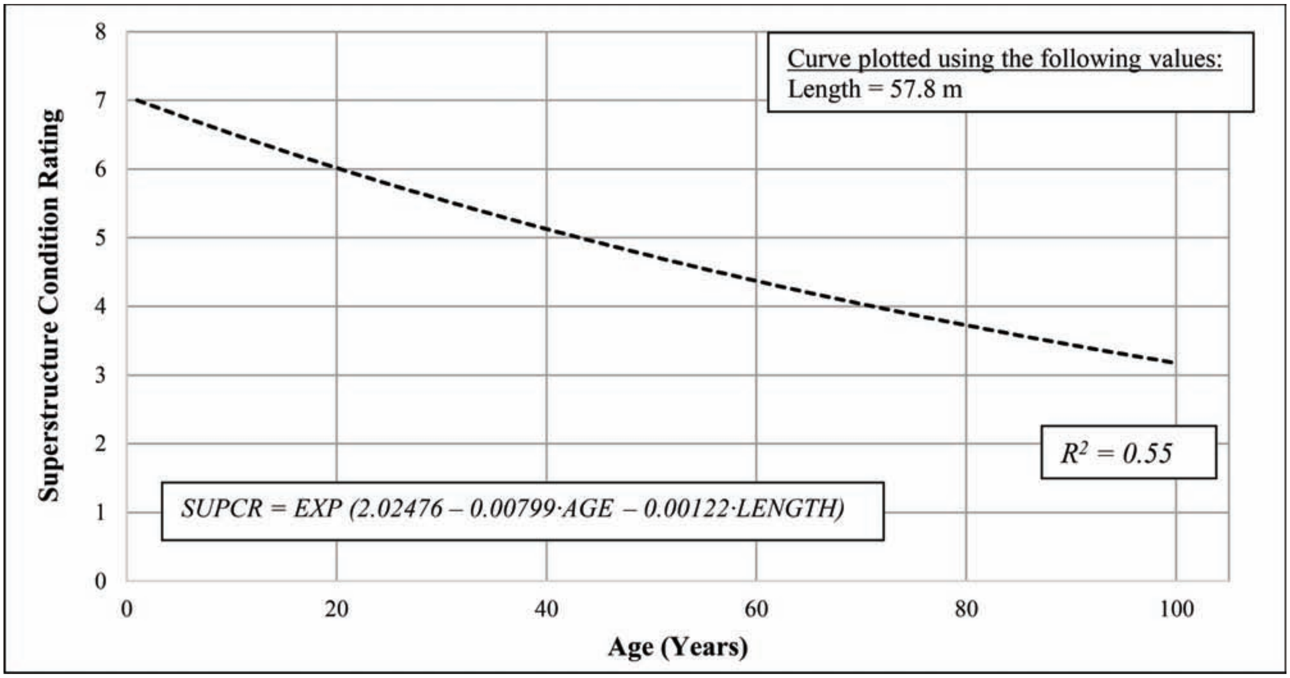


Figure 4.12 Example plot of the "cast-in-place concrete arch deck" superstructure model—Central districts, NHS.

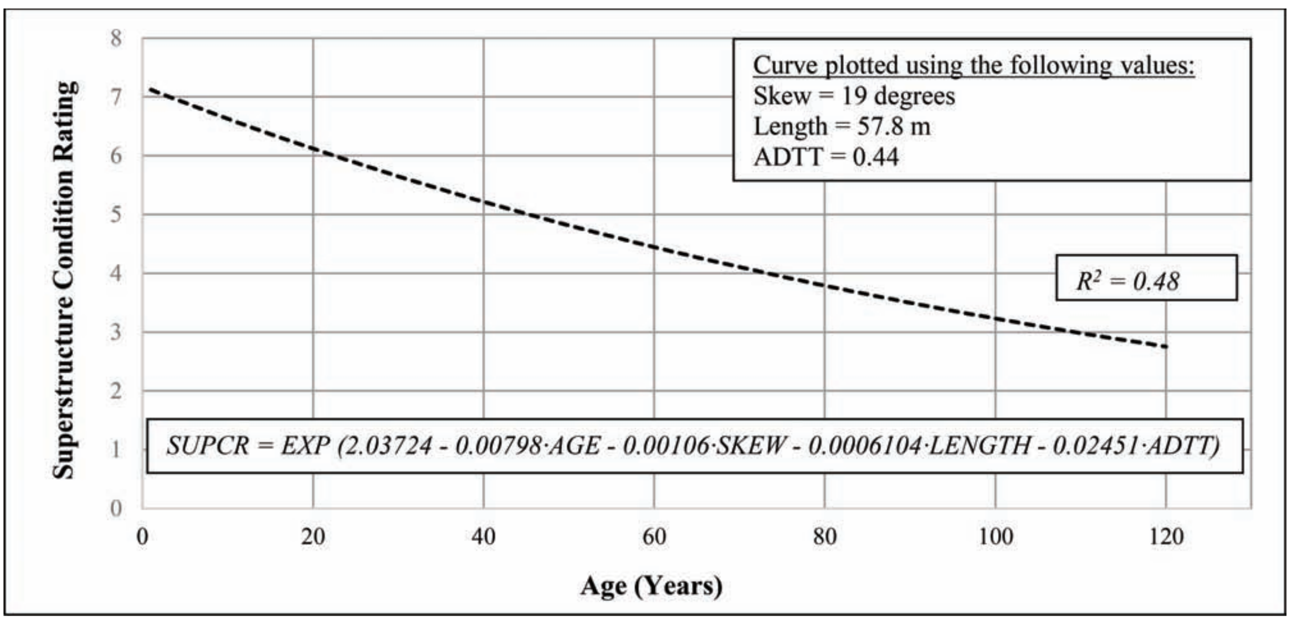


Figure 4.13 Example plot of the "cast-in-place concrete arch deck" superstructure deterioration model—Central districts, non-NHS.

superstructure age and the climatic variables (freeze index and number of freeze-thaw cycles) were significant. All other variables were insignificant at 95% confidence. The model accounts for only 22% of the variation in superstructure condition rating and has a predictive ability (RMSE) of 0.57. The deterioration curve is shown in Figure 4.37.

4.3.2.4 Models for Prestressed Concrete Box Beam Single Superstructures, Northern Districts. For this family of models, the observations were insufficient for box beam single superstructures in the Central districts. Therefore, the Northern and Central districts were combined. Five variables were found to be significant for box beam single superstructures on the NHS in Indiana's Northern districts at 95% confidence: superstructure age, functional class, the number of spans in the main unit, freeze index, and the number of freeze-thaw cycles (Table 4.10). A second-order polynomial functional form was found to best fit the data and had a coefficient of determination of 46%. For the non-NHS superstructures in this family (Table 4.10),

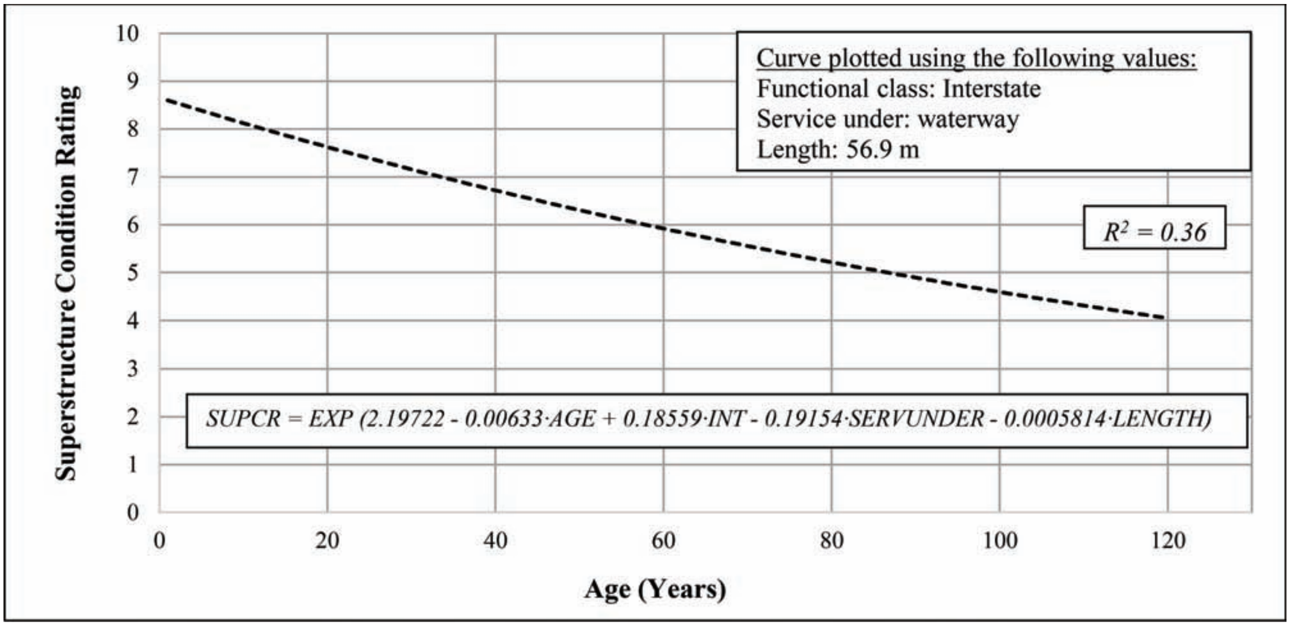


Figure 4.14 Example plot of the "cast-in-place concrete arch deck" superstructure deterioration model—Southern districts, NHS.

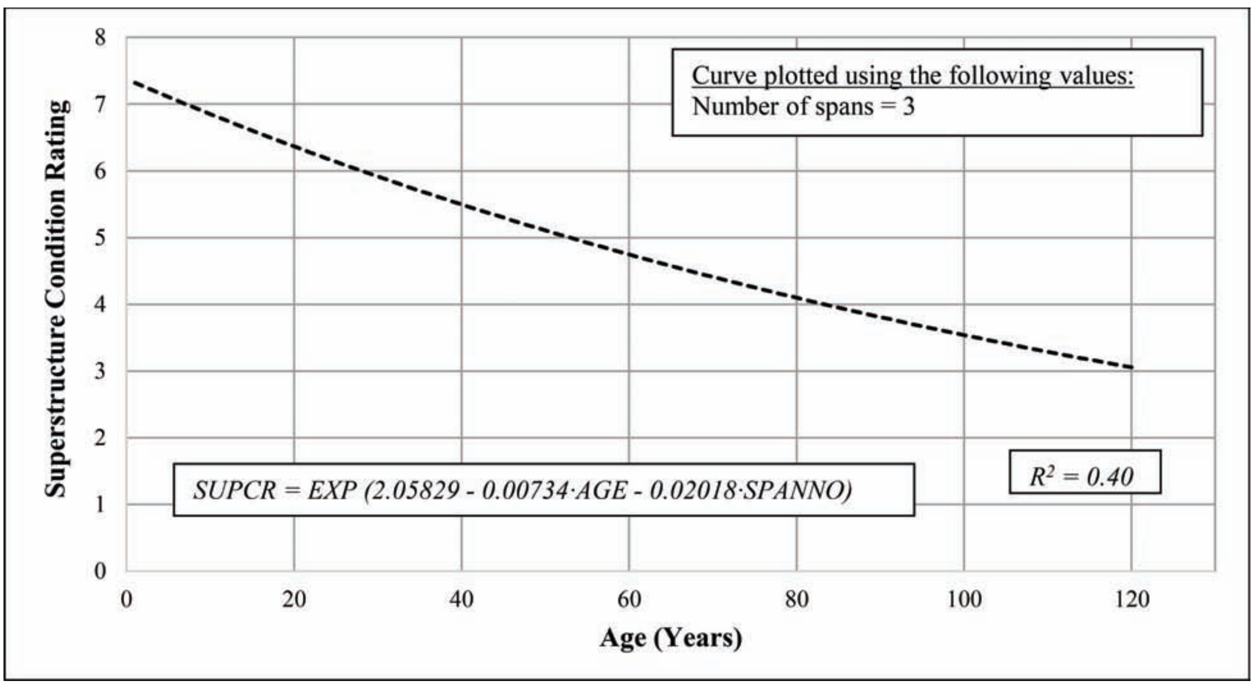


Figure 4.15 Example plot of the "cast-in-place concrete arch deck" superstructure deterioration model—Southern districts, non-NHS.

the significant variables were superstructure age, service under the bridge, bridge length, and truck traffic. The model accounted for 38% of the variation in the superstructure condition rating. The RMSE for the models on the NHS and non-NHS were determined as 0.64 and 0.69, respectively. The plotted curves shown in Figures 4.38 and 4.39 represent the superstructure condition rating corresponding to specific values of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.3.2.5 Models for Prestressed Concrete Box Beam Single Superstructures, Southern Districts. The model results for this family of bridge components suggest that the condition rating for box beam single superstructures in the Southern districts were explained by four variables: age, functional class, bridge length, and freeze index (Table 4.10). This outcome suggested that the design and climate variables are the main factors of superstructure deterioration. The model explained 59% of the variation in the superstructure condition rating. For their non-NHS

TABLE 4.7
"Cast-in-Place Concrete Slab" Superstructure Deterioration Model (Deterministic)

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	Parameter Estimate	t-stat	Parameter Estimate	t-stat	Parameter Estimate	t-stat	Parameter Estimate	t-stat	Parameter Estimate	t-stat	Parameter Estimate	t-stat
Constant	9.5820	60.65	8.85183	143.80	2.10131	130.46	2.13095	247.79	8.1804	96.22	9.00	–
Design Factors												
Age	-0.27195	-25.32	-0.22032	-23.89	-0.01135	-42.14	-0.01255	-57.02	-0.02287	-4.85	-0.09891	-14.17
Age-Squared	0.00874	16.63	0.00598	14.94	–	–	–	–	-0.00058022	-5.27	0.00108	3.33
Age-Cubed	-0.0000933	-13.94	-0.00005627	-11.62	–	–	–	–	–	–	-0.00000876	-2.18
Interstate (1 if on the Interstate, 0 otherwise)	-0.1991	-6.90	–	–	-0.01968	-4.92	–	–	–	–	–	–
Skew	–	–	–	–	–	–	-0.00027854	-2.21	–	–	-0.00458	-5.26
Service Under (1 if waterway, 0 otherwise)	-0.17981	-4.25	–	–	–	–	–	–	–	–	–	–
Number of Spans in Main Unit	–	–	–	–	-0.01845	-3.48	-0.01169	-4.65	-0.06369	-1.95	-0.11453	-7.61
Length	–	–	–	–	–	–	–	–	-0.00942	-3.74	–	–
Climate Factors												
Freeze Index (1000)	-0.71169	-4.10	–	–	–	–	–	–	-0.74059	-5.71	-1.01643	-9.02
Number of Freeze-Thaw Cycles	–	–	–	–	–	–	–	–	–	–	–	–
Operational Factors												
ADTT(1000)	–	–	-0.11229	-3.90	–	–	–	-7.17	-0.29919	-11.36	-0.21873	-4.85
Model Fit Statistics												
Observations	1743		2289		2233		2658		1430		2306	
R-Squared	0.551		0.3715		0.4520		0.5501		0.4372		0.5615	

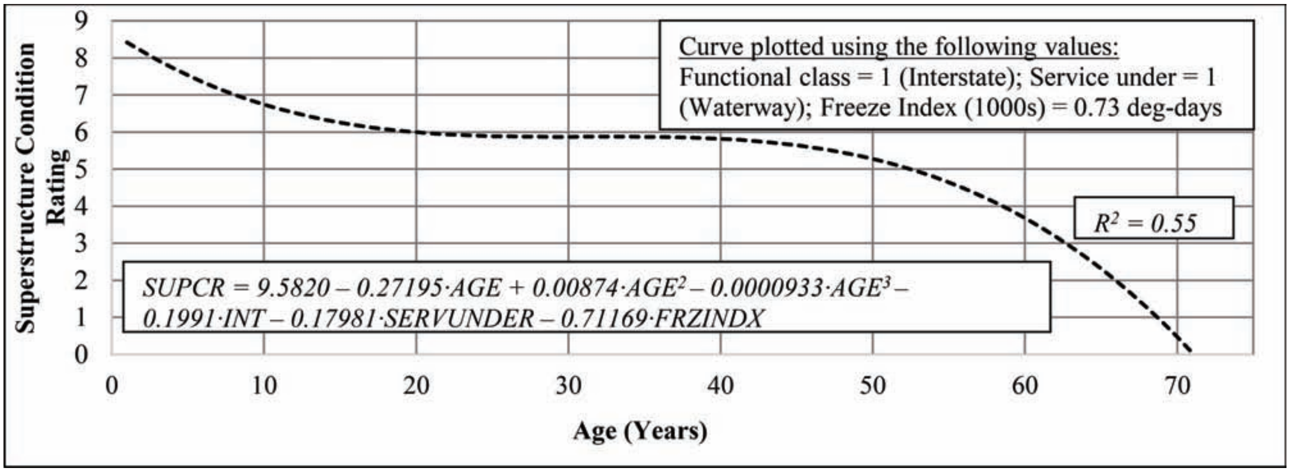


Figure 4.16 Example plot of the "cast-in-place concrete slab" superstructure deterioration model—Northern districts, NHS.

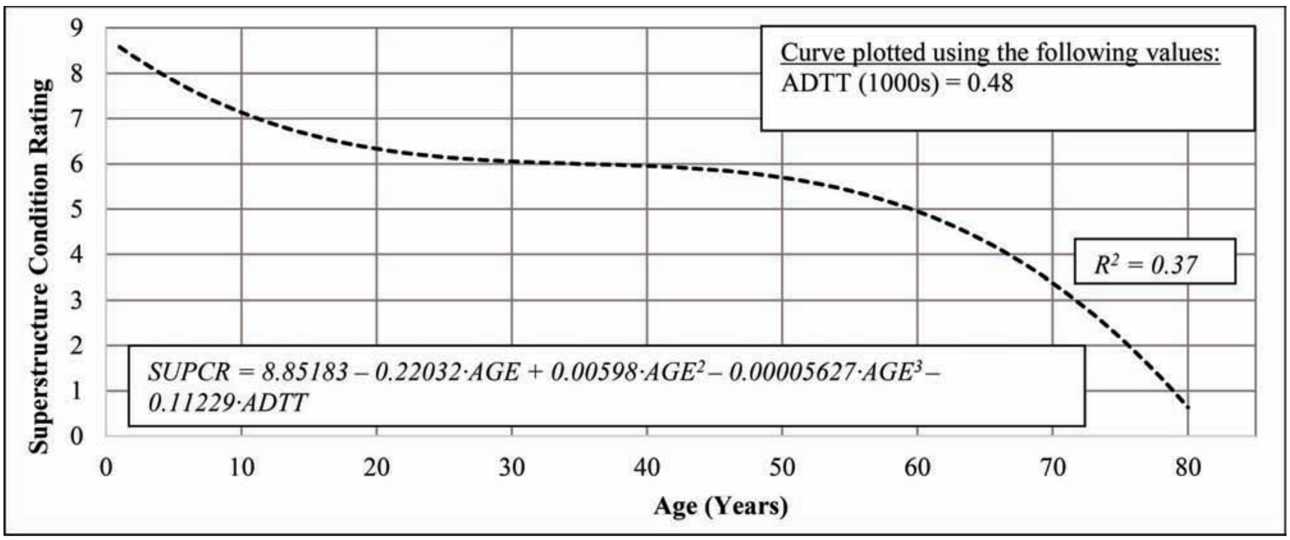


Figure 4.17 Example plot of the "cast-in-place concrete slab" superstructure deterioration model—Northern districts, non-NHS.

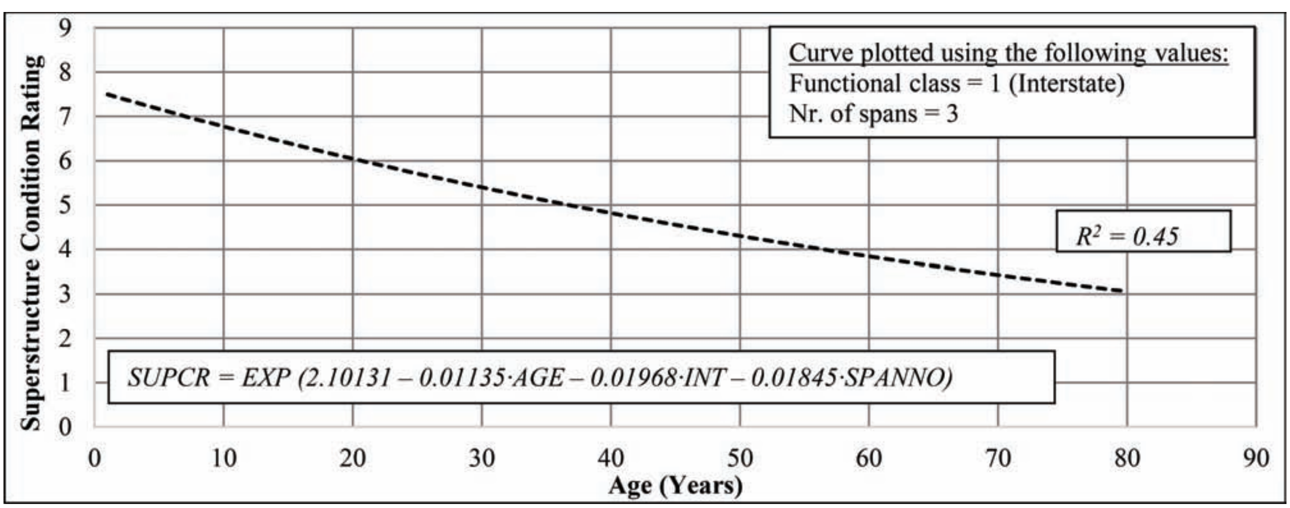


Figure 4.18 Example plot of the "cast-in-place concrete slab" superstructure deterioration model—Central districts, NHS.

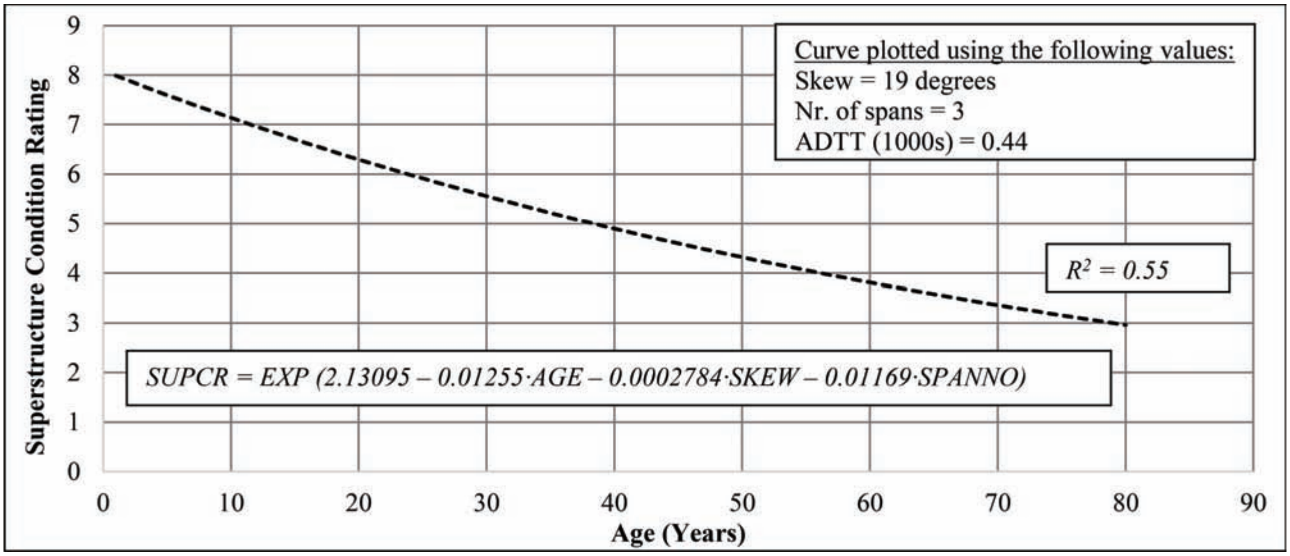


Figure 4.19 Example plot of the "cast-in-place concrete slab" superstructure deterioration model—Central districts, non-NHS.

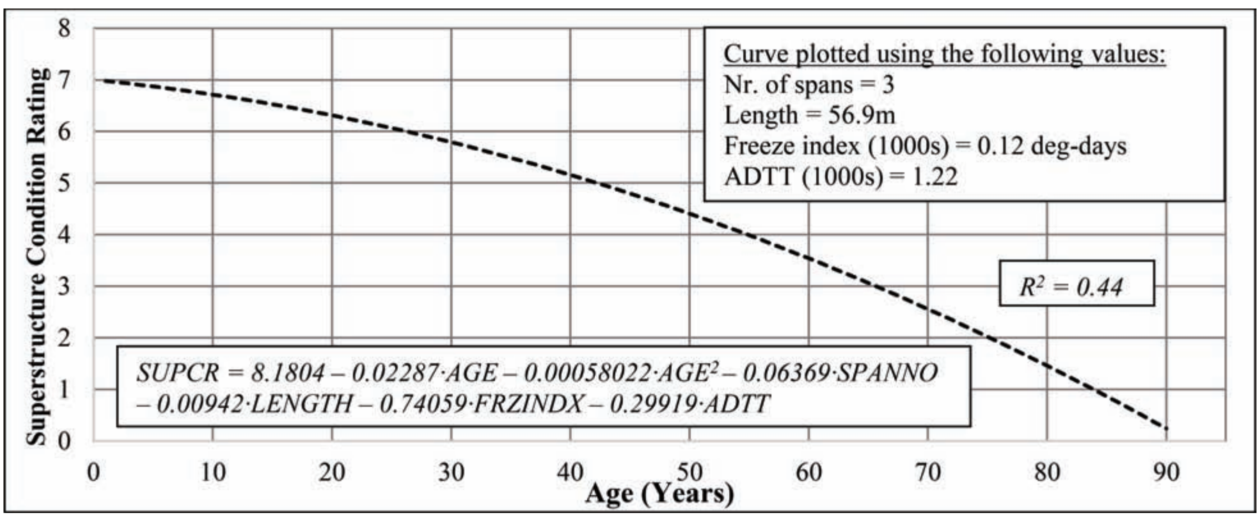


Figure 4.20 Example plot of the "cast-in-place concrete slab" superstructure deterioration model—Southern districts, NHS.

counterparts (Table 4.10), only the age and number of freeze-thaw cycles were significant. A polynomial model of the third order was found to account for 41% of the variation in the superstructure condition. Figures 4.40 and 4.41 show the plot of the model for prestressed concrete box beam single superstructures on the NHS and non-NHS, respectively.

4.3.2.6 Models for Prestressed Concrete Stringer, Northern Districts. A detailed analysis of the prestressed concrete stringer superstructure deterioration model on the NHS in the Northern districts showed that age, functional class, bridge length, freeze index, and the number of freeze-thaw cycles were significant at 95% confidence (Table 4.11). The second order polynomial model was deemed to fit the data well and explained about 30% of the variation in the superstructure condition rating. For the non-NHS bridges in this family (Table 4.11), a third-order polynomial model was found to be the best fit. This model suggested that the superstructure age, bridge skew, freeze index, and the number of spans in the main unit, were significant. The model accounted for 37% of the variation in the superstructure condition rating. The signs of the parameter estimates of the significant variables were intuitive and suggested that an increase in these variables cause a decrease in the superstructure condition rating. The predictive accuracy as determined by the RMSE was 0.54 and 0.66 for models on the NHS and non-NHS, respectively. Figures 4.42 and 4.43 show the plot of the model for prestressed concrete stringer superstructures on the NHS and non-NHS, respectively.

4.3.2.7 Models for Prestressed Concrete Stringer, Central Districts. Table 4.11 presents the deterioration models developed for this family of bridges on the NHS

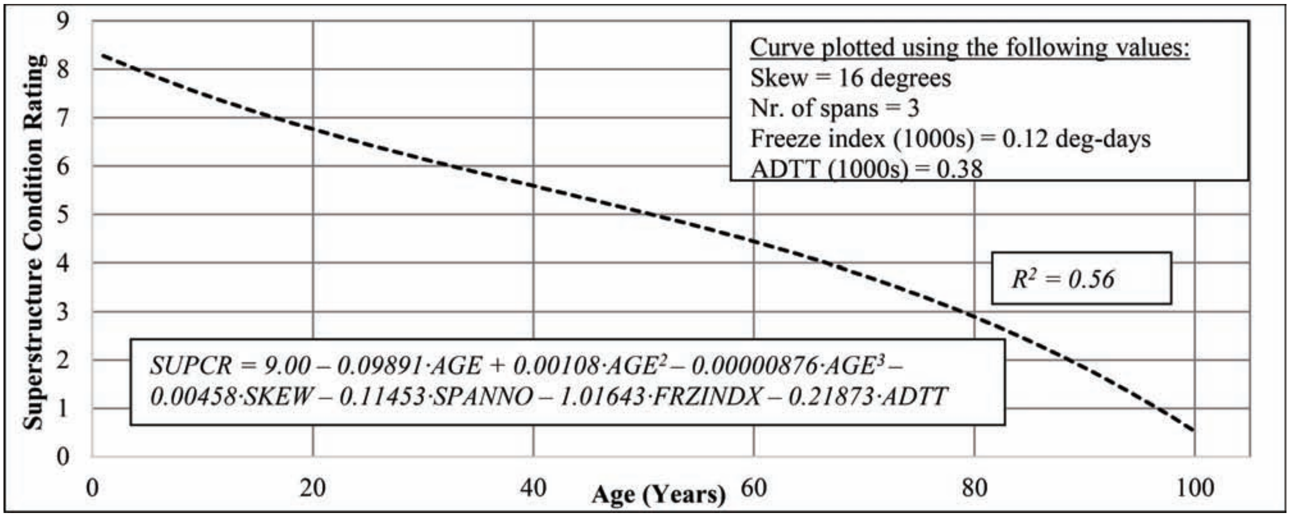


Figure 4.21 Example plot of the “cast-in-place concrete slab” superstructure deterioration model—Southern districts, non-NHS.

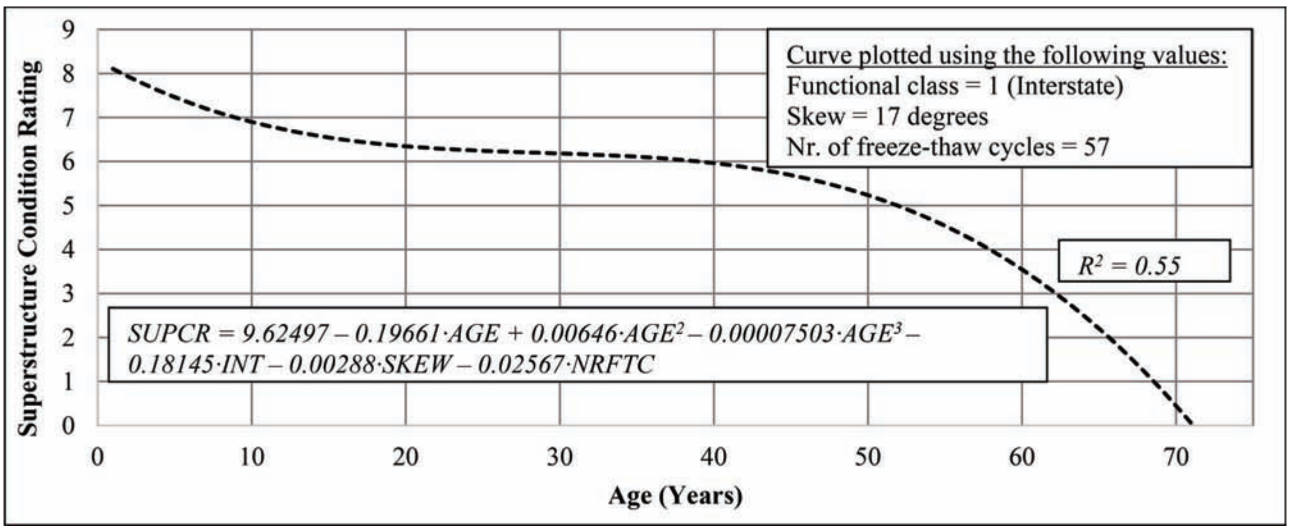


Figure 4.22 Example plot of the “cast-in-place concrete stringer” superstructure deterioration model—Northern districts, NHS.

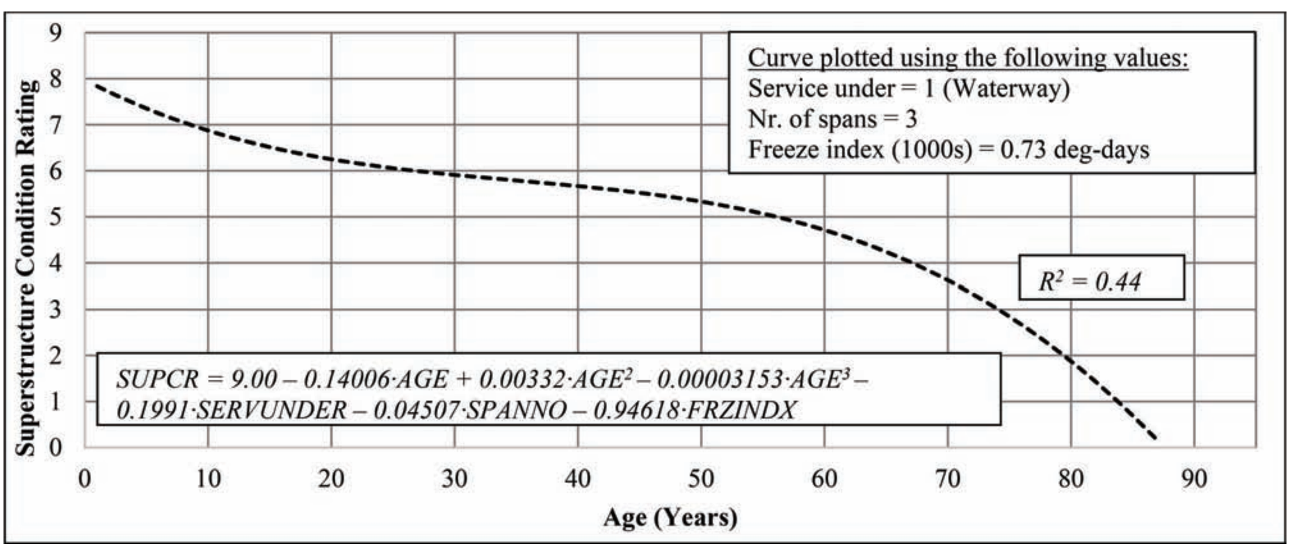


Figure 4.23 Example plot of the “cast-in-place concrete stringer” superstructure deterioration model—Northern districts, non-NHS.

TABLE 4.8
"Cast-in-Place Concrete Stringer" Superstructure Deterioration Model (Deterministic)

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.62497	27.36	9.00	–	9.00	–	9.00	–	9.00	–	2.19722	–
Design Factors												
Age	-0.19661	-10.98	-0.14006	-9.19	-0.0709	-6.82	-0.09665	-9.58	-0.13354	-7.78	-0.00866	-27.12
Age-Squared	0.00646	7.96	0.00332	6.43	0.0015	3.17	0.00143	4.21	0.00495	5.85	–	–
Age-Cubed	-0.00007503	-7.66	-0.00003153	-6.27	-0.00002415	-4.14	-0.00001223	-3.68	-0.00007504	-6.06	–	–
Interstate (1 if on the Interstate, 0 otherwise)	0.18145	4.39	–	–	0.15440	5.59	–	–	–	–	–	–
Skew	-0.00288	-2.12	–	–	–	–	–	–	-0.00866	-6.31	–	–
Service Under (1 if waterway, 0 otherwise)	–	–	-0.1991	-3.08	-0.12283	-4.24	-0.2726	-8.22	–	–	-0.07182	-6.82
Number of Spans in Main Unit	–	–	-0.04507	-2.31	–	–	–	–	-0.01625	-8.91	–	–
Length	–	–	–	–	–	–	–	–	–	–	–	–
Climate Factors												
Freeze Index (1000)	–	–	-0.94618	-4.91	–	–	–	–	–	–	-0.06813	-2.34
Number of Freeze-Thaw Cycles	-0.02567	-4.75	–	–	-0.02661	-22.56	-0.0154	-10.00	–	–	-0.00161	-6.97
Operational Factors												
ADTT(1000s)	–	–	–	–	–	–	-0.22006	-6.16	-0.04244	-5.47	-0.01764	-2.41
Model Fit Statistics												
Observations	706		671		1549		1565		1176		969	
R-Squared	0.551		0.4369		0.4347		0.5737		0.3223		0.4641	

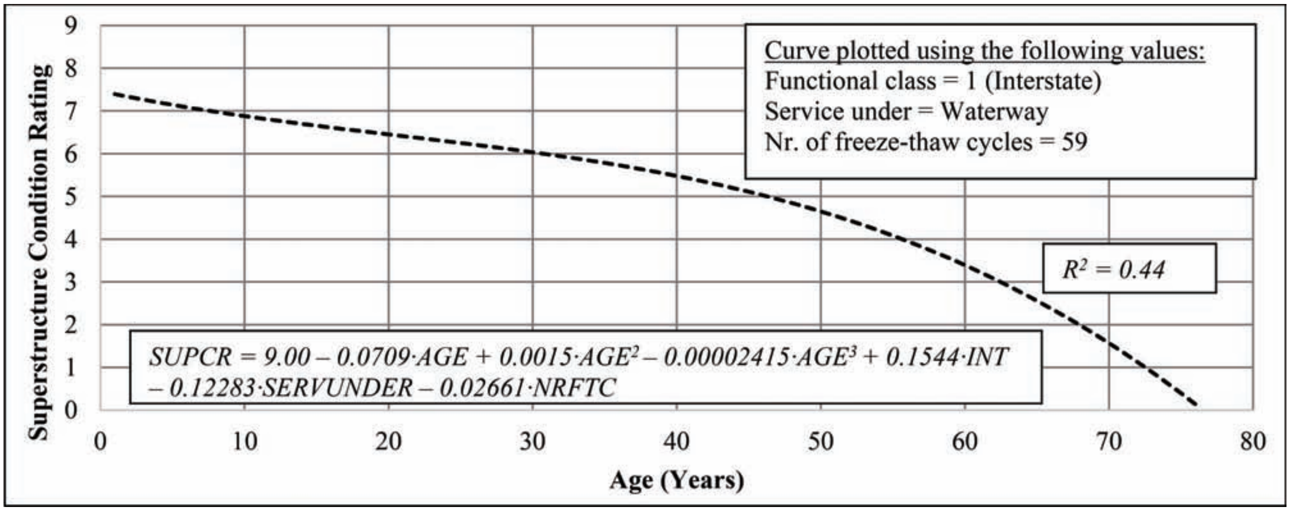


Figure 4.24 Example plot of the "cast-in-place concrete stringer" superstructure deterioration model—Central districts, NHS.

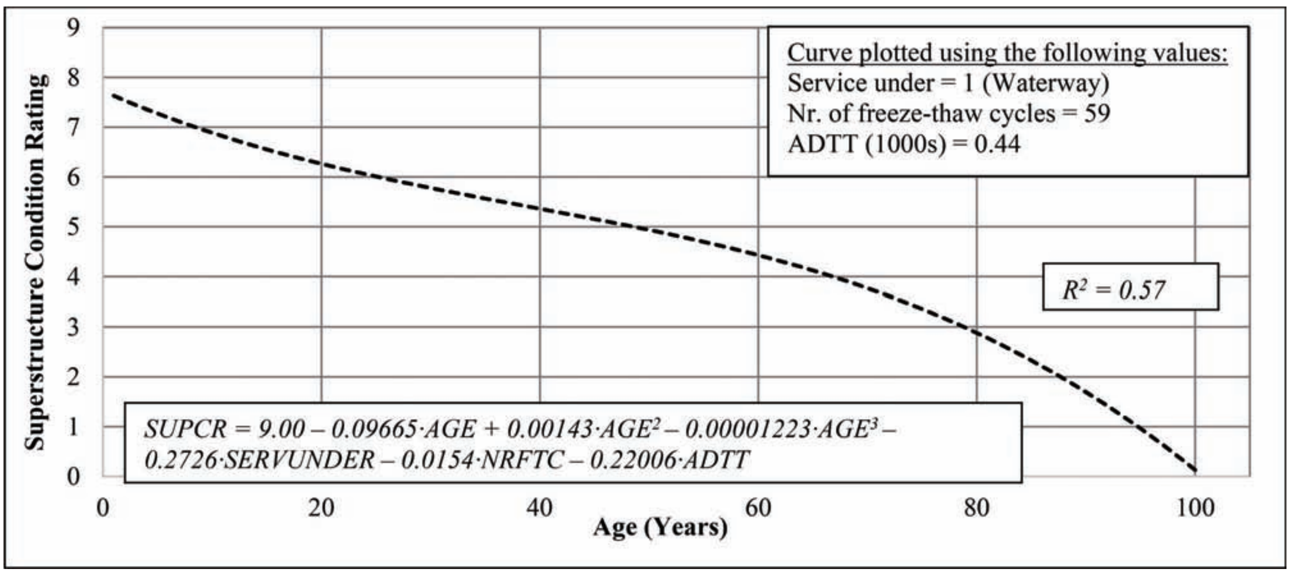


Figure 4.25 Example plot of the "cast-in-place concrete stringer" superstructure deterioration model—Central districts, non-NHS.

and non-NHS system. The superstructure age, the number of spans in the main unit, and the number of freeze-thaw cycles were found to be significant for prestressed concrete stringers on the NHS in the Central districts of Indiana. The model accounted for 28% of the variation in the superstructure condition rating. A second order polynomial model was found to fit the data well and had a RMSE of 0.69. For the prestressed concrete stringer superstructures on the non-NHS, age, skew, length, and the number of freeze-thaw cycles were statistically significant at 95% confidence (Table 4.11). The model explained 33% of the variation in the superstructure condition rating. The model had a RMSE of 0.67. In Figures 4.44 and 4.45, the plotted curves represent the superstructure condition rating versus the superstructure age corresponding to specific values of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.3.2.8 Models for Prestressed Concrete Stringer Superstructures, Southern Districts. The results of the analysis (Table 4.11) indicate that superstructure age, bridge length, and ADTT were the only significant variables at 95% confidence that affected the prestressed concrete superstructure deterioration. The polynomial functional form of the third order was found to provide the best fit for the data and explained 44% of the variation in the superstructure condition rating. For the non-NHS model, age, service under the bridge, bridge length, and the number of freeze-thaw cycles were significant (Table 4.11). The model explained 44% of the variation in the superstructure condition rating. The signs of the parameter estimates for both models were intuitive and showed that an increase in the significant variables led to a decrease in the superstructure condition rating. The NHS and non-NHS models had predictive efficiencies of 0.55 and 0.61 as

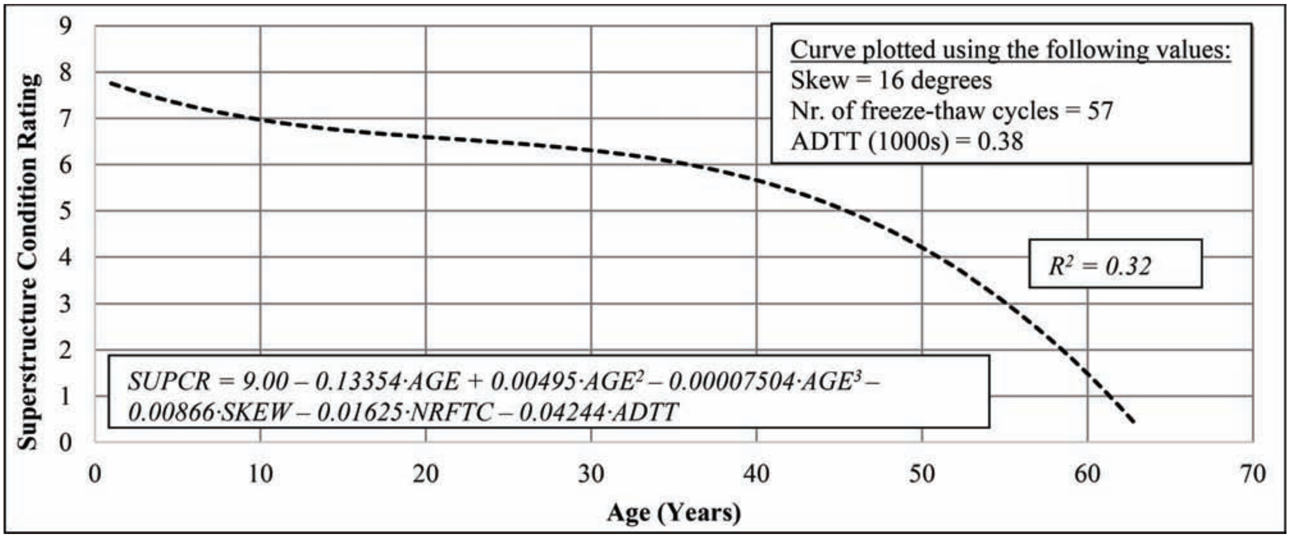


Figure 4.26 Example plot of the "cast-in-place concrete stringer" superstructure deterioration model—Southern districts, NHS.

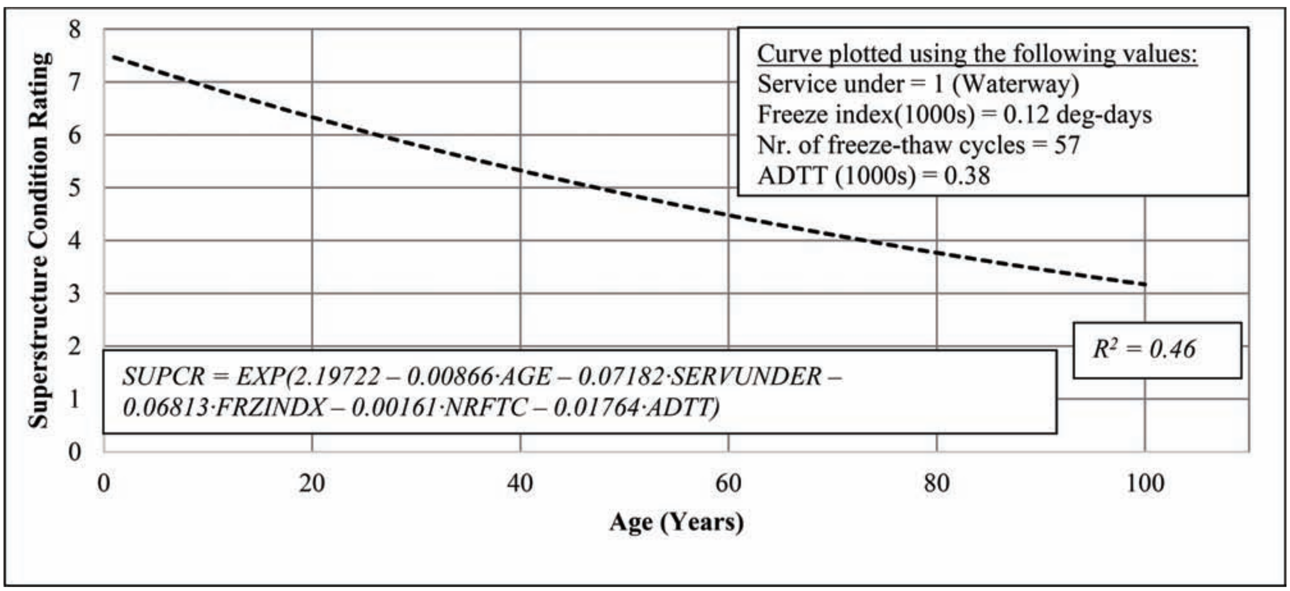


Figure 4.27 Example plot of the "cast-in-place concrete stringer" superstructure deterioration model—Southern districts, non-NHS.

determined by the RMSE. Figures 4.46 and 4.47 show the plotted curves representing deterioration curves for the models on the NHS and non-NHS, respectively.

4.3.3 Deterministic Models for Steel Superstructures

Figure 4.48 shows the distribution of the superstructure design types for steel bridges. The distribution suggested that stringer, truss thru, and girder were the predominant superstructure design types. Deterioration models were developed for stringer and truss thru superstructures. However, no models were developed for girder and the other design types due to insufficient observations. Figure 4.49 presents a photo illustration of a bridge with "steel stringer" superstructure.

4.3.3.1 Models for Steel Stringer Superstructures, Northern Districts. The deterioration model developed for steel stringer superstructures on the NHS in the Northern districts in Indiana was found to be best defined by a third-order polynomial functional form which had a coefficient of determination of 31%. The significant variables at 95% confidence for this model were age and average precipitation (Table 4.12). The design and operational variables did not have enough variation to be significant for this model. For the non-NHS steel stringer, the third-order polynomial model was found to provide the best fit for the observed data, and the significant variables were only the superstructure age and truck traffic (ADTT). The model explained 31% of the variation in the superstructure condition

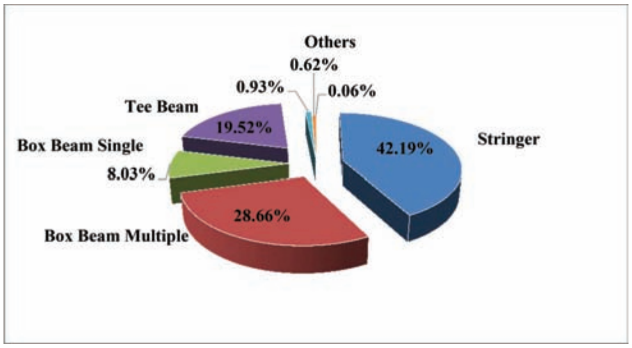


Figure 4.28 Bridge distribution of prestressed concrete superstructure design types.

Figure 4.29 Example image of bridge with "prestressed concrete box beam single" superstructure. (Source: www.pacadar.com.)

rating. The RMSE for the deterioration models on the NHS and non-NHS were 0.58 and 0.54, respectively. In Figures 4.50 and 4.51, the plotted curves represent the superstructure condition rating plotted against age, using specific values of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.3.3.2 Models for Steel Stringer Superstructures, Central Districts. For steel stringer superstructures in Indiana's Central districts on the NHS, the model results suggest that the superstructure age, functional class, service under the bridge, length, and the number of freeze-thaw cycles were significant at 95% confidence (Table 4.12). A third-order polynomial functional form was found to provide the best fit to the data and had a coefficient of determination of 23%. For the non-NHS bridges, age, bridge skew, and the number of freeze-thaw cycles were found to be significant at 95% confidence (Table 4.12). The third-order polynomial functional form explained 34% of the variation in the superstructure condition rating. The signs of the parameter estimates of the significant variables were intuitive and indicated that an increase in the parameters decreased the superstructure condition rating. The RMSE for the models were found to be 0.45 and 0.54 for the models representing steel stringer on the NHS and non-NHS, respectively. Figures 4.52 and 4.53 show plotted curves representing the superstructure condition rating corresponding to specific values of the independent variables.

Figure 4.30 Example image of bridge with "prestressed concrete box beam multiple" superstructure. (Source: www.osdcconsultants.com.)

Figure 4.31 Example image of bridge with "prestressed concrete stringer superstructure. (Source: www.fhwa.gov.)

4.3.3.3 Models for Steel Stringer Superstructures, Southern Districts. As shown in Table 4.12, for NHS steel stringer superstructures located in Indiana's Southern districts, the model outcomes suggest that the superstructure condition rating was significantly influenced by age, bridge skew, average precipitation, freeze index, number of freeze-thaw cycles and ADTT. The model explains a rather low level (24%) of the variation in the superstructure condition rating. A polynomial model of the third-order was found to be the best fit to the observed data and had a RMSE of 0.71. For the bridges on non-NHS in the Southern Indiana districts, the significant variables, at 95% confidence, were found to be age, service under the bridge, and ADTT (Table 4.12). The model explained

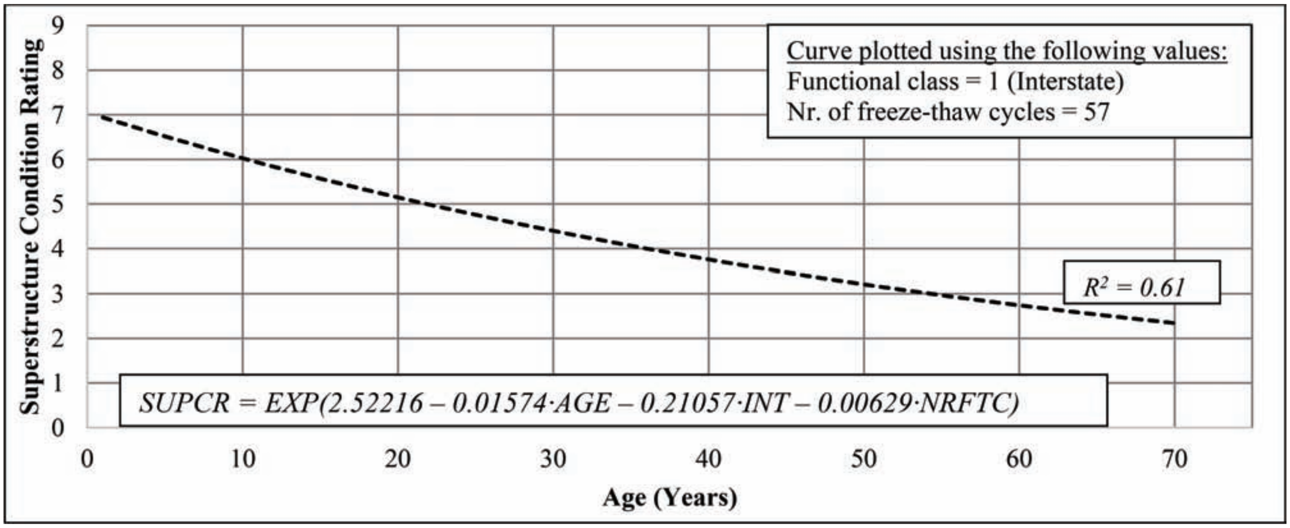


Figure 4.32 Example plot of the "prestressed concrete box beam multiple" superstructure deterioration model—Northern districts, NHS.

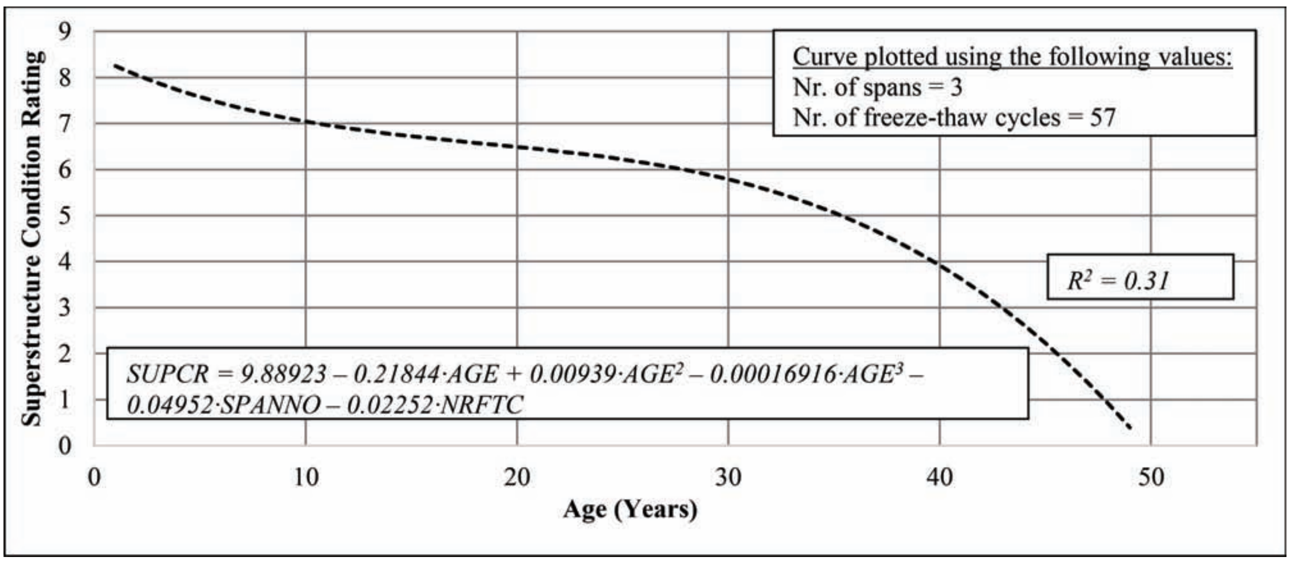


Figure 4.33 Example plot of the "prestressed concrete box beam multiple" superstructure deterioration model—Northern districts, non-NHS.

26% of the variation in the superstructure condition rating with a predictive efficiency of 0.70 as determined by the RMSE. Figures 4.54 and 4.55 show plotted curves representing the superstructure condition rating corresponding to specific values of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.3.3.4 Models for the Steel thru Truss Superstructures, Northern Districts. Due to insufficient observations, deterioration models were developed for only steel thru truss superstructures of non-NHS bridges in the Northern and Southern districts. The model results (Table 4.13) suggest that only the superstructure age and precipitation significantly influence the deterioration. Other design, climatic, and operations variables were insignificant at 95% confidence. The polynomial form, which explained 46% of the variation in the superstructure condition rating, was found to provide the closest fit to the data. Figure 4.56 illustrates the trend in this superstructure condition rating versus the superstructure age, plotted using specific values of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.3.3.5 Models for the Steel thru Truss Superstructures, Southern Districts. For steel truss thru superstructures in Southern Indiana, the condition rating was found to be explained by four variables: age, bridge skew, average precipitation, and freeze index. As shown in the model results (Table 4.13), the signs of all the variables were intuitive; for each of these variables, a

TABLE 4.9
"Prestressed Concrete Box Beam Multiple" Superstructure Deterioration Model (Deterministic)

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	2.52216	17.63	9.88923	21.00	7.86526	34.60	8.85961	27.91	9.00	–	9.00	–
Design Factors												
Age	-0.01574	-13.24	-0.21844	-4.73	–	–	–	–	-0.33126	-10.83	–	–
Age-Squared	–	–	0.00939	3.62	-0.00146	-4.85	-0.00163	-24.65	0.01619	5.80	-0.00085258	-21.33
Age-Cubed	–	–	-0.00017	-3.78	–	–	–	–	-0.00029693	-4.95	–	–
Interstate (1 if on the Interstate, 0 otherwise)	-0.21057	-5.80	–	–	0.89263	9.89	–	–	–	–	–	–
Skew	–	–	–	–	-0.02073	-5.90	-0.00583	-3.47	–	–	–	–
Service Under (1 if waterway, 0 otherwise)	–	–	–	–	–	–	-0.32021	-3.36	–	–	–	–
Number of Spans in Main Unit	–	–	-0.04952	-2.80	–	–	-0.10322	-4.72	–	–	–	–
Length	–	–	–	–	–	–	–	–	–	–	–	–
Climate Factors												
Freeze Index (1000)	–	–	–	–	-1.08296	-2.69	–	–	–	–	-0.51398	-3.30
Number of Freeze-Thaw Cycles	-0.00629	-2.69	-0.02252	-3.37	–	–	-0.02203	-4.64	–	–	-0.03316	-62.77
Operational Factors												
ADTT(1000)	–	–	–	–	–	–	–	–	–	–	–	–
Model Fit Statistics												
Observations	164		781		135		1009		156		2348	
R-Squared	0.6051		0.3123		0.551		0.4026		0.5196		0.221	

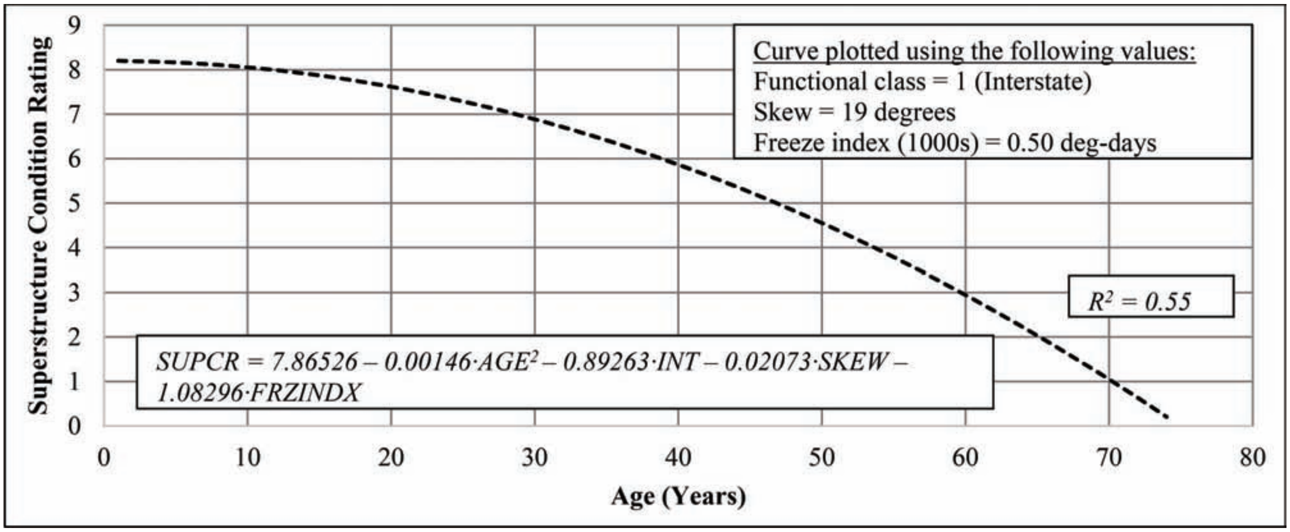


Figure 4.34 Example plot of the "prestressed concrete box beam multiple" superstructure deterioration model—Central districts, NHS.

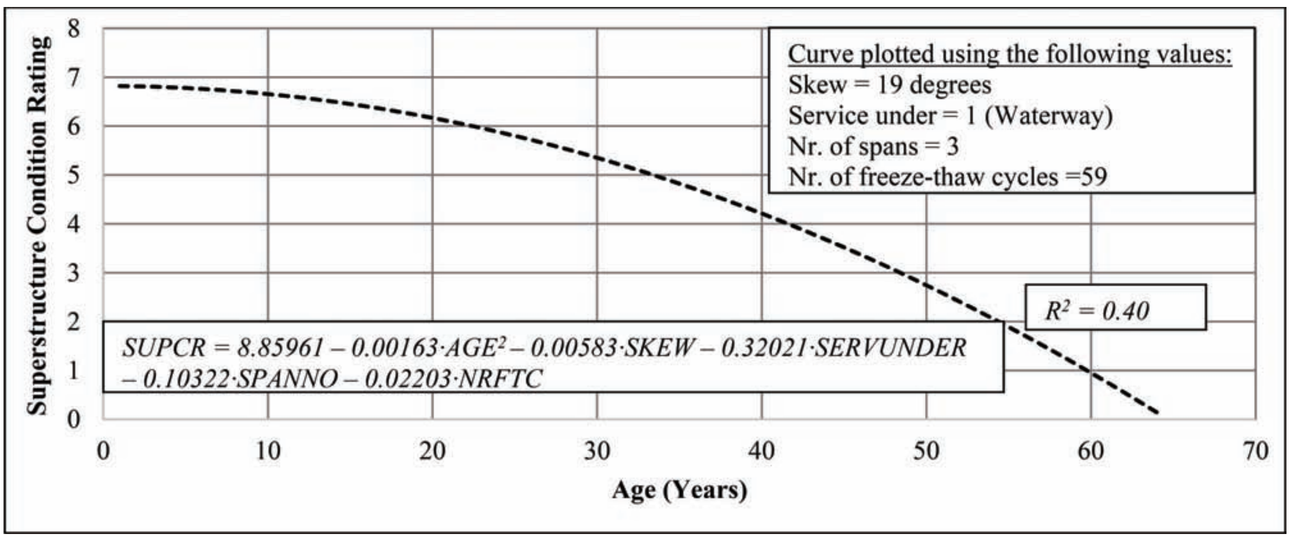


Figure 4.35 Example plot of the "prestressed box beam multiple" superstructure deterioration model—Central districts, non-NHS.

higher level was found to be associated with a lower superstructure condition rating. The exponential model for this family of bridges explained 43% of the variation in the condition rating. Figure 4.57 explains the trends in the superstructure condition rating versus the superstructure age and was plotted using specific values of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.4 Deterministic Substructure Deterioration Models

Six deterministic deterioration models were developed for the substructure. The classification of substructures was based on the highway district and the highway system. Table 4.14 shows the variables used for the substructure deterioration models. Two main functional forms were investigated for the best fit: exponential and polynomial. Second and third order polynomial functional forms were considered for developing the best models for the substructure.

4.4.1 Models for Substructures

4.4.1.1 Models for Substructures, Northern Districts. For substructures on the NHS in the Northern districts, the condition rating was found to be explained by age, the number of spans in the main unit, and truck traffic. As shown in the model results (Table 4.15), the signs of all the variables were intuitive; for each of these variables, a higher level was found to be associated with a lower substructure condition rating. The polynomial functional form to the third-order was found

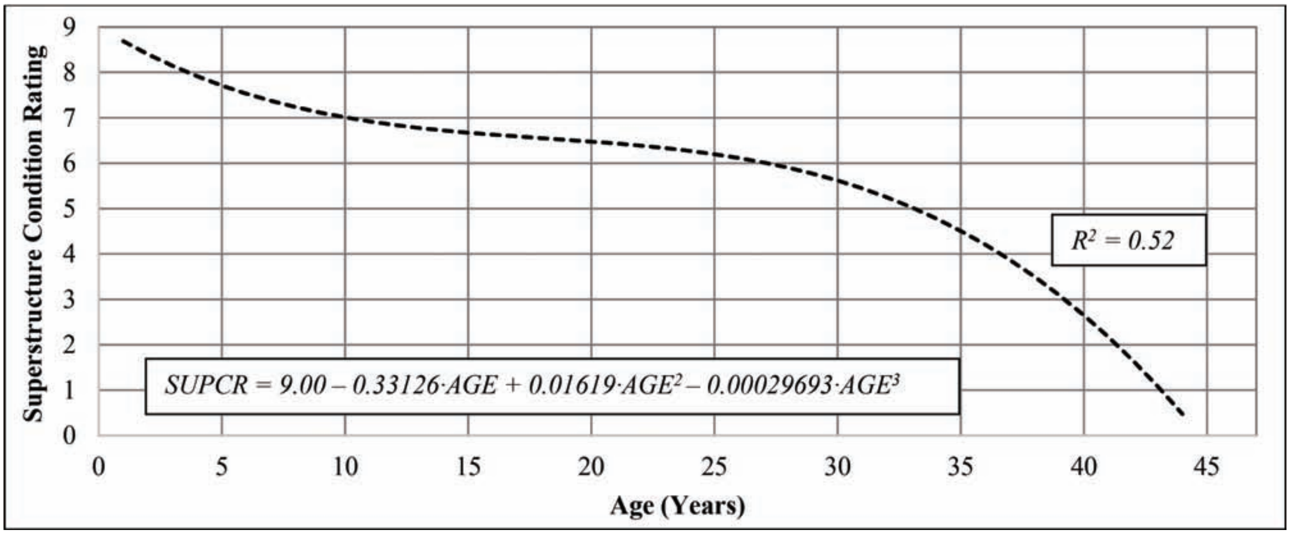


Figure 4.36 Example plot of the "prestressed concrete box beam multiple" superstructure deterioration model—Southern districts, NHS.

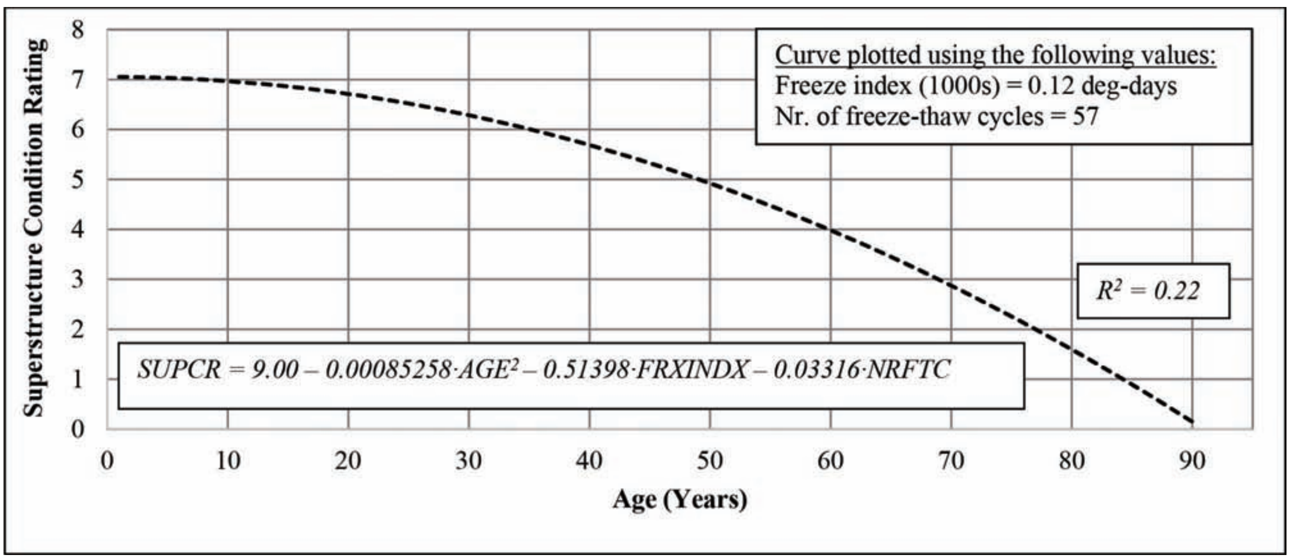


Figure 4.37 Example plot of the "prestressed concrete box beam multiple" superstructure deterioration model—Southern districts, non-NHS.

to be the best fit for the data and had a coefficient of determination of 0.29. The predictive efficiency for this model as determined by the RMSE was 0.61. For non-NHS substructures in the Northern districts of Indiana, the results suggest that only two variables were significant in the model: age and truck traffic (ADTT). The model explained 37% of the variation in the substructure condition rating. The model had a RMSE of 0.70. Figures 4.58 and 4.59 below illustrate the trends in substructure condition rating versus the substructure age plotted using specific values of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.4.1.2 Models for Substructures, Central Districts. The results of the analysis for substructure condition rating for bridges on the NHS in the Central district indicate that age, functional class, service under the bridge, length, and the number of freeze-thaw cycles were significant (Table 4.15), which suggests that operational, design, and climate factors all play a role in the deterioration of this substructure family. The third order polynomial functional form (Figure 4.60), which was found to provide the best fit to the data accounted for approximately 31% of the variation in the substructure condition rating. For substructures on the non-NHS in Indiana's Central Districts, the significant

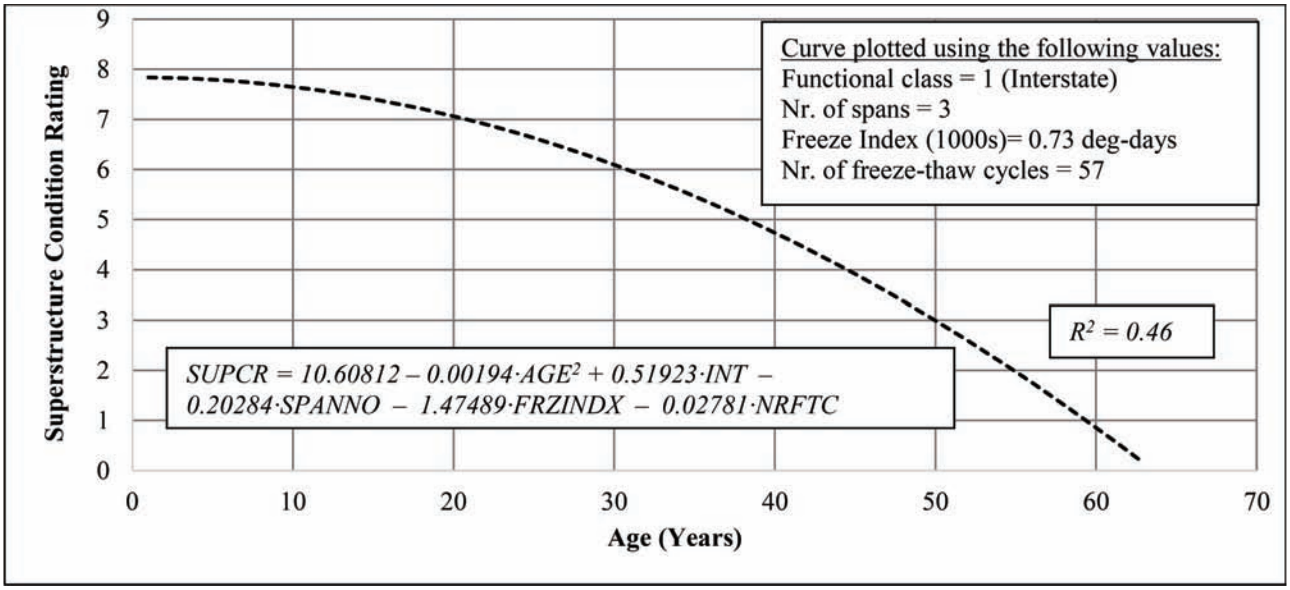


Figure 4.38 Example plot of the "prestressed concrete box beam single" superstructure deterioration model—Northern districts, NHS.

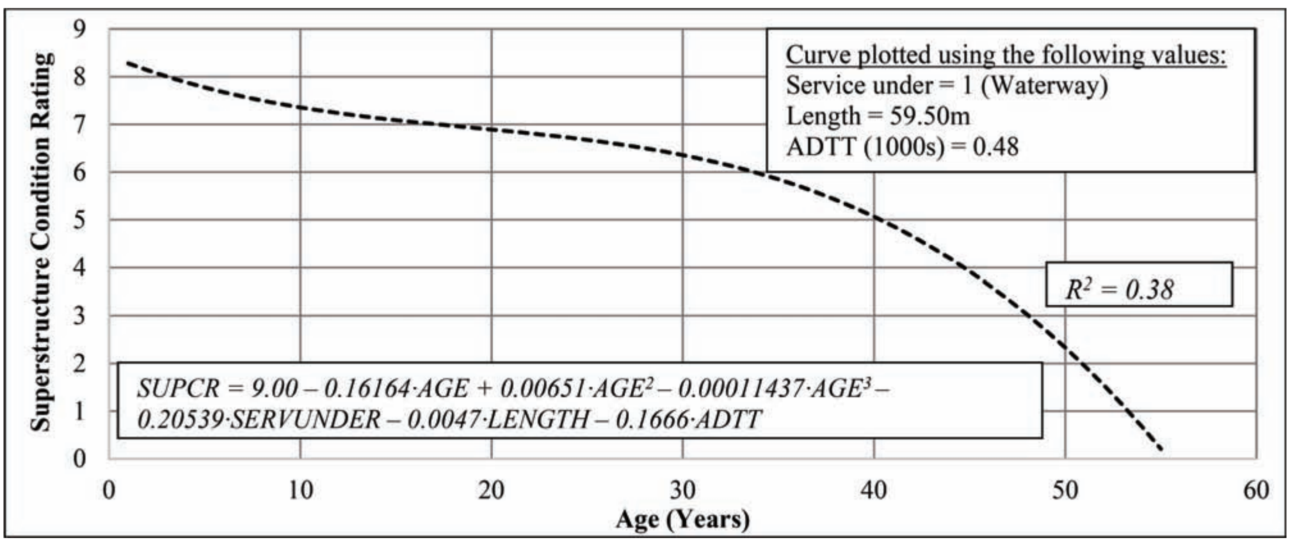


Figure 4.39 Example plot of the "prestressed concrete box beam single" superstructure deterioration model—Northern districts, non-NHS.

variables were found to be age, service under the bridge, bridge length, the number of freeze-thaw cycles, and ADTT (Table 4.15). The polynomial model accounted for 41% of the variation in the substructure condition rating and is shown in Figure 4.61. The predictive efficiency for both models on the NHS and non-NHS as determined by the RMSE were 0.47 and 0.65, respectively.

4.4.1.3 Models for Substructures, Southern Districts. From the analysis of the results (Table 4.15), it was concluded that for NHS substructures in the Southern districts of Indiana, substructure age, bridge skew, service under the bridge, the number of spans in the main unit, freeze index, the number of freeze-thaw cycles and ADTT were the significant variables that affected substructure deterioration. The model explained 29% of the variation in the substructure condition rating and had a RMSE of 0.57. For the Non–NHS bridges in Southern Indiana, it was found that the significant variables influencing substructure deterioration were substructure age, service under the bridge, and truck traffic (Table 4.15). The polynomial model was found to be the best fit for the data and accounted for 35% of the variation in substructure condition rating. The model had a predictive

TABLE 4.10
"Prestressed Concrete Box Beam Single" Superstructure Deterioration Model (Deterministic)

	North				South			
	NHS		Non-NHS		NHS		Non-NHS	
Variable	Parameter Estimate	t-stat	Parameter Estimate	t-stat	Parameter Estimate	t-stat	Parameter Estimate	t-stat
Constant	10.60812	15.15	9.00	–	9.00	–	9.00	–
Design Factors								
Age	–	–	-0.16164	-7.81	–	–	-0.162	-3.02
Age-Squared	-0.00194	-9.26	0.00651	4.34	-0.00221	-11.43	0.00904	2.52
Age-Cubed	–	–	-0.00011437	-3.63	–	–	-0.00020555	-3.01
Interstate (1 if on the Interstate, 0 otherwise)	0.51923	4.34	–	–	-0.17157	-2.25	–	–
Skew	–	–	–	–	–	–	–	–
Service Under (1 if waterway, 0 otherwise)	–	–	-0.20539	-2.16	–	–	–	–
Number of Spans in Main Unit	-0.20824	-7.00	–	–	–	–	–	–
Length	–	–	-0.0047	-4.07	-0.00568	-3.22	–	–
Climate Factors								
Freeze Index (1000)	-1.47489	-3.50	–	–	-2.97178	-16.49	–	–
Number of Freeze-Thaw Cycles	-0.02781	-2.48	–	–	–	–	-0.00996	-2.53
Operational Factors								
ADTT(1000)	–	–	-0.1666	-2.88	–	–	–	–
Model Fit Statistics								
Observations	283		519		137		133	
R-Squared	0.4615		0.3788		0.585		0.4092	

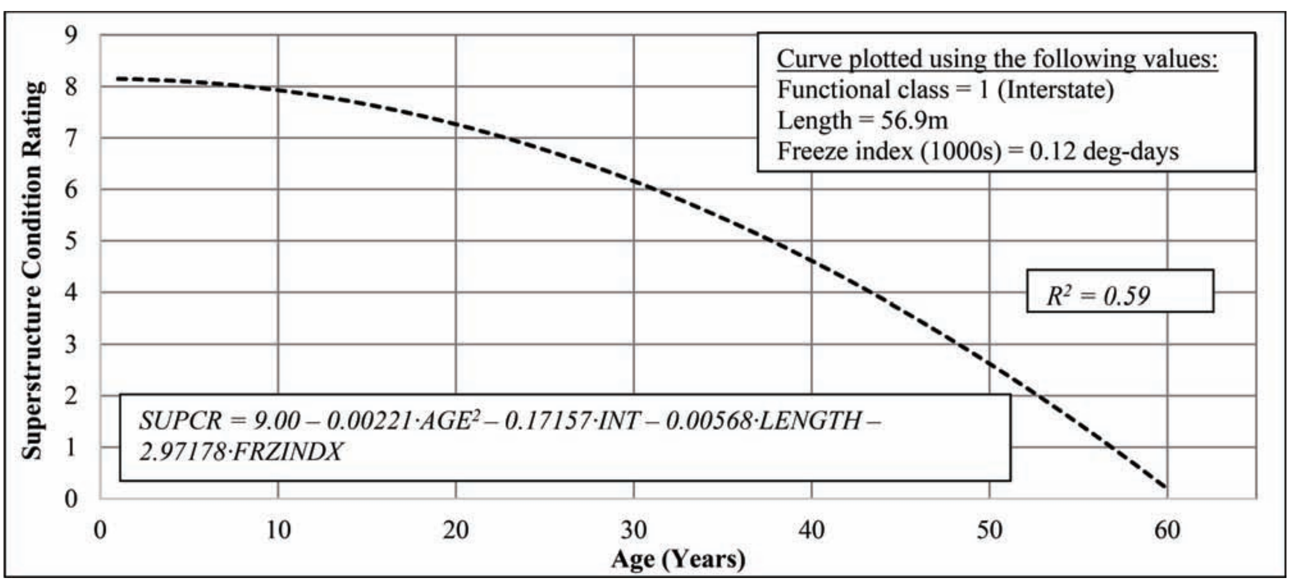


Figure 4.40 Example plot of the "prestressed concrete box beam single" superstructure deterioration model—Southern districts, NHS.

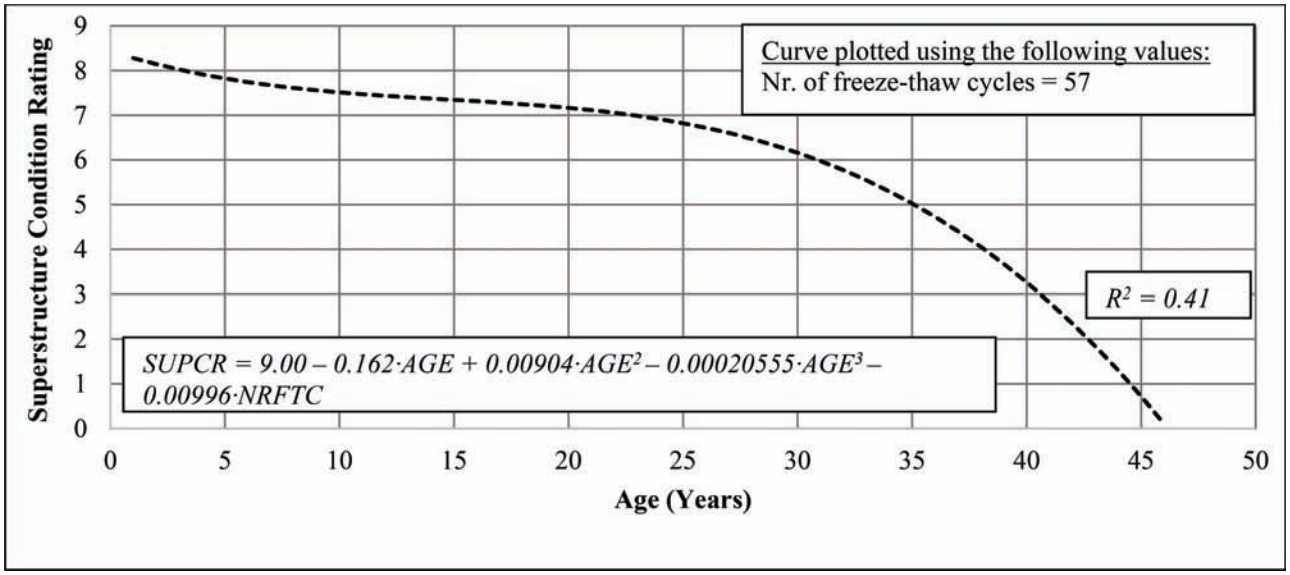


Figure 4.41 Example plot of the "prestressed concrete box beam single" superstructure deterioration model—Southern districts, non-NHS.

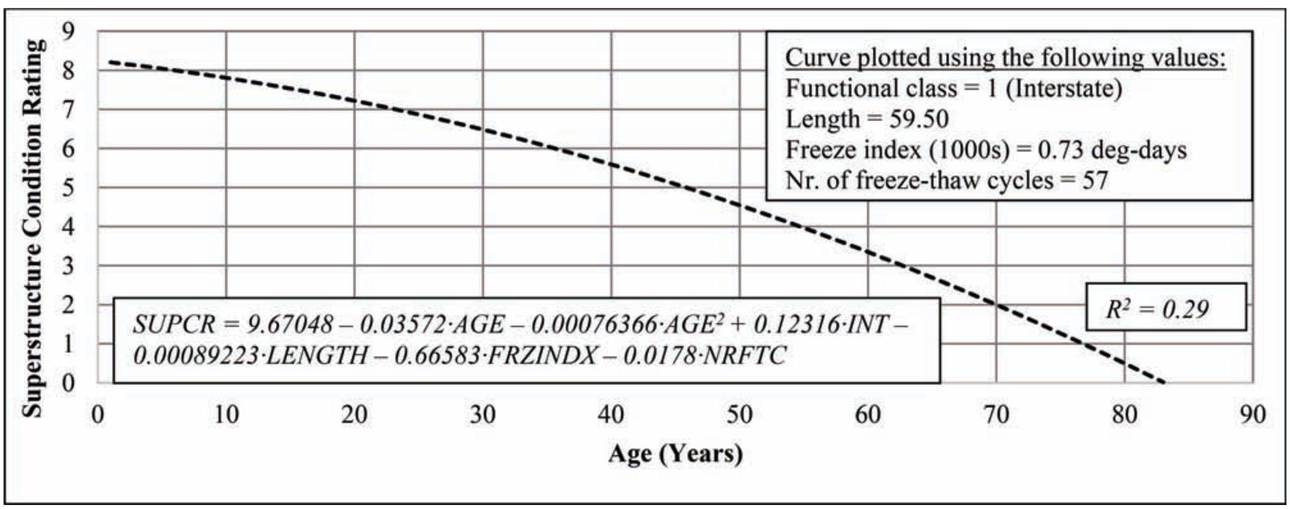


Figure 4.42 Example plot of the "prestressed concrete stringer" superstructure deterioration model—Northern districts, NHS.

efficiency of 0.73 as determined by the RMSE. Figures 4.62 and 4.63, which illustrate the relationship between substructure condition rating and age were plotted using specific values of the independent variables (as shown in the upper right box) of the general model presented in the lower left box.

4.5 Results for the Probabilistic Deterioration Modeling

The final selection of the variables for deck, superstructure, and substructure models are presented separately in Table 4.16. The results of the deterioration models developed using the binary probit approach and calibrated on a LIMDEP platform, are presented in Table 4.17(a), (b), and (c). The significant variables were determined using a hypothesis test at a 5% level of significance ($\alpha = 0.05$). The estimated models are presented as Equations A, B, and C.

Deck.

$$Pr[Z(i,t)=1]=\Phi[-2.041-0.699\cdot Z(i,t-1)+0.043 \cdot YRTOTRAN+0.024\cdot ADTT-0.113\cdot SOUTH +0.005\cdot COLDDAY+0.136\cdot HNRFTC-0.276\cdot IFEPBI +0.149\cdot URBAN+0.075\cdot SERVUNDER-0.006 \cdot AGE-0.047\cdot RATING+0.561\cdot DECKIMPROV] \quad (A)$$

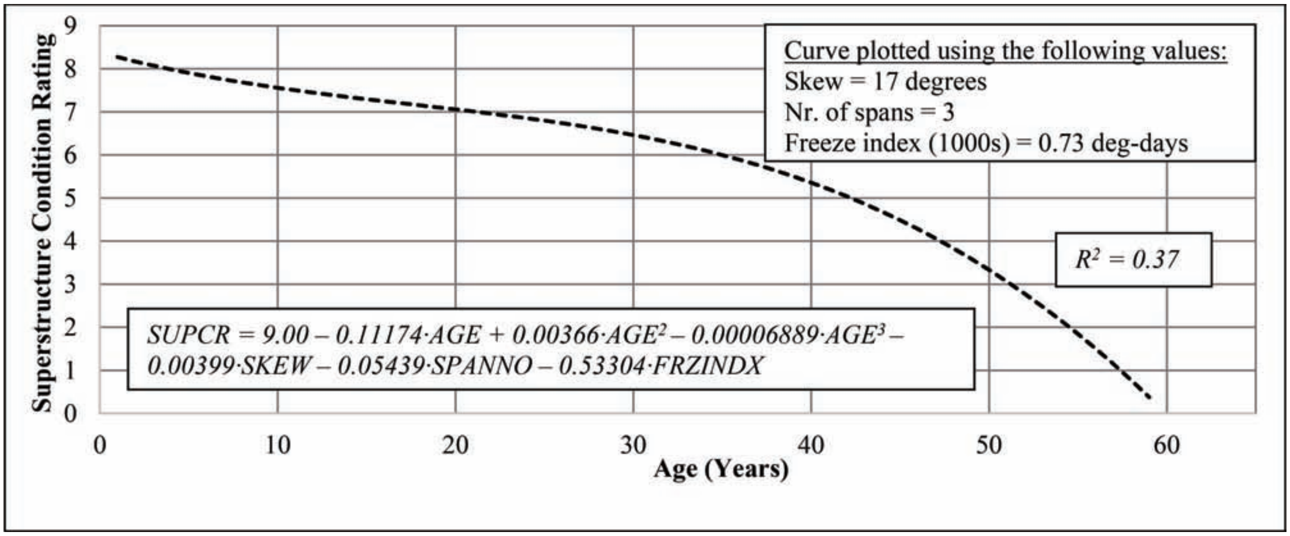


Figure 4.43 Example plot of the "prestressed concrete stringer" superstructure deterioration model—Northern districts, non-NHS.

Superstructure.

$$Pr[Z(i,t)=1]=\Phi[-1.382-0.282 \cdot Z(i,t-1)+0.028 \cdot YRTOTRAN+0.186 \cdot SOUTH +0.217 \cdot HNRFTC+0.397 \cdot IFSTEEL +0.102 \cdot URBAN+0.096 \cdot SERVUNDER-0.006 \cdot AGE-0.0124 \cdot RATING +0.263 \cdot SUPERIMPROV] \quad (B)$$

Substructure.

$$Pr[Z(i,t)=1]=\Phi[-1.582-0.285 \cdot Z(i,t-1)+0.023 \cdot YRTOTRAN+0.190 \cdot SOUTH +0.228 \cdot HNRFTC+0.056 \cdot URBAN-0.292 \cdot SERVUNDER-0.007 \cdot AGE -0.0126 \cdot RATING+0.257 \cdot SUBIMPROV] \quad (C)$$

Where: $\Pr[Z(i,t) = 1]$ is the probability of transitioning to a lower condition state. All other symbols are as defined in Table 3.5.

The results of the analysis showed that age, current rating, transition in last inspection period, and number of years to last transition were the most significant factors that influenced the likelihood of a bridge component transitioning to a lower condition state. Also, for all three components, the variables of functional class, region variable, freeze-thaw cycles, and rehabilitation status were found to be influential. ADTT, type of wearing surface, and number of cold days were found to be significant only for the deck deterioration model; and superstructure material type was a significant independent variable only for the superstructure deterioration model. Besides, the factor of service under bridge (waterway) was found to be more significant in the substructure deterioration model than it was in the deck and superstructure models. Furthermore, it was observed that the coefficients of ADTT, service under bridge (of waterway), number of cold days, and freeze-thaw cycle (exceeding 60) had positive signs while region (South) and superstructure material type (if steel) had negative signs.

Intuitively, in the current time period (t), a bridge was found to be less likely to deteriorate to a lower condition state if it had deteriorated to a lower state in the previous time period (t–1). The number of years to last transition had a positive sign, which was intuitive as well because the longer the duration to the last transition, the higher the probability that the transition occurs in the current period. It was expected that a bridge with a poor condition rating deteriorates faster than a bridge in good condition. However, in this model, when the factors of the condition rating and the number of years to last transition were considered together, the age of the bridge was found to have a negative sign, which means that for bridges with the same condition rating and similar time elapsed since the last transition, the older bridge would have a lower transition probability compared to the newer bridge.

The variable representing the status of recent rehabilitation was found to have a positive sign if there was any improvement of 2 or more in the condition rating within the recent five inspection periods, indicating that if recent condition improvement occurred, the transition

TABLE 4.11
"Prestressed Concrete Stringer" Superstructure Deterioration Model (Deterministic)

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.67048	33.46	9.0000	–	10.51217	28.39	8.9232	42.46	8.50758	154.50	9.00	–
Design Factors												
Age	-0.03572	-4.26	-0.11174	-5.72	–	–	–	–	-0.02473	-3.95	-0.05674	-4.49
Age-Squared	-0.00076366	-2.33	0.00366	2.93	-0.00208	-13.66	-0.00177	-24.12	-0.00101	-5.00	0.00123	1.66
Age-Cubed	–	–	-0.00006889	-2.92	–	–	–	–	–	–	-0.00003815	-3.06
Interstate (1 if on the Interstate, 0 otherwise)	0.12316	3.92	–	–	–	–	–	–	–	–	–	–
Skew	–	–	-0.00399	-3.59	–	–	-0.00465	-4.73	–	–	–	–
Service Under (1 if waterway, 0 otherwise)	–	–	–	–	–	–	–	–	–	–	-0.43769	-11.14
Number of Spans in Main Unit	–	–	-0.05439	-6.35	-0.06621	-2.27	–	–	–	–	–	–
Length	-0.00089223	-2.50	–	–	–	–	-0.00153	-2.41	-0.00481	-9.77	-0.00319	-7.98
Climate Factors												
Freeze Index (1000)	-0.66583	-3.01	–	–	–	–	–	–	–	–	–	–
Number of Freeze-Thaw Cycles	-0.0178	-4.37	-0.53304	-4.40	-0.0421	-6.65	-0.01915	-5.43	–	–	-0.00402	-3.21
Operational Factors												
ADTT(1000)	–	–	–	–	–	–	–	–	-0.15089	-7.80	–	–
Model Fit Statistics												
Observations	1334		994		676		1190		1266		1497	
R-Squared	0.2938		0.3711		0.2833		0.3337		0.4429		0.4400	

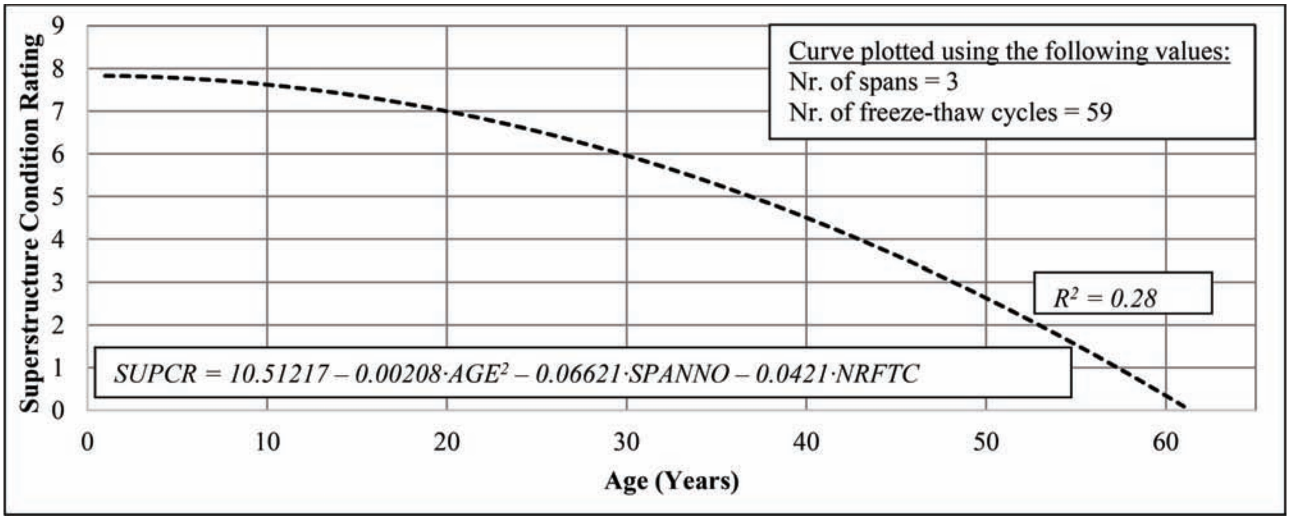


Figure 4.44 Example plot of the "prestressed concrete stringer" superstructure deterioration model—Central districts, NHS.

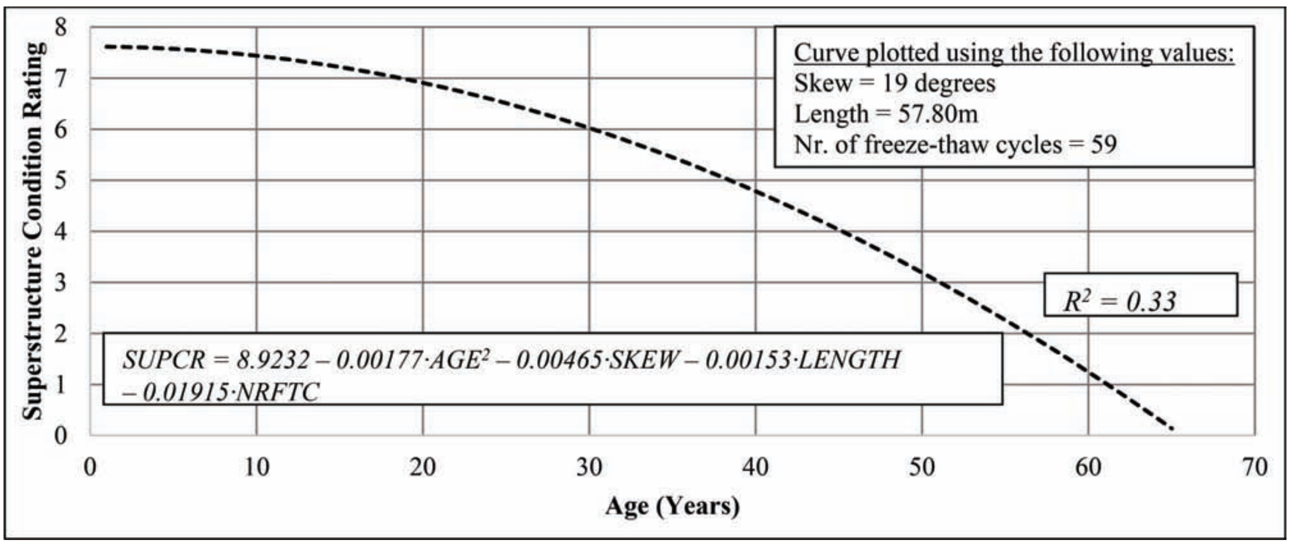


Figure 4.45 Example plot of the "prestressed concrete stringer" superstructure deterioration model—Central districts, non-NHS.

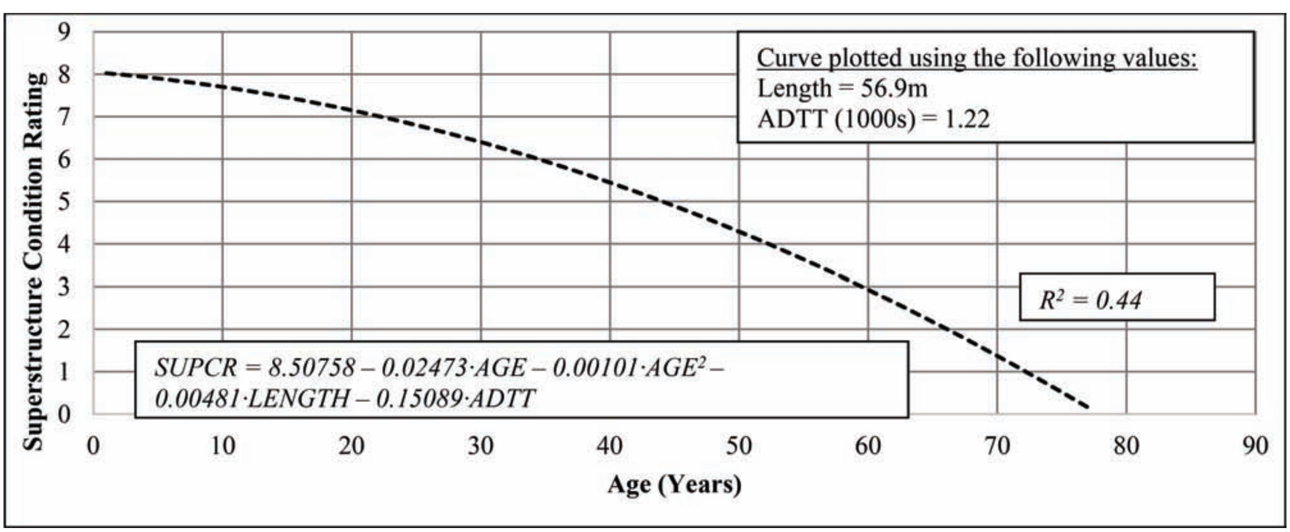


Figure 4.46 Example plot of the "prestressed concrete stringer" superstructure deterioration model—Southern districts, NHS.

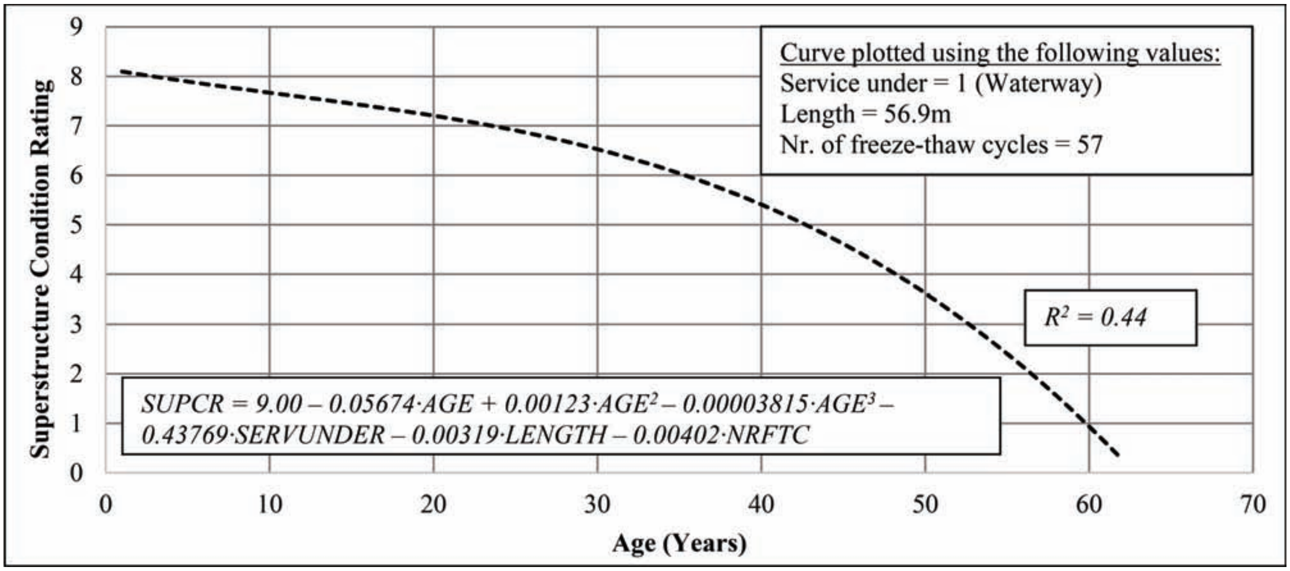


Figure 4.47 Example plot of the "prestressed concrete stringer" superstructure deterioration model—Southern districts, non-NHS.

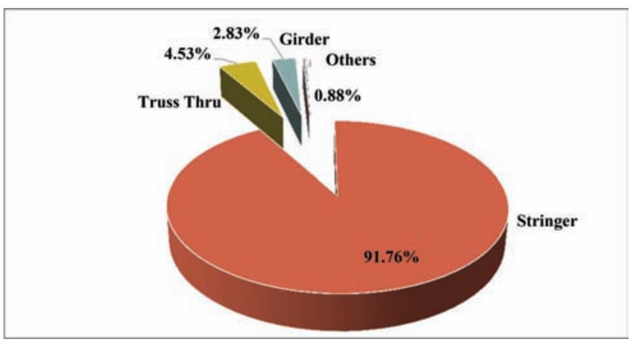


Figure 4.48 Bridge distribution of steel superstructure design types.

Figure 4.49 Example image of bridge with "steel stringer" superstructure. (Source: www.bphod.com.)

probability is higher. Generally, bridges in colder climates, such as Northern Indiana, are generally expected to deteriorate faster compared to those in milder climates, such as Southern Indiana, because of the effects of deicing salts which are applied to road surfaces during wintertime; and the model results confirmed this supposition. It was determined that the factors representing the number of cold days and freeze-thaw cycles each had positive signs; this supports the intuitive hypothesis that bridges located in more severe climates generally have a greater propensity to transition to a lower condition state. Also, it was observed that bridges with high truck traffic volumes deteriorate at a faster rate, which also is consistent with the model outcome. The coefficient of the superstructure type was negative, indicating that the probability of transitioning to a lower condition state is generally higher for bridges with concrete superstructure compared to their steel counterparts. The coefficient for the service type variable, (water under bridge or otherwise) was positive for all three components, which indicated that being close to water generally increases the bridge component deterioration rate. The functional class variable had a positive sign, which indicated that bridges located in urban areas generally have higher deterioration rates.

For each bridge component, different physical, operational and environmental conditions served as inputs into the model equations using the MATLAB program. This was done for each individual bridge on Indiana's state roads in the NBI database. After the program was run 10,000 times, the average of the number of years a bridge stays in each condition rating was assumed to be the predicted number of years that a bridge stays in one condition. A user interface was developed in MATLAB to visualize the bridge component deterioration process (Figure 4.64).

Figures 4.64 and 4.65 show the user interface of the program developed and the results of a simulation for the deck, superstructure and substructure of Bridge #0010. There are separate display windows for the results of deck, superstructure and substructure simulations. The interface allows the input of any bridge

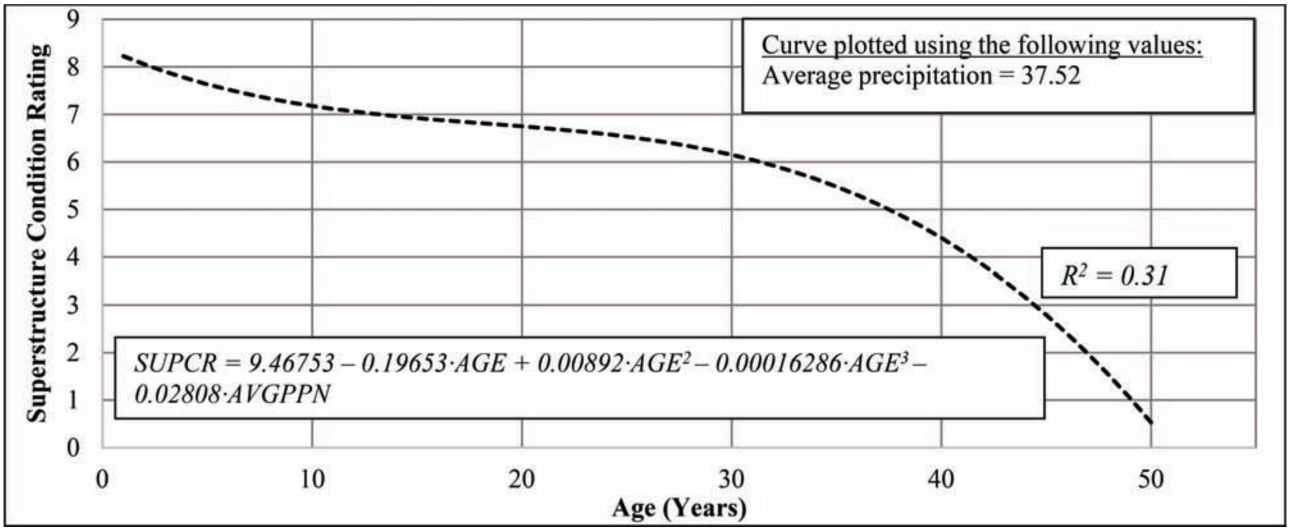


Figure 4.50 Example plot of the steel stringer superstructure deterioration model—Northern districts, NHS.

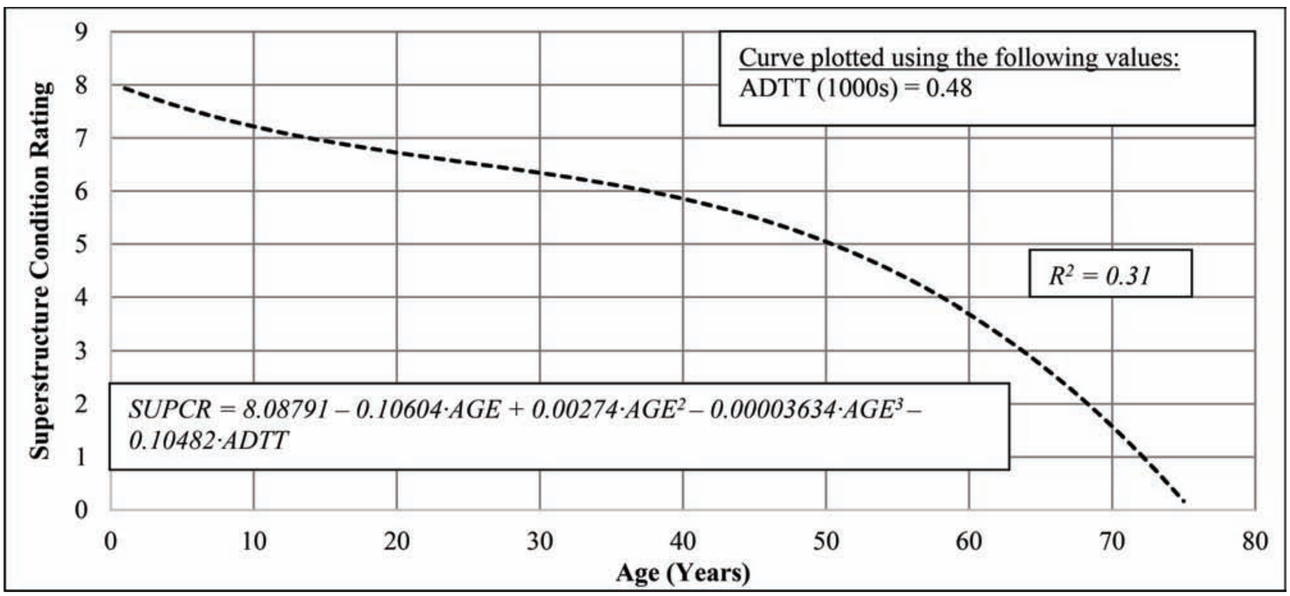


Figure 4.51 Example plot of the "steel stringer" superstructure deterioration model—Northern districts, non-NHS.

number located on Indiana state highways. The program is linked to the NBI database and displays the historical and predicted results. A window allows modifications to be made to the condition ratings in the event of repairs and the updated trends are displayed.

The dots in Figure 4.64 show the historical condition of the bridge component and the circles indicate the prediction of the future bridge condition. For example, the results for the deck of Bridge #0010 shows the bridge condition up to year 2014 when it reaches a condition rating of 5. The prediction of the deck condition shows that the deck of this bridge will continue to deteriorate and reach a condition rating of 4 at year 2020.

The same simulation indicates that from the historical data, the superstructure condition dropped to a condition rating of 7 from condition 8, where it remained up to 2014. The prediction implies the superstructure will remain in condition rating 7 and above until year 2022, from where it will deteriorate through several condition ratings until it reaches condition 4 at year 2040. The probability plots also displayed show the comparisons of the deterioration of the deck, substructure and superstructure for Bridge #0010.

Figure 4.65 displays the effects of future repair on the deck, superstructure, and substructure for Bridge #0010. The scheduled maintenance would improve the deck condition to 9, and 8 for both the superstructure and substructure at year 2030. Subsequent repairs about 20 years later will be expected to improve the deck condition to 8. Figure 4.65 also shows that after receiving the indicate treatments, the deterioration of

TABLE 4.12
"Steel Stringer" Superstructure Deterioration Model (Deterministic)

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.4675	49.92	8.08791	126.95	7.86936	89.33	8.27835	65.89	9.00	–	8.05118	106.74
Design Factors												
Age	-0.19653	-18.37	-0.10604	-10.59	-0.09765	-13.86	-0.07275	-7.27	-0.10947	-11.79	-0.1127	-8.96
Age-Squared	0.00892	12.79	0.00274	6.01	0.00415	9.64	0.00104	2.07	0.00533	10.53	0.00444	6.87
Age-Cubed	-0.0016286	-12.05	-0.00003634	-6.25	-0.00008244	-10.26	-0.00001068	-1.47	-0.00009904	-12.13	-0.00007786	-7.79
Interstate (1 if on the Interstate, 0 otherwise)	–	–	–	–	-0.05396	-4.05	–	–	–	–	–	–
Skew	–	–	–	–	–	–	-0.00138	-3.11	-0.00297	-7.98	–	–
Service Under (1 if waterway, 0 otherwise)	–	–	–	–	-0.02771	-2.51	–	–	–	–	-0.10251	-4.40
Number of Spans in Main Unit	–	–	–	–	–	–	–	–	–	–	–	–
Length	–	–	–	–	-0.000027153	-4.74	–	–	–	–	–	–
Climate Factors												
Freeze Index (1000)	–	–	–	–	–	–	–	–	-0.87639	-10.49	–	–
Number of Freeze-Thaw Cycles	–	–	–	–	-0.00362	-2.63	-0.00882	-4.60	-0.00786	-2.80	–	–
Average Precipitation	-0.02808	-5.82	–	–	–	–	–	–	-0.0148	-4.14	–	–
Operational Factors												
ADTT(1000)	–	–	-0.10482	-5.06	–	–	–	–	-0.0204	-4.60	-0.14818	-7.01
Model Fit Statistics												
Observations	4886		2573		8182		3682		4113		2710	
R-Squared	0.3111		0.3124		0.2314		0.3395		0.2444		0.2623	

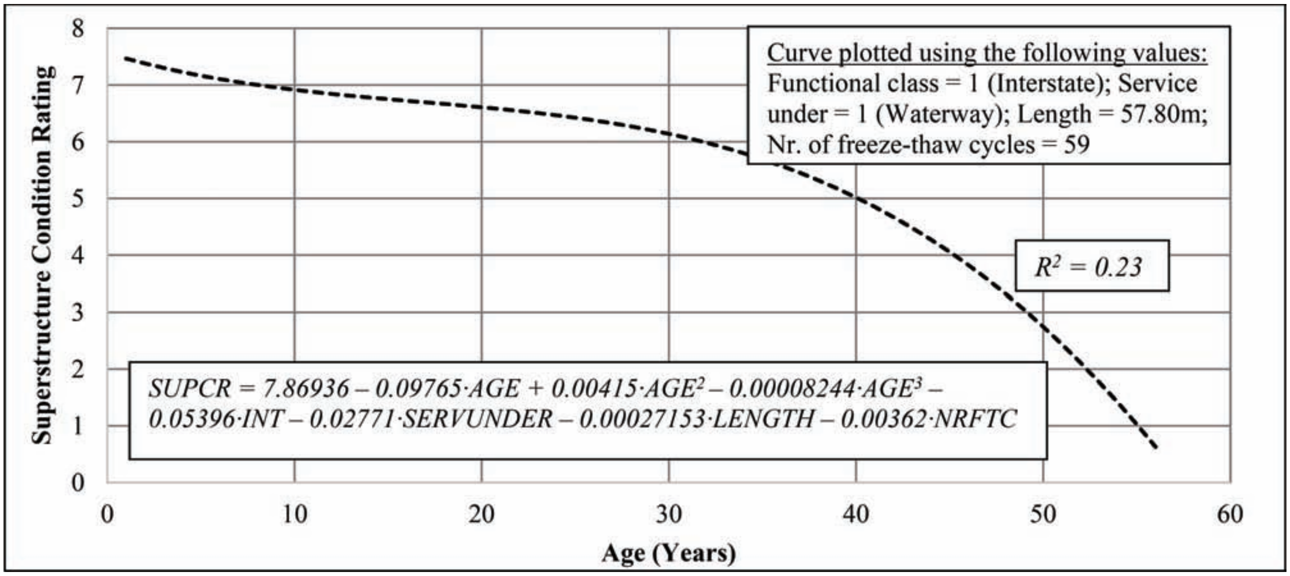


Figure 4.52 Example plot of the "steel stringer" superstructure deterioration model—Central districts, NHS.

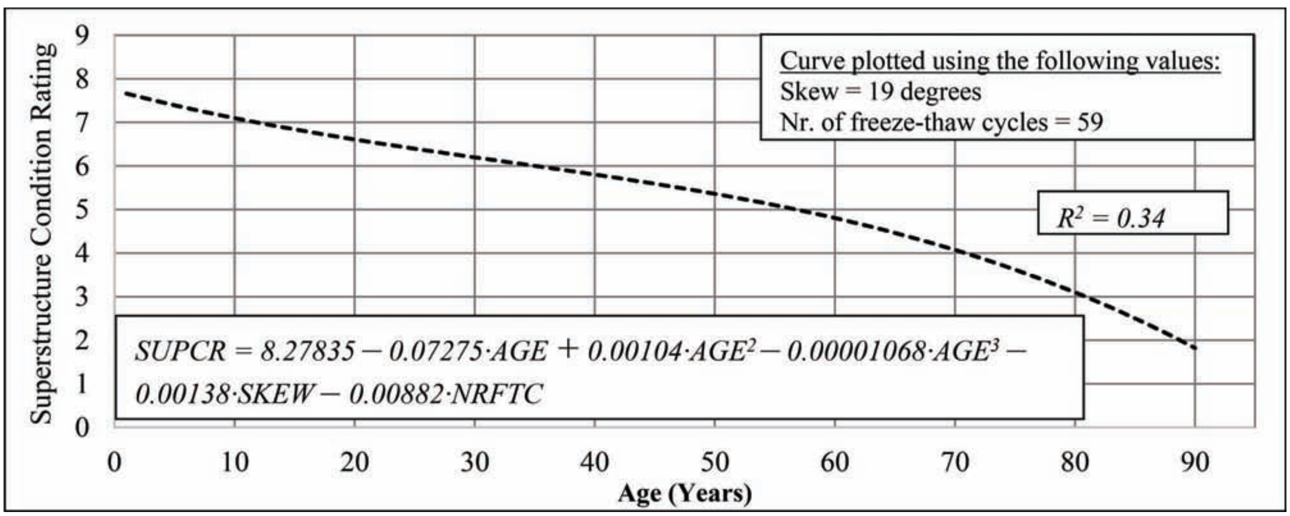


Figure 4.53 Example plot of the "steel stringer" superstructure deterioration model—Central districts, non-NHS.

Bridge #0010 will subsequently proceed to a condition rating 3 at year 2030. Thereafter, improvements to the deck will bring the condition back to 9, from where it will deteriorate to 6 at year 2050. Further maintenance activities around 2050 will be expected to improve the deck condition to 8 and subsequent deterioration will be expected to take the deck condition to 4 at year 2070. The display also shows the number of years each bridge component will stay in a particular condition rating.

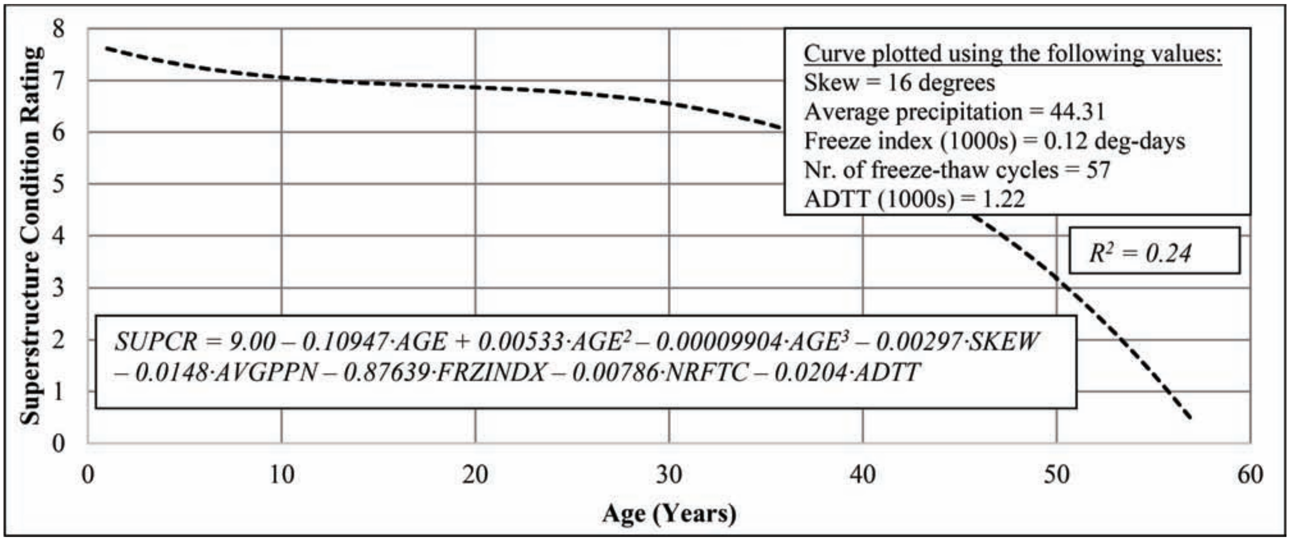


Figure 4.54 Example plot of the "steel stringer" superstructure deterioration—Southern districts, NHS.

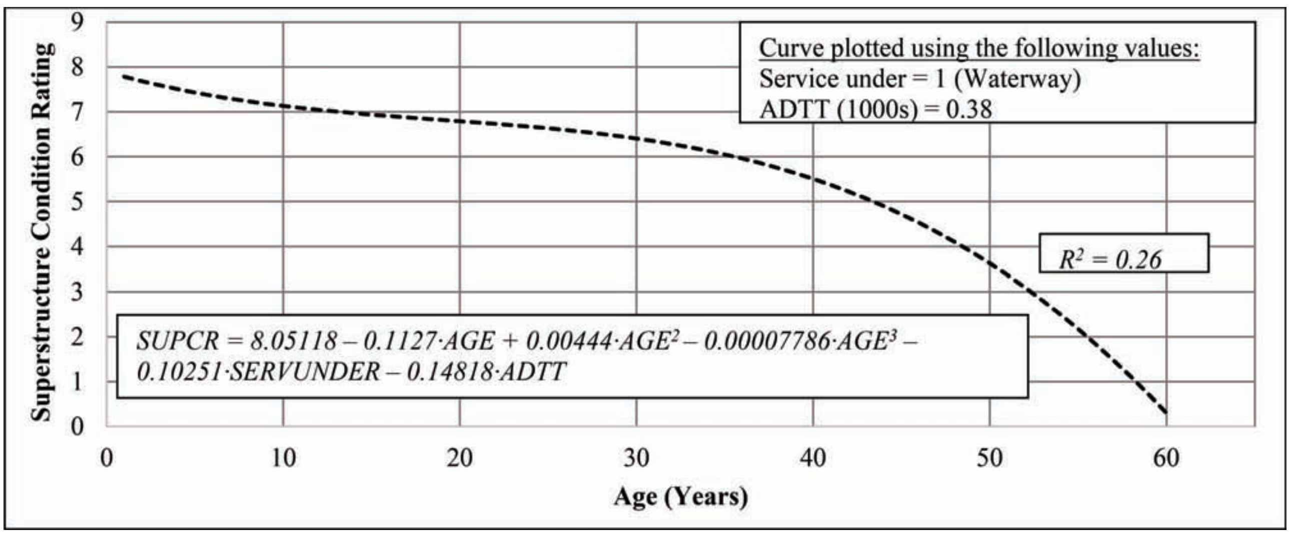


Figure 4.55 Example plot of the "steel stringer" superstructure deterioration model—Southern districts, non-NHS.

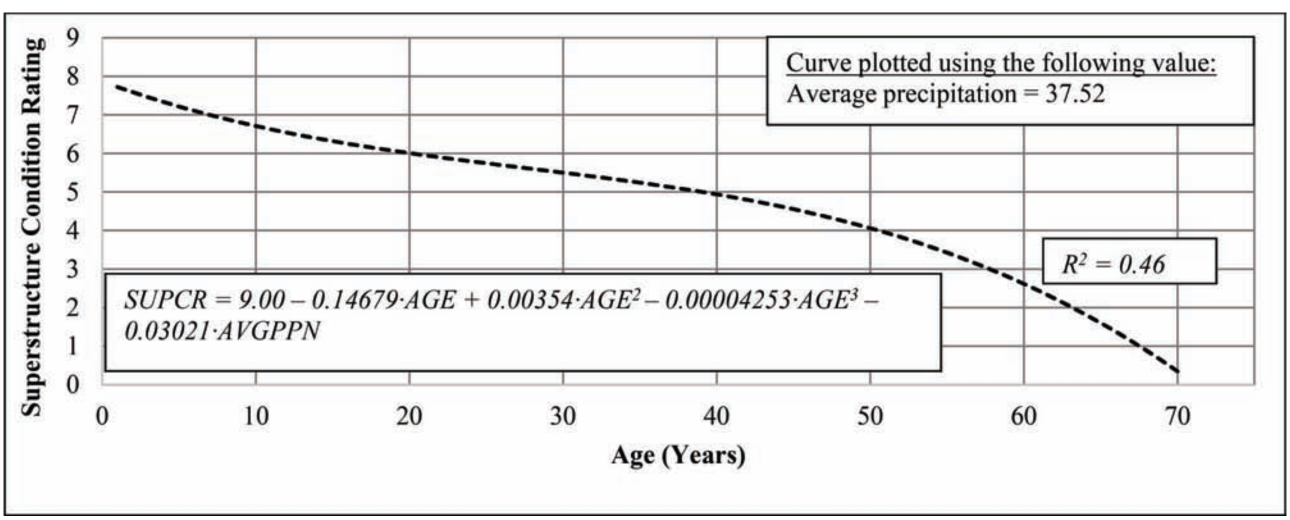


Figure 4.56 Example plot of the "steel thru truss" superstructure deterioration model—Northern districts, NHS.

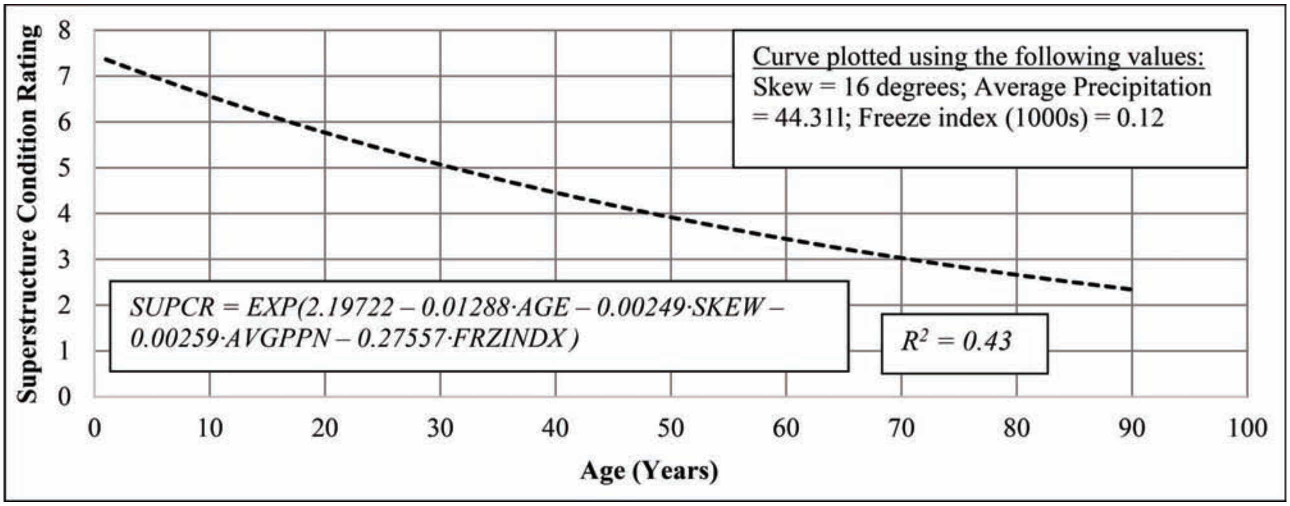


Figure 4.57 Example plot of the "steel thru truss" superstructure deterioration model—Southern districts, non-NHS.

TABLE 4.13
"Steel thru Truss" Superstructure Deterioration Model (Deterministic)

	North		South	
	Parameter Estimate	**t-stat**	**Parameter Estimate**	**t-stat**
Variable	**Non-NHS**		**Non-NHS**	
Constant	9.00	–	2.19722	–
Design Factors				
Age	-0.14679	-4.62	-0.01288	-16.84
Age-Squared	0.00354	2.84	–	–
Age-Cubed	-0.00004253	-2.84	–	–
Interstate (1 if on the Interstate, 0 otherwise)	–	–	–	–
Skew	–	–	-0.00249	-2.38
Service Under (1 if waterway, 0 otherwise)	–	–	–	–
Number of Spans in Main Unit	–	–	–	–
Length	–	–	–	–
Climate Factors				
Freeze Index (1000)	–	–	-0.27557	-5.88
Number of Freeze-Thaw Cycles	–	–	–	–
Average Precipitation	-0.03021	-4.65	-0.00259	-5.81
Operational Factors				
ADTT(1000)	–	–	–	–
Model Fit Statistics				
Observations	318		425	
R-Squared	0.4598		0.4256	

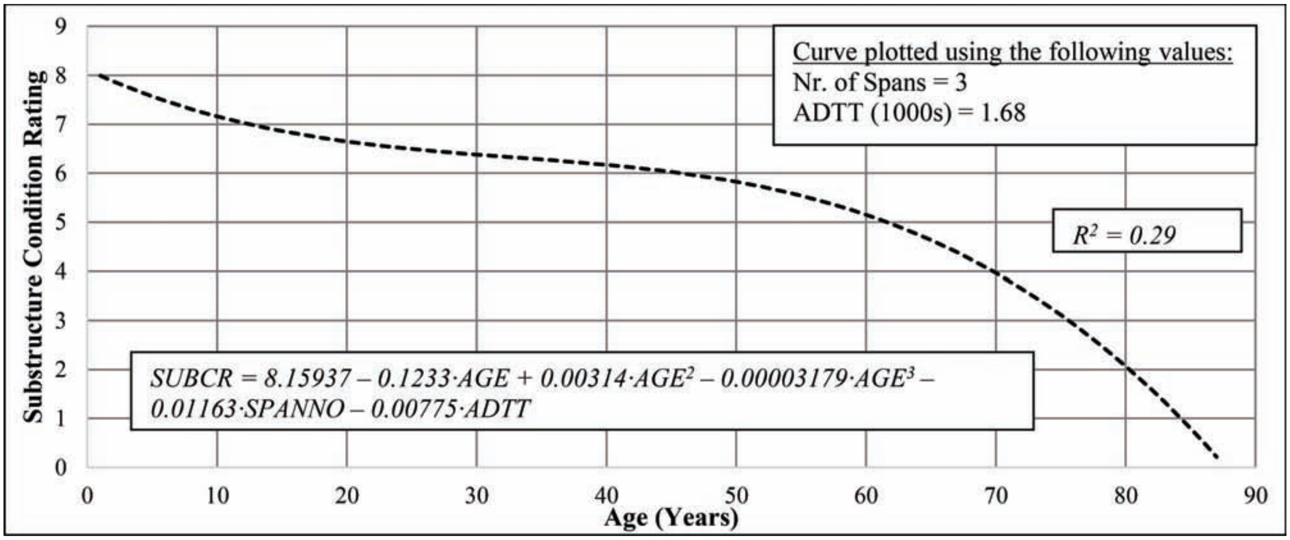


Figure 4.58 Example plot of the substructure deterioration model—Northern districts, NHS.

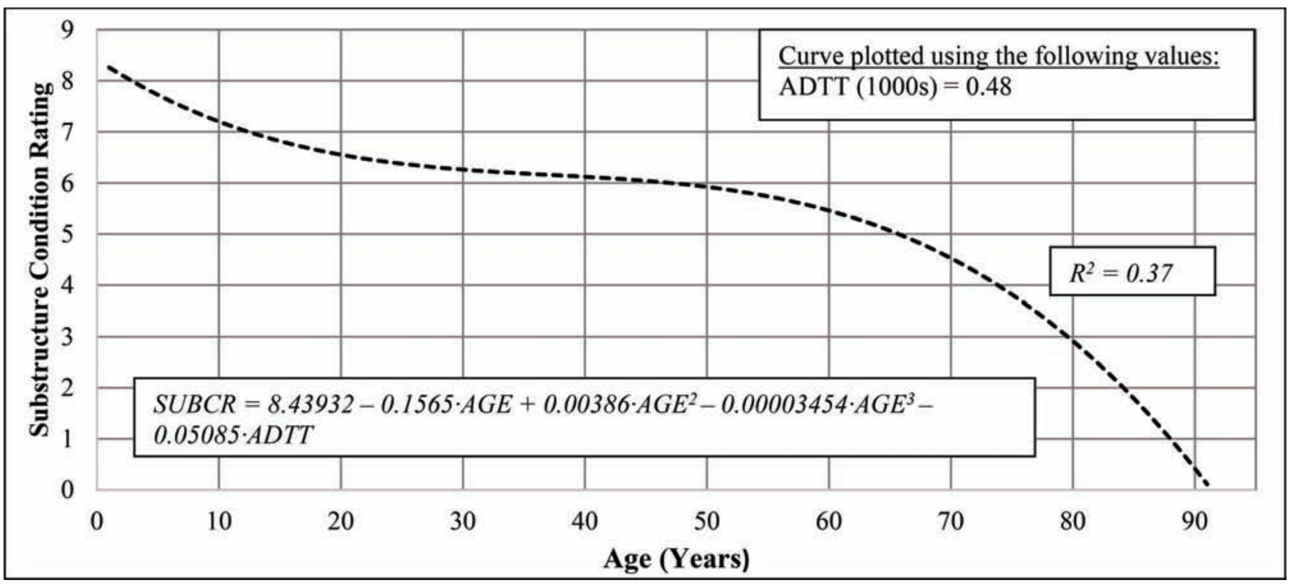


Figure 4.59 Example plot of the substructure deterioration model—Northern districts, non-NHS.

TABLE 4.14
Variables Used for Substructure Deterioration Modeling

Variable	Code
Substructure Condition Rating	*SUBCR*
Substructure Age (years)	*AGE*
Interstate (1 if located on Interstate, 0 Otherwise)	*INT*
Bridge skew	*SKEW*
Bridge length	*LENGTH*
Type of Service Under Bridge	*SERVUNDER*
Number of spans in main unit of the bridge	*SPANNO*
Freeze Index (1000's of degree-days)	*FRZINDX*
Number of freeze-thaw cycles	*NRFTC*
Average daily truck traffic (in 1000's)	*ADTT*

TABLE 4.15
Substructure Deterioration Model (Deterministic)

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	8.15937	271.90	8.43932	247.56	8.25023	127.52	8.48942	103.90	8.96898	80.46	8.5448	245.00
Design Factors												
Age	-0.1233	-26.02	-0.1565	-35.09	-0.10552	-32.03	-0.13866	-37.18	-0.07394	-17.13	-0.12212	-29.86
Age-Squared	0.00314	13.97	0.00386	22.75	0.00274	18.12	0.00312	22.03	0.00161	8.04	0.00255	16.74
Age-Cubed	-0.00003179	-11.43	-0.00003454	-19.25	-0.00002766	-15.00	-0.00002722	-18.11	-0.00001654	-6.5	-0.00002126	-13.01
Interstate (1 if on the Interstate, 0 otherwise)	–	–	–	–	-0.03816	-3.82	–	–	–	–	–	–
Skew	–	–	–	–	–	–	–	–	-0.00199	-6.25	–	–
Service Under (1 if waterway, 0 otherwise)	–	–	–	–	-0.08212	-9.60	-0.09838	-7.28	-0.09562	-7.19	-0.29416	-16.33
Number of Spans in Main Unit	-0.01163	-3.73	–	–	–	–	–	–	-0.01205	-4.01	–	–
Length	–	–	–	–	-0.00045568	-8.22	-0.00054403	-3.42	–	–	–	–
Climate Factors												
Freeze Index (1000)	–	–	–	–	–	–	–	–	-0.72823	-15.03	–	–
Number of Freeze-Thaw Cycles	–	–	-0.01397	-6.52	-0.00648	-6.25	-0.00255	-2.02	-0.01557	-7.88	–	–
Operational Factors												
ADTT(1000)	-0.00775	-3.72	-0.05085	-3.75	–	–	-0.0933	-7.17	-0.06789	-14.75	-0.0407	-2.57
Model Fit Statistics												
Observations	9587		8778		13937		12149		9108		12426	
R-Squared	0.2851		0.3715		0.3077		0.4063		0.2942		0.353	

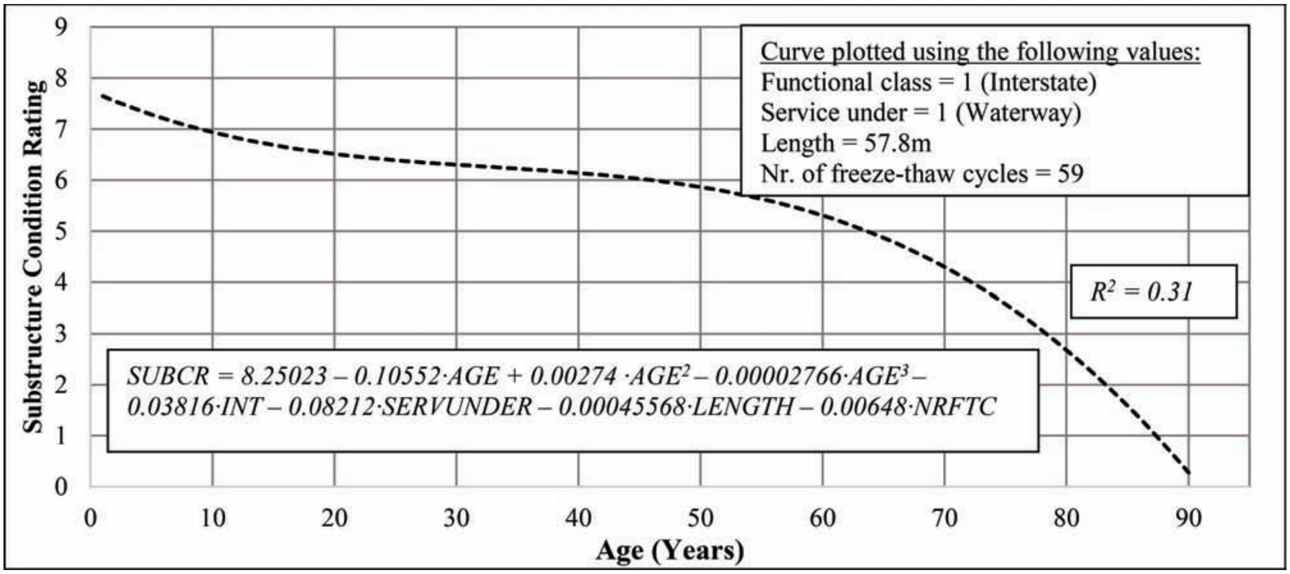


Figure 4.60 Example plot of the substructure deterioration model—Central district, NHS.

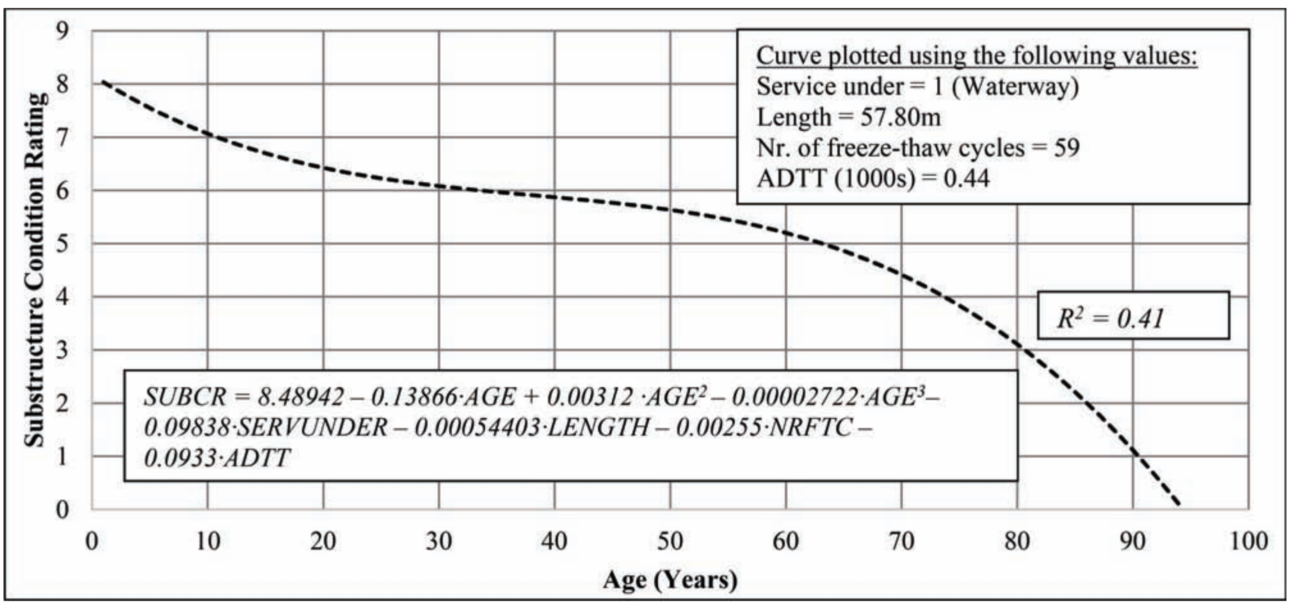


Figure 4.61 Example plot of the substructure deterioration model—Central district, non-NHS.

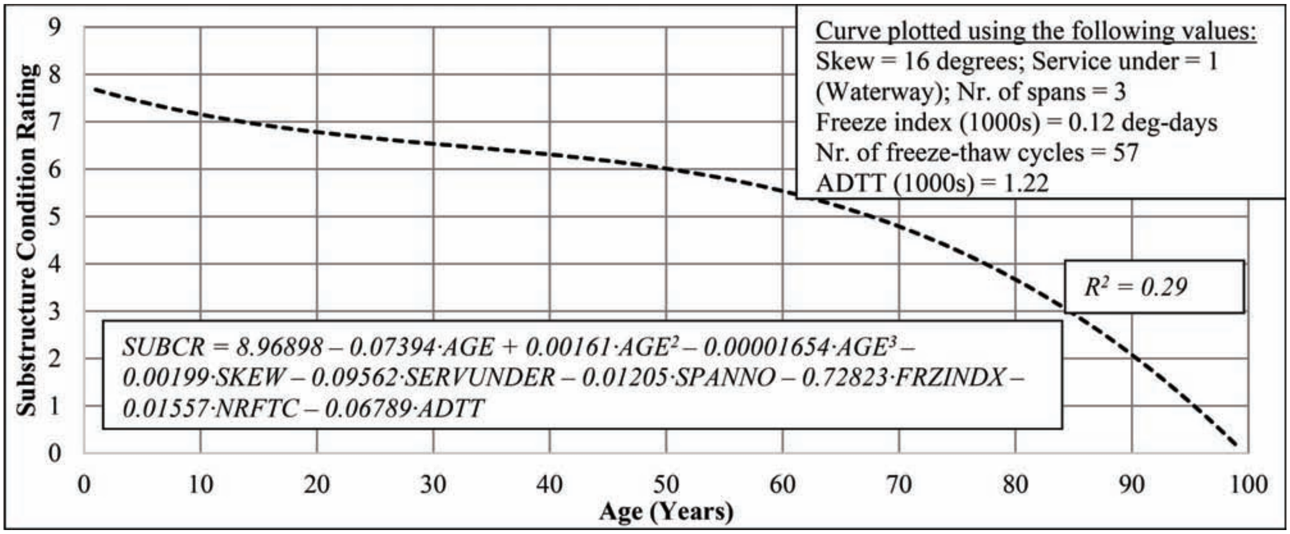


Figure 4.62 Example plot of the substructure deterioration model—Southern districts, NHS.

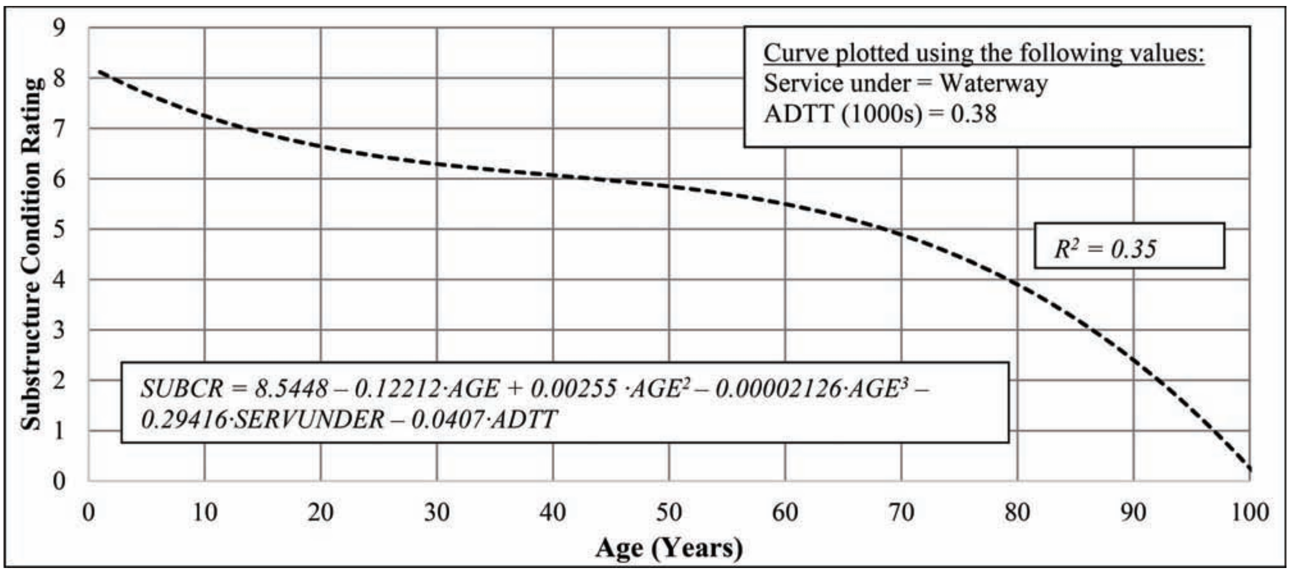


Figure 4.63 Example plot of the substructure deterioration model—Southern districts, non-NHS.

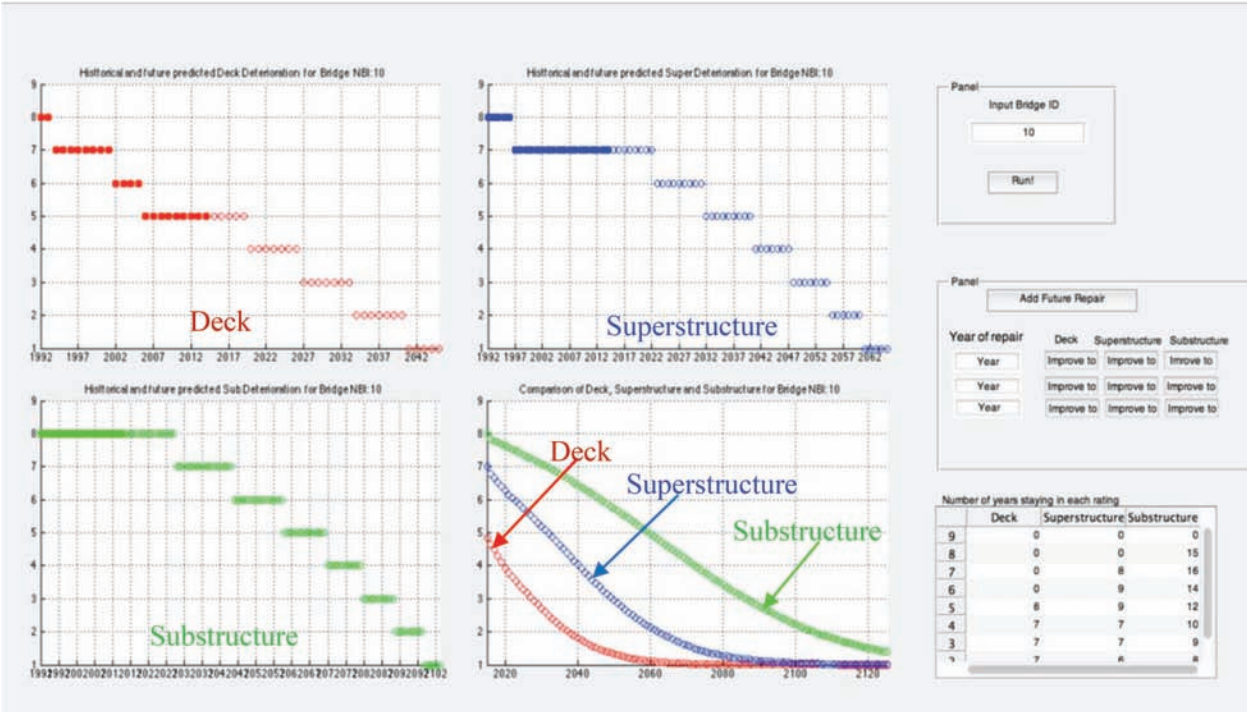


Figure 4.64 User interface presenting modeling results for Bridge #0010 after 10,000 simulations.

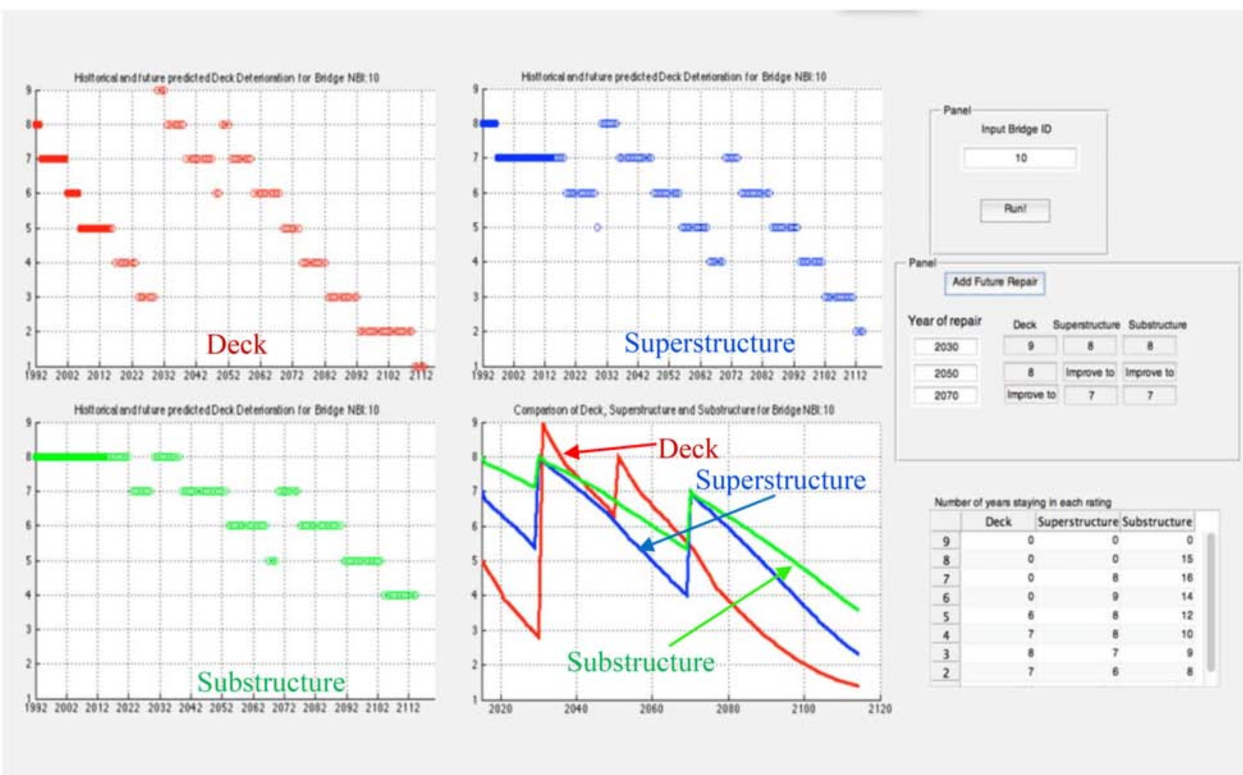


Figure 4.65 Simulation example of the effects of future repair.

TABLE 4.16
Significant Variables in the Probabilistic Model

Component	Independent Variables
Deck	Primary age Transition statue in the last inspection period The number of years to last transition Type of wearing surface Functional classification of inventory route Daily truck traffic Number of cold days per year Number of freeze-thaw cycles Service under bridge structure Deck rating found in current inspection period Rehabilitation history (If there is any improvement in the rating observed in the past 5 periods)
Superstructure	Primary age Transition statue in the last inspection period The number of years to last transition Type of superstructure material Functional classification of inventory route Annually number of cold days Number of freeze-thaw cycles Service under bridge structure Superstructure rating found in current inspection period Rehabilitation history (If there is any improvement in the rating observed in the past 5 periods)
Substructure	Primary age Transition statue in the last inspection period The number of years to last transition Functional classification of inventory route

TABLE 4.17
LIMDEP Results for Binary Probit Models

Variable	Coefficient	Standard Error	t-Statistic	P[|Z|>z]	Mean of X
(a) Deck Deterioration					
Constant	-2.04	0.110	-18.59	<0.0001	
Z0 (= $Z(i,t-1)$)	-0.69	0.049	-13.95	<0.0001	0.13
YRTOTRAN	0.04	0.004	9.75	<0.0001	4.74
ADTT	0.02	0.007	3.51	<0.0001	0.98
SOUTH	-0.11	0.042	-2.69	0.0071	0.34
COLDDAY	0.01	0.001	5.05	<0.0001	71.97
HNRFTC	0.14	0.027	5.08	<0.0001	0.29
IFEPBI	-0.28	0.048	-5.70	<0.0001	0.11
URBAN	0.15	0.030	5.02	<0.0001	0.30
SERVUNDER	0.08	0.029	2.62	0.0089	0.66
AGE	-0.01	0.001	-9.05	<0.0001	35.59
RATING	-0.05	0.008	-5.70	<0.0001	6.54
DECKIMPROV	0.57	0.025	22.62	<0.0001	0.36
(b) Superstructure Deterioration					
Constant	-1.38	0.075	-18.43	<0.0001	
Z0 (= $Z(i,t-1)$)	-0.28	0.021	-13.54	<0.0001	0.002
YRTOTRAN	0.03	0.004	6.57	<0.0001	5.52
SOUTH	-0.19	0.031	-6.05	<0.0001	0.34
HNRFTC	0.22	0.030	7.33	<0.0001	0.29
IFSTEEL	-0.40	0.035	-11.30	<0.0001	0.40
URBAN	0.10	0.034	3.03	0.0025	0.30
SERVUNDER	0.10	0.037	2.58	0.0100	0.66
AGE	-0.01	0.001	-8.53	<0.0001	35.84
RATING	-0.12	0.009	-13.97	<0.0001	6.59
SUPIMPROV	0.26	0.031	8.44	<0.0001	0.30
(c) Substructure Deterioration					
Constant	-1.58	0.073	-21.61	<0.0001	
Z0 (= $Z(i,t-1)$)	-0.29	0.021	-13.63	<0.0001	0.002
YRTOTRAN	0.02	0.004	5.46	<0.0001	5.52
SOUTH	-0.19	0.031	-6.17	<0.0001	0.34
HNRFTC	0.23	0.030	7.70	<0.0001	0.29
URBAN	0.06	0.033	1.70	0.0898	0.30
SERVUNDER	0.29	0.033	8.79	<0.0001	0.66
AGE	-0.01	0.001	-9.27	<0.0001	35.84
RATING	-0.13	0.009	-14.18	<0.0001	6.59
SUBIMPROV	0.26	0.031	8.24	<0.0001	0.30

TABLE 4.18
Sample Prediction of Deck Rating Using the Simulation

Year	Age	Utility [U]	Probability of Transition [P]	Current Transition [Z_i]	Last Transition [Z_{i-1}]	Deck Rating	Years to Last Transition	Years to Last Improvement
2013	28	-2.064	0.113	0	1	7	1	3
2014	29	-1.356	0.205	1	0	7	2	4
2015	30	-2.071	0.112	0	1	6	0	5
2016	31	-1.935	0.126	0	0	6	1	6
2017	32	-1.895	0.131	0	0	6	2	7
2018	33	-1.855	0.135	1	0	6	3	8
2019	34	-2.616	0.068	0	1	5	0	9
2020	35	-1.909	0.129	0	0	5	1	10
2021	36	-1.868	0.134	1	0	5	2	11
2022	37	-2.583	0.070	0	1	4	0	12
2023	38	-1.876	0.133	0	0	4	1	13
2024	39	-1.836	0.138	0	0	4	2	14
2025	40	-1.796	0.142	0	0	4	3	15
2026	41	-1.756	0.147	1	0	4	4	16
2027	42	-2.562	0.072	0	1	3	0	17
2028	43	-1.855	0.135	0	0	3	1	18
2029	44	-1.815	0.140	0	0	3	2	19
2030	45	-1.775	0.145	0	0	3	3	20
2031	46	-1.735	0.150	0	0	3	4	21
2032	47	-1.695	0.155	0	0	3	5	22
2033	48	-1.655	0.160	0	0	3	6	23
2034	49	-1.615	0.166	0	0	3	7	24
2035	50	-1.575	0.172	1	0	3	8	25
2036	51	-2.565	0.071	0	1	2	0	26

5. SUMMARY AND CONCLUSIONS

5.1 Summary

The bridge deterioration models currently in use in the Indiana BMS were developed over two decades ago. Since then, significant changes have taken place in the intervening years in the inspection methods, technologies, and statistical tools for data analysis. Also, because of the lack of reliable data in the past, items such as truck traffic were not included in the analysis. These obstacles no longer exist in the same order of magnitude. Therefore, the time is ripe to update the deterioration models for the various bridge components to make them more reliable and useful for bridge engineers at INDOT.

In addressing this research need, the present study developed families of curves representing deterioration models for the bridge deck, superstructure, and substructure components. The NBI database was employed; and the models used the NBI condition ratings as the response variable. The model families were categorized by administrative region, functional class, and superstructure material type. The independent variables included traffic volume, truck traffic, design type, climatic condition, and design features.

In this study, environmental variables were considered in the deterioration model development, and it was confirmed that they play a significant role in bridge deterioration. For several of the deterioration models, the climate variables of freeze index, number of freeze-thaw cycles, and average precipitation were found to be significant predictors of bridge component deterioration. From the results, it can be seen that the climate variables and bridge design variables influenced deck and substructure deterioration more than they influenced the superstructure. Compared to the superstructure and substructure, the deck deterioration was much more affected by traffic loading. Also, for the same bridge material type and traffic loading, there were generally some differences in deterioration across the Indiana districts, but was not always the case. Models were also developed separately for bridges with prior repair and those without prior repair. These model results are presented not in the main report but in Appendix A. It was also observed that bridge components that had undergone some repair since their construction exhibited patterns of deterioration that were different compared to those that had not received any such repairs, which can be explained by the salubrious effect of the repair actions.

5.2 Future Research

In addressing the objectives of the present study, it was seen that there exist a number of areas that could be investigated to enhance the bridge models further. In the future, as data become available, studies on deterioration modeling could go beyond the three components in this study to develop models for each bridge element as defined in PONTIS. Also, future studies could incorporate the bridge design type as a potential independent variable in the models.

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APPENDICES

APPENDIX A: OTHER TECNIQUES FOR MODELING BRIDGE DETERIORATION (FROM THE LITERATURE REVIEW)

Markov Chains

In order to apply the Markov chain, the primary task is to derive the transition matrix, Z, and the initial state vector Z(0). The future condition vector Z (t) for both groups of bridges and individual bridges at any number of transition periods (t) can be obtained as shown in the equation below (Collins, 1972). Transition probabilities in the matrix can be estimated either from condition monitoring data or by experts' judgments and ideas (DeStefano & Grivas, 1998; Thompson & Shepard, 1994). The transition matrix also can be updated any time after variables change.

As a stochastic process, a Markov chain can be considered as a series of transitions between predetermined condition states. If the probability of a future condition state is only dependent on the present state, the stochastic process is treated as a first-order Markov process. For a discrete stochastic parameter (Yt) with a discrete space as:

$$Z\left(Y_{t+1}=j_{j+1}\,\middle|\,Y_t=j_t, Y_{t-1}=j_{t-1}, Y_{t-2}=j_{t-2},\ldots,\right.$$
$$\left.Y_1=j_1, Y_0=j_0\right)=Z\left(Y_{t+1}=j_{j+1}\,\middle|\,Y_t=j_t\right)$$

where, j_t=state of the process at time t; and Z=conditional probability of any future event given the present and past events.

The Markov chain is used in infrastructure management to develop and predict infrastructure performance, especially for infrastructure types with discrete condition states. Using the Markov chain, a performance prediction model for bridge elements can be developed by first defining the discrete condition states, and then computing the accumulating probability of transition from one state to another over several discrete time intervals. The usual form of the transition matrix Z, is represented by a matrix of order (m x m), where m is the number of possible condition states. An element, $z_{j,k}$, in the Z matrix, corresponds to the probability that the condition of a bridge element will transit from state *(j)* to state *(k)* during a predetermined transition period. When the initial bridge element condition, also described as the present condition, Z(0), is given or known, then using the future vector bridge condition, Z(t) at any given transition period can be computed (Collins, 1972) as:

$$Z(t)=Z(0)\times Z^t$$

where,

$$Z=\begin{bmatrix} z_{1,1} & z_{1.2} & z_{1,3} & z_{1,4} & \cdots & z_{1,m} \\ z_{2,1} & z_{2,2} & z_{2,3} & z_{2,4} & \cdots & z_{2,m} \\ . & . & . & . & \cdots & . \\ . & . & . & \cdots & \cdots & . \\ . & . & . & \cdots & \cdots & . \\ z_{m,1} & z_{m,2} & z_{m,3} & z_{m,4} & \cdots & z_{m,m} \end{bmatrix}$$

The transition probabilities can be derived either from accumulated bridge condition data or from expert opinion. Generally, agencies with adequate accumulated data can adopt a statistical analysis while agencies with inconsistent or insufficient data may adopt the expert opinion approach. The use of an expert opinion will require the involvement of a number of bridge engineers (Thompson & Shepard, 1994); and after a significant and consistent size of condition data becomes available, a statistical updating can be considered.

In practice, either the regression-based optimization approach or percentage prediction approach can used to generate the transition probability matrix. The regression-based approach clusters bridges into groups of homogenous independent variables because the transition probabilities are a function of the independent variables. In order to develop a bridge deterioration model, using linear regression, the response variable is considered as the bridge condition while the bridge age is the independent variable. The transition matrix is then estimated for each group of homogenous independent variables, through an optimization process, which minimizes the sum of the squared differences between the condition state value predicted by the regression model and the value expected from the Markov transition probabilities (Carnahan et al., 1987; Jiang et al., 1988). When the regression-based optimization approach is adopted, the transition probabilities are estimated by solving the nonlinear optimization as follows:

$$\min \sum_{t=1}^{M} |\psi(t)-\xi(t)|$$
$$s.t\ 0\leq z_{j,k}\leq 1 \text{ for j,k}=1,2,\ldots,\text{m}$$
$$\sum_{t=1}^{m} z_{j,k}=1$$

where, M=total number of transition periods; ψ(t) = bridge condition at transition period number t on the basis of regression curve; and ξ(t) =expected value of bridge condition at transition period number t *based on* ξ(t)=Z(t)Q, where Q= is a vector of condition states.

The regression-based optimization approach faces a number of challenges due to prior maintenance activities, whose records may not be available to the analyst. The regression-based optimization approach fails to capture the structure of the bridge deterioration process because when a change in condition takes place within an inspection period, the developed model cannot be able to adequately capture it as a function of independent variables, and the dependent variable is discrete, not continuous as restricted by the linear regression approach. In order to avoid this issue, the percentage prediction approach (Jiang et al., 1988), $Z_{j,k}=m_{j,k}/m_j$ (where $m_{j,k}$ is the number of transitions from state j to state k within a given time period; and m_j = the total number of bridges in state j before the transition) has been found to be a robust alternative in the literature. In order to use the percentage prediction approach and generate reliable transition probabilities, the analyst should have at a minimum, two successive bridge condition records without any maintenance interventions, for a significant number of bridge elements at different condition states.

Count and Discrete Data Modeling Techniques

A number of count data modeling techniques have been used in the past to develop bridge deterioration models. The two most commonly used techniques include Poisson and negative binomial regression models. These models were used in conjunction with the Markovian behavior of bridge deterioration. In the past, Poisson regression models were used to model bridge deterioration by constructing a discrete incremental model where the response variable becomes the change in bridge condition from one inspection period to the next. The developed Poisson model was then used to derive the transition matrix (Madanat & Ibrahim, 1995).

The deterioration models developed by Poisson regression are both incremental and discrete models, because they predict changes in condition over time and are the function of independent variables such as weather, traffic load, and maintenance actions. The main advantages of the Poisson regression model over the linear regression model are significant. First, bridge deterioration is adequately linked to the statistically significant independent variables, which removes the challenge of manually clustering the sample as observed in the linear regression approach. Second, this approach allows the analyst to use the entire bridge condition data and to facilitate the development of a complete transition matrix, without restricting some elements in the transition matrix to be zero; thus, enhancing a robustness of the estimated parameters. Third, taking account of the discrete nature of the response variable, the Poisson approach is inherently suitable compared to the linear regression approach.

While the Poisson approach may be a possible approach for developing bridge deterioration models, it has a significant restriction. The Poisson restricts the mean of the random variable to be equal to the variance; and if not, then the data can be said to be either over-dispersed or under-dispersed, and the estimated parameters will be biased (Washington, Karlaftis, & Mannering, 2011). In order to overcome the dispersion restrictions, the negative binominal regression can be considered. The negative binomial is flexible and relaxes the assumption of the mean being equal to the variance.

Although count data techniques have been used in the past, the developed models were limited in use because the bridge's condition deterioration was not overtly linked to the independent variables, and the models did not account for the ordinal scale of the bridge condition ratings. In order to capture the ordinal nature of the condition states and to link deterioration to the independent variables, discrete modeling techniques, the traditional logit/probit models, also have been considered. The traditional logit/probit model nonetheless fails to account for the heterogeneity and state dependence present in panel data usage (Bulusu & Sinha, 1997). Furthermore, one of the critical limitations of the logit model is the assumption that the bridge condition states are independent and identically distributed. In order to resolve this challenge, Madanat and Ibrahim (1995) used an ordered probit model to develop a bridge condition deterioration model to reflect the discrete nature of the bridge condition ratings; however, the ordered probit model approach cannot account for the panel nature of bridge data.

The binary probit random effects model is another technique appropriate for incorporating state dependence and heterogeneity in the modeling framework. To account for state dependency, the previous bridge condition rating is included as an independent variable and heterogeneity is accounted for due to the random effects nature of the model. The binary probit model (random effects) also has been considered in the modeling of bridge deterioration. The binary probit model employs a 0/1 indicator response variable. If the condition state switches to a lower state, the indicator will be 1. If not, the indicator will be 0. This approach considers discrete condition states, rather than as a continuous state, and directly links the deterioration process to different related independent variables and treats facility deterioration as a latent variable at the same time (Madanat et al., 1997).

The binary probit model is much more efficient and simpler than the normal probit model, which is very time consuming when using panel data. The binary probit model can facilitate the estimation of the deterioration process by including heterogeneity and state dependence. When state dependence is considered, the condition state rating in the previous inspection time period can be treated as independent variables and will have an effect on the future state, which the Markov chain method cannot do. While the binary probit (random effects) approach or ordered probit models could converge at similar modeling results, a binary probit model with random effects may provide results that are more intuitive and less time-consuming.

The Bayesian Technique

The Bayesian technique is formulated on the basis of the Bayes' theorem, which contends that subjective judgments or prior information established through probabilistic analysis is critical in estimating statistical models. Thus, in order to arrive at a solution considered balanced, the prior information on the parameter values is expected to be systematically incorporated into the modeling framework in addition to the present observed data. Under the Bayesian technique, the unknown parameters of a distribution are assumed to be random variables (Lee, 2012). Using Bayes Theorem, the uncertainty associated with the estimation of the parameters is merged with the inherent variability of a random variable. In order to use the Bayesian technique, subjective judgments from experience can be analytically combined with observed data to arrive at consistent and unbiased estimation (Attoh-Okine & Bowers, 2006).

The Bayesian technique can be used to update bridge transition probability values. In order to formulate the Bayesian technique, the probability of a bridge condition transitioning from state j to state k or the probability that the condition of a bridge element is expected to transition from one condition to another over time. This theorem represents the Markov process. In order to accurately estimate the condition state of a bridge element, the Bayesian technique should be combined with the Markov chain approach. The prior information is derived from the opinions of bridge experts, and it can be combined with observed condition data to estimate the condition of bridge elements via the transition probabilities. Prior information of bridge elements, which represents the initial condition values of the transition matrix, is based on the experience of bridge inspectors. The judgment provided from bridge experts can help reduce the uncertainties connected with prediction errors when using a number of independent variables because bridge inspection data have been found to contain a number of errors and uncertainties due to incorrect inspection and data collection methods or inherent uncertainties in the deterioration process. The benefit of seeking the knowledge of a bridge expert is in the revision and updating of previous numbers in the Markov transition probability matrix (Enright & Frangopol, 1999). In order to update and revise the transition matrix of bridge elements, the multinomial model has been proven to provide consistent estimates (Bulusu & Sinha, 1997). The multinomial model is especially useful when the information provided is very limited and also is a good choice for a small sample size.

In Indiana, the Bayesian technique and binary probit random effects model were both used to predict bridge condition states of bridge components, and the results were not significantly different from the observed conditions. The prediction results from both methods were found to be consistent and matched the observed bridge condition states. Although, the binary probit approach proved to be more robust and sounder compared to the Bayesian technique, it was found to require too many analytical manipulations compared to the Bayesian technique (Bulusu & Sinha, 1997).

APPENDIX B: DETERMINISTIC MODELS FOR BRIDGES WITH AND WITHOUT PRIOR REPAIR

For greater predictive accuracy, deterioration models were developed separately for bridges with and without prior repairs. For decks and substructures, different models were developed for components at different locations (Northern, Central, and Southern districts) and highway functional class (NHS and non-NHS). For the bridge superstructure, models were developed for different material types, districts, and functional class. A summary of the results are presented in Tables B.1 and B.2. This is followed by detailed presentation of the model results for each component.

B.1 Deterministic Deck Deterioration Models

Six models were developed for bridge decks without major repairs or replacement based on the classification parameters identified in Chapter 3. Two main functional forms were investigated for the best fit; exponential and polynomial. Second- and third-order polynomial functional forms were considered for developing the best models in this study. Table B.3 presents the variables for deck deterioration models, and Table B.4 and B.5 present the detailed modeling results for the decks of bridges without and with prior repair, respectively.

B.1.1 Decks of Bridges without Prior Repair

(a) Models for Decks of Bridges without Prior Repairs, Northern Districts. This model was developed for both NHS and non-NHS bridge decks without prior repairs in Indiana's Northern districts as there appeared to be little difference between them. The results suggest that age was the most significant variable of deck deterioration, thus confirming the a-priori expectation from the literature review. Also, the number of spans in the main unit and the freeze index were found to be statistically significant at 95% confidence. For the non-NHS bridge decks, the skew, service feature, and number of freeze-thaw cycles were found to be the significant factors. ADTT is often a significant variable in deck deterioration models; however, in these two models, it was not significant. The models also show that NHS bridge decks generally deteriorated faster compared to their non-NHS counterparts. The models accounted for 49% and 46% of the variability in deck condition rating, respectively, for the NHS and non-NHS bridge decks. Figures B.1 and B.2 below illustrate the trends in deck condition rating vs. deck age, plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The predictive efficiency of the models as determined by the RMSE was found to be 0.64 for both the NHS and non-NHS bridge deck models in the Northern districts.

(b) Models for Decks of Bridges without Prior Repair, Central Districts. Similar to the case for the Northern districts, age was the most significant variable in NHS bridge deck deterioration in Indiana's Central districts. ADTT was found to be significant at 95% confidence in both models (Table B.4). Also, skew and number of spans were significant in both models. Figures B.3 and B.4 present the trends in deck condition ratings as a function of the deck age, plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The models explain approximately 59% and 53% of the variation of the condition of the NHS and non-NHS bridge decks, respectively. The RMSE for the models of bridge decks on the NHS was found to be 0.55 and 0.57 for decks on the non-NHS roads in the Central districts.

(c) Models for Decks of Bridges without Prior Repair, Southern Districts. For the Southern district bridge decks without prior repairs, age and climatic factors were found to be most influential to their deterioration (Table B.4). For the NHS bridge decks, skew, service under the bridge decks, ADTT, freeze index, and number of freeze-thaw cycles were found to be the influential factors in deck deterioration. For their non-NHS counterparts, these factors were not found to be influential, not necessarily because they do not affect the deck condition but because the data showed relatively small statistical variation in those variables; for their non-NHS counterparts, only the deck age and freeze index were found to be significant for bridge decks on this class of highways. The two models explained a relatively high variation (57% and 61%) for the condition ratings of NHS and non-NHS bridge decks, respectively. Figures B.5 and B.6 below illustrate the relationship between the deck condition rating and the deck age, which was plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The predictive efficiency of the models as determined by the RMSE was found to be 0.49 and 0.53, respectively, for bridge decks on the NHS and non-NHS roads in the Southern districts.

B.1.2 Decks of Bridges with Prior Repair

(a) Models for Decks of Bridges with Prior Repair, Northern Districts. For NHS bridge decks with prior repair in the Northern districts, the condition rating was found to be explained by the following operational, design, and climatic factors: age, skew, service under the bridge, freeze index, and ADTT (Table B.5). For their non-NHS counterparts, age, number of spans in main unit, and freeze index were significant at 95% confidence. The models accounted for approximately 45% and 40% of the variability in the deck condition rating, and the polynomial functional form for both models fit the data well. The NHS decks experience higher levels of traffic load and therefore were expected to suffer faster deterioration, however, they also are designed to higher standards compared to their non-NHS counterparts. The model results indicate that the decks on these two highway systems deteriorated at similar rates, which

TABLE B.1
Bridges without Prior Repair

Bridge Component	Districts	Functional Class	Deterioration Model
deterDECK	Northern	NHS	$DCR = 9 - 0.19065 \cdot AGE + 0.00887 \cdot AGE^2 - 0.00020541 \cdot AGE^3 - 0.02094 \cdot SPANNO - 0.66157 \cdot FRZINDX$
		Non-NHS	$DCR = 9 - 0.22608 \cdot AGE + 0.0102 \cdot AGE^2 - 0.00020169 \cdot AGE^3 - 0.00289 \cdot SKEW - 0.19359 \cdot SERVUNDER - 0.00351 \cdot NRFTC$
	Central	NHS	$DCR = 9 - 0.20745 \cdot AGE + 0.00923 \cdot AGE^2 - 0.00018556 \cdot AGE^3 - 0.13388 \cdot SERVUNDER - 0.04286 \cdot SPANNO - 0.00573 \cdot NRFTC - 0.06456 \cdot ADTT$
		Non-NHS	$DCR = 9 - 0.12851 \cdot AGE + 0.00437 \cdot AGE^2 - 0.00010651 \cdot AGE^3 - 0.00198 \cdot SKEW - 0.05784 \cdot SPANNO - 0.00968 \cdot NRFTC - 0.06364 \cdot ADTT$
	Southern	NHS	$DCR = 9 - 0.01803 \cdot AGE - 0.00171 \cdot AGE^2 - 0.00302 \cdot SKEW - 0.09422 \cdot SERVUNDER - 1.29465 \cdot FRZINDX - 0.0111 \cdot NRFTC - 0.05091 \cdot ADTT$
		Non-NHS	$DCR = 8.30787 - 0.04197 \cdot AGE - 0.0014 \cdot AGE^2 - 0.65646 \cdot FRZINDX$
Cast–in–Place Concrete Superstructure	Northern	NHS	$\mathrm{SUPCR} = 11.20026 - 0.20674 \cdot AGE + 0.00496 \cdot AGE^2 - 0.00004929 \cdot AGE^3 - 1.0498 \cdot SERVUNDER - 1.92669 \cdot FRZINDX - 0.00912 \cdot NRFTC$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.21722 - 0.01126 \cdot AGE - 0.00209 \cdot NRFTC$
	Central	NHS	$SUPCR = 8.8491 - 0.19572 \cdot AGE + 0.00466 \cdot AGE^2 - 0.00004589 \cdot AGE^3 - 0.00736 \cdot SKEW$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.33523 - 0.01395 \cdot AGE - 0.00060848 \cdot SKEW - 0.18807 \cdot SERVUNDER$
	Southern	NHS	$SUPCR = 8.40296 - 0.05096 \cdot AGE - 0.00035479 \cdot AGE^2 - 1.82996 \cdot FRZINDX$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.20021 - 0.01307 \cdot AGE - 0.00045256 \cdot SKEW - 0.13064 \cdot FRZINDX$
Prestressed Concrete Superstructure	Northern	NHS	$SUPCR = 9.19361 - 0.00209 \cdot AGE^2 - 0.02539 \cdot SPANNO - 1.32202 \cdot FRZINDX - 0.02672 \cdot ADTT$
		Non-NHS	$SUPCR = 9.65668 - 0.05087 \cdot AGE - 0.00061396 \cdot AGE^2 - 0.00387 \cdot SKEW - 0.01721 \cdot NRFTC$
	Central	NHS	$SUPCR = 8.52923 - 0.00179 \cdot AGE^2 - 0.00215 \cdot SKEW - 0.38201 \cdot SERVUNDER - 0.6489 \cdot FRZINDX$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.40586 - 0.01091 \cdot AGE - 0.01679 \cdot SPANNO - 0.00385 \cdot NRFTC$
	Southern	NHS	$SUPCR = 8.23375 - 0.00181 \cdot AGE^2 - 0.00365 \cdot SKEW - 0.11058 \cdot SERVUNDER$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.16278 - 0.0083 \cdot AGE - 0.00557 \cdot SPANNO - 0.01575 \cdot ADTT$

(Continued)

TABLE B.1
(Continued)

Bridge Component	Districts	Functional Class	Deterioration Model
Steel Superstructure	Northern	NHS	$\mathrm{LN}(SUPCR) = 2.56882 - 0.01243 \bullet AGE - 0.00492 \bullet AVGPPN - 0.10169 \bullet FRZINDX - 0.00221 \bullet NRFTC - 0.00258 \bullet ADTT$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.585 - 0.01234 \bullet AGE - 0.0052 \bullet AVGPNN - 0.1034 \bullet FRZINDX - 0.00232 \bullet NRFTC$
	Central	NHS	$SUPCR = 7.79797 - 0.00157 \bullet AGE^2 - 0.28086 \bullet SERVUNDER$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.19722 - 0.00929 \bullet AGE - 0.12848 \bullet FRZINDX - 0.05009 \bullet ADTT$
	Southern	NHS	$SUPCR = 9 - 0.00172 \bullet AGE^2 - 0.00325 \bullet SKEW - 0.30314 \bullet SERVUNDER - 0.01474 \bullet AVGPPN - 0.99109 \bullet FRZINDX$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.21129 - 0.01068 \bullet AGE - 0.03279 \bullet SERVUNDER - 0.02094 \bullet ADTT$
Substructure	Northern	NHS	$SUBCR = 9.44495 - 0.0301 \bullet AGE - 0.0008551 \bullet AGE^2 - 0.77064 \bullet FRZINDX - 0.01275 \bullet NRFTC - 0.01742 \bullet ADTT$
		Non-NHS	$\mathrm{LN}(SUBCR) = 2.32825 - 0.01013 \bullet AGE - 0.02856 \bullet SERVUNDER - 0.06839 \bullet FRZINDX - 0.00192 \bullet NRFTC$
	Central	NHS	$SUBCR = 8.71132 - 0.144459 \bullet AGE + 0.00472 \bullet AGE^2 - 0.00006995 \bullet AGE^3 - 0.1744 \bullet SERVUNDER - 0.27713 \bullet FRZINDX - 0.03907 \bullet ADTT$
		Non-NHS	$\mathrm{LN}(SUBCR) = 2.23878 - 0.01255 \bullet AGE - 0.00138 \bullet NRFTC - 0.01924 \bullet ADTT$
	Southern	NHS	$SUBCR = 9 - 0.00158 \bullet AGE^2 - 0.05531 \bullet SERVUNDER - 1.02942 \bullet FRZINDX - 0.01298 \bullet NRFTC - 0.01417 \bullet ADTT$
		Non-NHS	$\mathrm{LN}(SUBCR) = 2.19417 - 0.01037 \bullet AGE - 0.02081 \bullet SERVUNDER - 0.04876 \bullet FRZINDX$

TABLE B.2
Bridges with Prior Repair

Bridge Component	Districts	Functional Class	Deterioration Model
Deck	Northern	NHS	$DCR = 8.6143 - 0.22987 \cdot AGE + 0.00732 \cdot AGE^2 - 0.00010805 \cdot AGE^3 - 0.00137 \cdot SKEW - 0.05807 \cdot SERVUNDER - 0.24308 \cdot FRZINDX - 0.0125 \cdot ADTT$
		Non-NHS	$DCR = 8.82047 - 0.24361 \cdot AGE + 0.01051 \cdot AGE^2 - 0.00019009 \cdot AGE^3 - 0.02762 \cdot SPANNO - 0.67943 \cdot FRZINDX$
	Central	NHS	$DCR = 8.40174 - 0.16855 \cdot AGE + 0.00638 \cdot AGE^2 - 0.0001348 \cdot AGE^3 - 0.05922 \cdot INT - 0.08571 \cdot SERVUNDER - 0.00677 \cdot NRFTC$
		Non-NHS	$DCR = 9 - 0.19984 \cdot AGE + 0.00928 \cdot AGE^2 - 0.00018585 \cdot AGE^3 - 0.00138 \cdot SKEW - 0.07713 \cdot SERVUNDER - 0.03905 \cdot SPANNO - 0.01401 \cdot NRFTC$
	Southern	NHS	$DCR = 8.14694 - 0.05332 \cdot AGE - 0.0006275 \cdot AGE^2 - 0.21593 \cdot FRZINDX - 0.00822 \cdot NRFTC - 0.04037 \cdot ADTT$
		Non-NHS	$DCR = 7.69854 - 0.03433 \cdot AGE - 0.00098591 \cdot AGE^2 - 0.00199 \cdot SKEW - 0.03765 \cdot SPANNO - 0.52647 \cdot FRZINDX - 0.13994 \cdot ADTT$
Cast–in–Place Concrete Superstructure	Northern	NHS	$SUPCR = 9.19426 - 0.26002 \cdot AGE + 0.00902 \cdot AGE^2 - 0.00010795 \cdot AGE^3 - 0.07766 \cdot SERVUNDER - 0.00893 \cdot NRFTC$
		Non-NHS	$SUPCR = 8.70833 - 0.21532 \cdot AGE + 0.00724 \cdot AGE^2 - 0.00009014 \cdot AGE^3 - 0.0348 \cdot SPANNO - 0.33124 \cdot NRFTC$
	Central	NHS	$SUPCR = 8.29298 - 0.09522 \cdot AGE + 0.00149 \cdot AGE^2 - 0.000018 \cdot AGE^3 - 0.01066 \cdot NRFTC - 0.01554 \cdot ADTT$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.09519 - 0.01123 \cdot AGE - 0.04685 \cdot SERVUNDER - 0.01394 \cdot ADTT$
	Southern	NHS	$\mathrm{LN}(SUPCR) = 2.14361 - 0.00977 \cdot AGE - 0.00104 \cdot SKEW - 0.03918 \cdot FRZINDX - 0.00131 \cdot NRFTC - 0.00514 \cdot ADTT$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.13239 - 0.01024 \cdot AGE - 0.00045239 \cdot SKEW - 0.03926 \cdot SERVUNDER - 0.00659 \cdot SPANNO - 0.07007 \cdot FRZINDX - 0.01336 \cdot ADTT$
Prestressed Concrete Superstructure	Northern	NHS	$SUPCR = 9 - 0.00272 \cdot AGE^2 - 0.0211 \cdot NRFTC$
		Non-NHS	$SUPCR = 8.63239 - 0.06584 \cdot AGE - 0.00000676 \cdot AGE^2 - 0.01191 \cdot NRFTC$
	Central	NHS	$SUPCR = 10.38399 - 0.19175 \cdot AGE + 0.00837 \cdot AGE^2 - 0.00014513 \cdot AGE^3 - 0.03152 \cdot NRFTC$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.15446 - 0.01209 \cdot AGE - 0.00047226 \cdot SKEW - 0.00106 \cdot NRFTC$
	Southern	NHS	$SUPCR = 8.05478 - 0.04641 \cdot AGE - 0.00077021 \cdot AGE^2$
		Non-NHS	$SUPCR = 7.36848 - 0.02417 \cdot AGE - 0.00036227 \cdot AGE^2 - 0.39259 \cdot FRZINDX$

(Continued)

TABLE B.2
(Continued)

Bridge Component	Districts	Functional Class	Deterioration Model
Steel Superstructure	Northern	NHS	$SUPCR = 8.21857 - 0.02802 \cdot AGE - 0.00080051 \cdot AGE^2 - 0.00472 \cdot SKEW - 0.04806 \cdot SPANNO - 0.19053 \cdot FRZINDX - 0.0104 \cdot NRFTC - 0.0378 \cdot ADTT$
		Non-NHS	$SUPCR = 7.97937 - 0.04441 \cdot AGE - 0.0003097 \cdot AGE^2 - 0.00408 \cdot SKEW - 0.22323 \cdot SERVUNDER - 0.04812 \cdot SPANNO - 0.49499 \cdot FRZINDX - 0.07858 \cdot ADTT$
	Central	NHS	$SUPCR = 7.38503 - 0.01763 \cdot AGE - 0.00066787 \cdot AGE^2 - 0.03158 \cdot SERVUNDER - 0.00301 \cdot NRFTC$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.19722 - 0.0088 \cdot AGE - 0.01953 \cdot SERVUNDER - 0.00269 \cdot \mathrm{AVGPPN} - 0.00069317 \cdot NRFTC$
	Southern	NHS	$SUPCR = 9.02484 - 0.01203 \cdot AGE - 0.00056892 \cdot AGE^2 - 0.03952 \cdot \mathrm{AVGPPN} - 0.83976 \cdot FRZINDX - 0.00878 \cdot ADTT$
		Non-NHS	$\mathrm{LN}(SUPCR) = 2.04373 - 0.00713 \cdot AGE - 0.01782 \cdot SERVUNDER - 0.04835 \cdot FRZINDX - 0.02072 \cdot ADTT$
Substructure	Northern	NHS	$SUBCR = 9 - 0.03943 \cdot AGE - 0.000385 \cdot AGE^2 - 0.78509 \cdot FRZINDX - 0.016695 \cdot NRFTC$
		Non-NHS	$\mathrm{LN}(SUBCR) = 2.06711 - 0.00844 \cdot AGE - 0.0142 \cdot SERVUNDER - 0.06222 \cdot FRZINDX$
	Central	NHS	$SUBCR = 9 - 0.01446 \cdot AGE - 0.00085 \cdot AGE^2 - 0.02948 \cdot INT - 0.0839 \cdot SERVUNDER - 0.03028 \cdot NRFTC$
		Non-NHS	$\mathrm{LN}(SUBCR) = 2.19722 - 0.00894 \cdot AGE - 0.03062 \cdot SERVUNDER - 0.00264 \cdot NRFTC - 0.00932 \cdot ADTT$
	Southern	NHS	$SUBCR = 9 - 0.00104 \cdot AGE^2 - 0.04217 \cdot SERVUNDER - 0.09126 \cdot FRZINDX - 0.03017 \cdot NRFTC - 0.03017 \cdot ADTT$
		Non-NHS	$\mathrm{LN}(SUBCR) = 2.03824 - 0.008 \cdot AGE - 0.02444 \cdot SERVUNDER - 0.0319 \cdot FRZINDX$

TABLE B.3
Variables for Deck Deterioration Modeling

Variable	Code
Deck Condition Rating	*DCR*
Deck Age (years)	*AGE*
Skew	*SKEW*
Type of Service Under Bridge	*SERVUNDER*
Number of Spans in Main Unit	*SPANNO*
Freeze Index (1000's of degree-days)	*FRZINDX*
Number of Freeze-Thaw Cycles	*NRFTC*
Average Daily Truck Traffic (in 1000s)	*ADTT*
Interstate (1 if located on Interstate, 0 otherwise)	*INT*

suggests that the design standard levels on NHS decks and their traffic load levels appeared to be commensurate with their NHS counterparts. In Figures B.7 and B.8, the plotted curves represent the deck condition ratings corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The RMSE of models for bridge decks with prior repair on the NHS and non-NHS was found to be 0.78 and 0.76, respectively.

(b) Models for Decks of Bridges with Prior Repair, Central Districts. For the NHS bridge decks with prior repair in the Central districts, the model suggests that the deck condition rating was sensitive to the age, service under the bridge, number of freeze-thaw cycles and functional class. For their non-NHS counterparts, age, skew, service under the bridge, the number of spans in main unit, and number of freeze-thaw cycles were the significant factors. From the t-statistics (Table B.5), the deck condition rating was found to be significantly influenced by the number of freeze-thaw cycles and age, which means that cold climatic conditions negatively affected the deck condition. The models accounted for about 39% and 37% of the deck condition rating. In Figures B.9 and B.10, the plotted polynomial curves represent the deck condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The predictive efficiency of the models as determined by the RMSE was 0.68 for bridge decks on both NHS and non-NHS roads in the Central districts.

TABLE B.4
Modeling Results for Decks of Bridges without Prior Repairs

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.000	42.83	9.00	–	9.000	–	9.000	–	9.000	–	8.30787	252.19
Operational Factors												
ADTT(1000)	–	–	–	–	–0.06456	–6.50	–0.06364	–2.52	–0.05091	–2.78	–	–
Design Factors												
Age	-0.19065	-11.76	-0.22608	-12.71	-0.20745	-10.43	-0.12851	-9.42	-0.01803	-2.97	-0.04197	-8.74
Age-Squared	0.00887	6.85	0.0102	7.69	0.00923	5.69	0.00437	4.30	-0.00171	–8.000	-0.0014	-8.93
Age-Cubed	-0.00021	-6.84	-0.00020	-6.91	-0.00019	-5.000	-0.00011	-4.81	–	–	–	–
Skew	–	–	-0.00289	-3.75	–	–	-0.00198	-3.14	-0.00302	-4.74	–	–
Service Under (1 if waterway, 0 other)	–	–	-0.19359	-6.01	-0.13388	-3.61	–	–	-0.09422	-3.71	–	–
Number of Spans in Main Unit	-0.02094	-4.77	–	–	-0.04286	-3.99	-0.05784	-4.89	–	–	–	–
Climate Factors												
Freeze Index (1000s)	-0.66157	-8.50	–	–	–	–	–	–	-1.2947	-10.67	-0.65646	-8.80
Number of Freeze-Thaw Cycles	–	–	-0.00351	-2.74	-0.00573	-4.62	-0.00968	-9.90	-0.0111	-11.66	–	–
Model Fit Statistics												
Observations	2338		2691		1069		2921		1537		3042	
R-Squared	0.508		0.457		0.59		0.534		0.572		0.613	

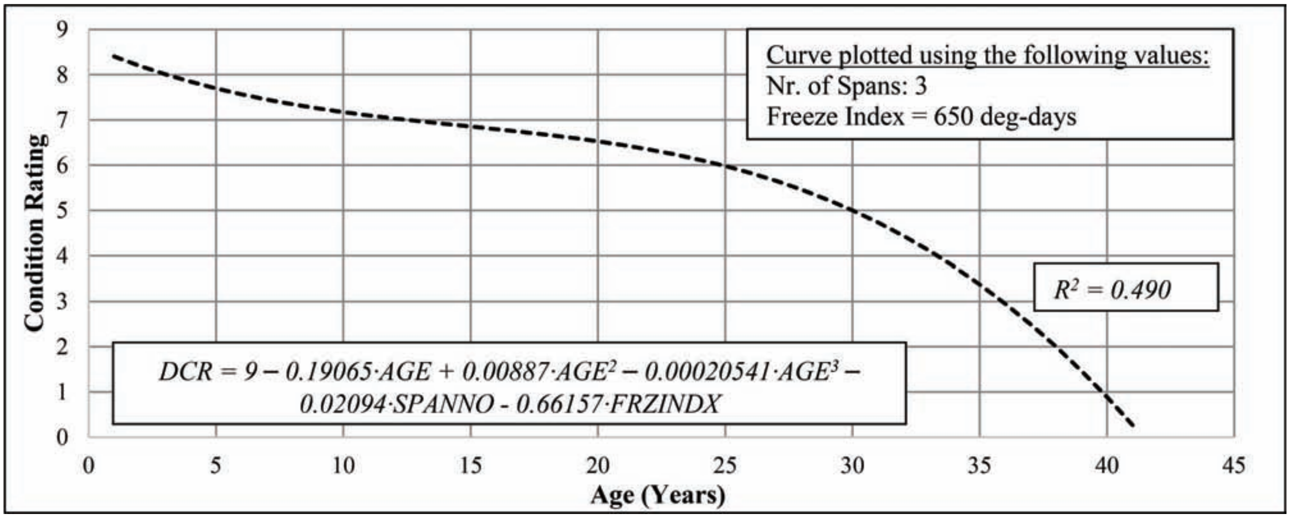

Figure B.1 Model for Decks of Bridges without Prior Repair—Northern Districts, NHS.

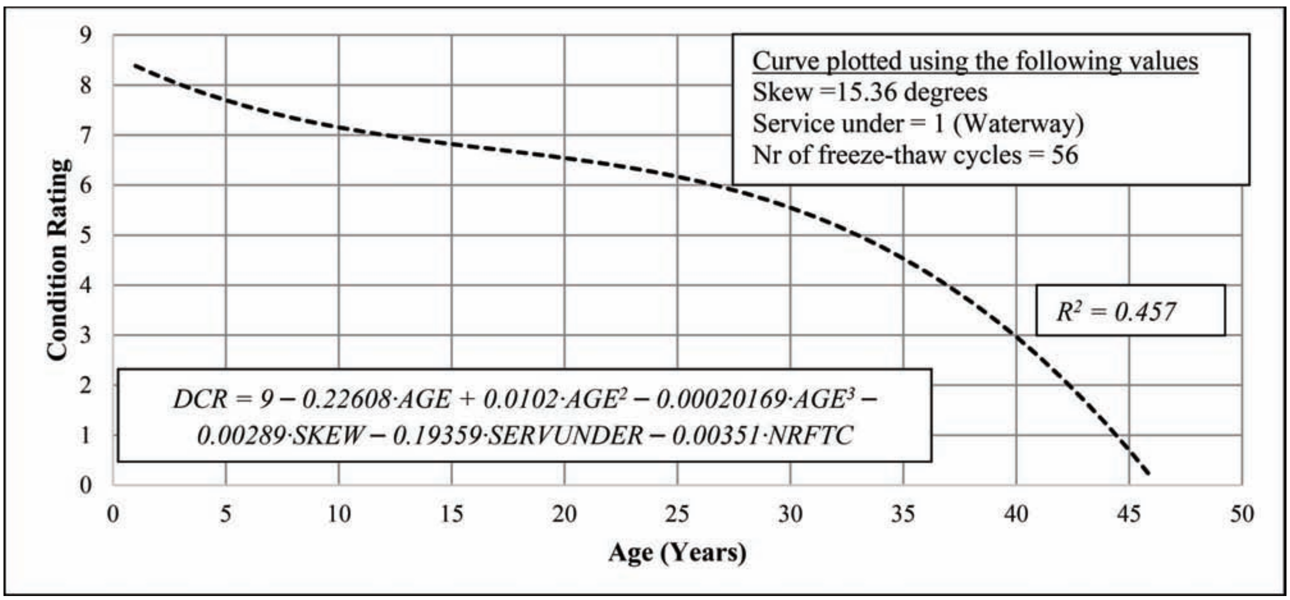

Figure B.2 Model for decks of bridges without prior repair—Northern districts, non-NHS.

(c) Models for Decks of Bridges with Prior Repair, Southern Districts. For NHS decks of bridges in this family of bridges, it was seen that age, freeze index, number of freeze-thaw cycles, and ADTT were the significant factors in deck deterioration (Table B.5). For their non-NHS counterparts, age, skew, service under the bridge, freeze index, and ADTT were the significant factors in deck deterioration. The models explained about 39% and 61% of the variation in deck condition ratings for the NHS and non-NHS bridges, respectively. In Figures B.11 and B.12, the plotted polynomial curves represent the deck condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The models had RMSE of 0.64 and 0.67, respectively, for bridge decks with prior repair on the NHS and non-NHS roads in Indiana's Southern districts.

(d) Discussion: Service Life of Bridge Decks. Bridge components are generally replaced before they reach a condition rating of 4; therefore, a rating of 4 is considered the threshold for bridge component replacement. Bridge decks are most vulnerable to deterioration because they receive direct traffic loads which are transmitted to the other components. Field observations indicate that decks are generally replaced every 20 to 25 years when they reach the end of their service lives. However, past studies—Table B.6) have estimated service lives >25 years when condition rating 4 had been reached. The results of this study indicate that bridge decks reach a condition rating of 4 between 35 and 45 years, which is consistent with past studies.

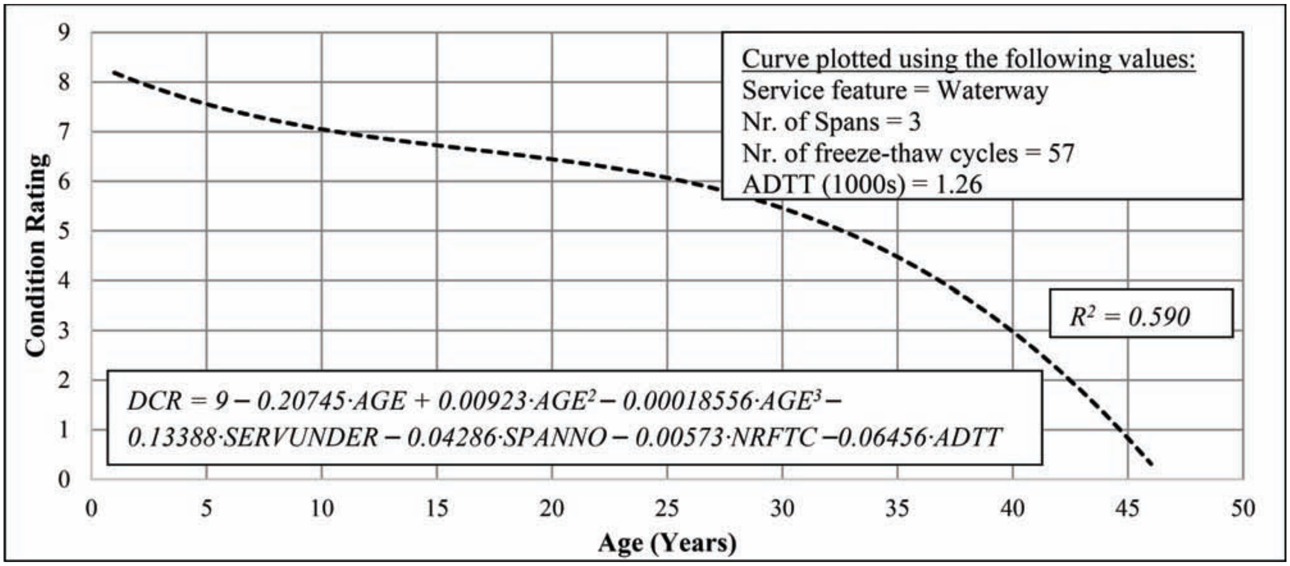

Figure B.3 Model for decks of bridges without prior repair—Central districts, NHS.

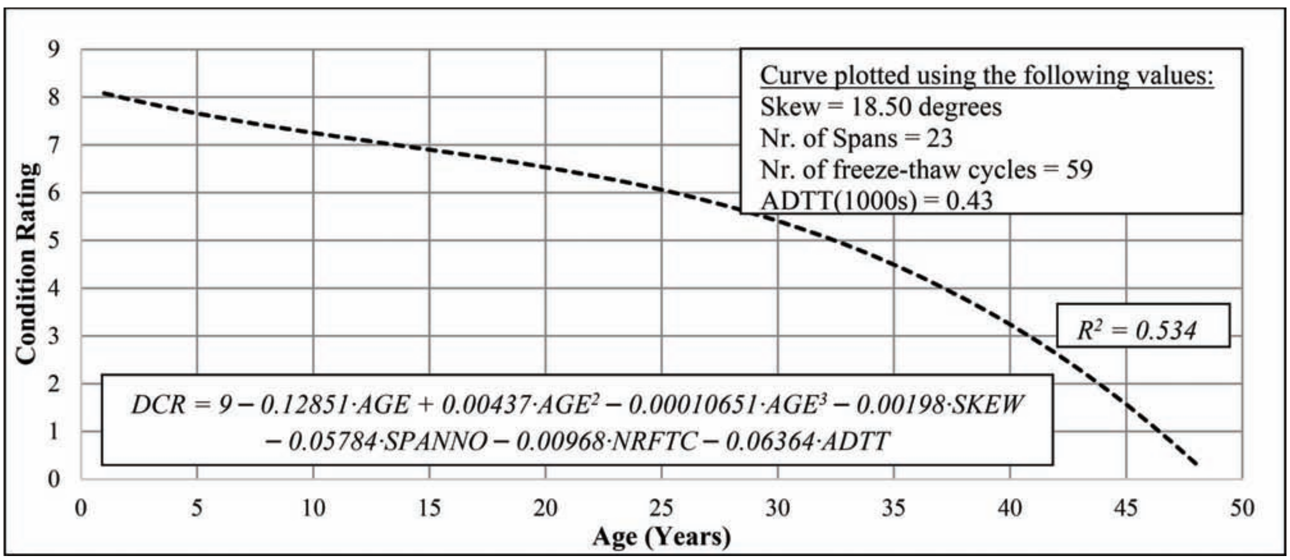

Figure B.4 Model for decks of bridges without prior repair—Central districts, non-NHS.

However, field observations and practical experience should be followed in the replacement of bridge decks.

B.2 Deterministic Superstructure Deterioration Models

A total of 36 superstructure deterioration models were developed. The classification of superstructures was based on whether the bridge had been repaired, the bridge material type, the highway district, and the highway system. There were 18 models each for bridges without major prior repairs and bridges with prior repairs. For each of these categories, models also were developed separately for cast-in-place concrete, prestressed concrete, and steel superstructures. Table B.7 presents the variables used in the superstructure deterioration modeling. Tables B.8 and B.9 present the modeling results for cast-in-place concrete superstructure of bridges without and with prior repair, respectively. Tables B.10 and B.11 present the modeling results for prestressed-concrete superstructure of bridges without and with prior repair, respectively. Also, Tables B.12 and B.13 present the modeling results for steel superstructure of bridges without and with prior repair, respectively.

Cast-in-Place Superstructures

B.2.1 Cast-in-Place Concrete Superstructure of Bridges without Prior Repair

(a) Models for Cast-in-Place Concrete Superstructure of Bridges without Prior Repair, Northern Districts. The polynomial model for NHS cast in-place concrete

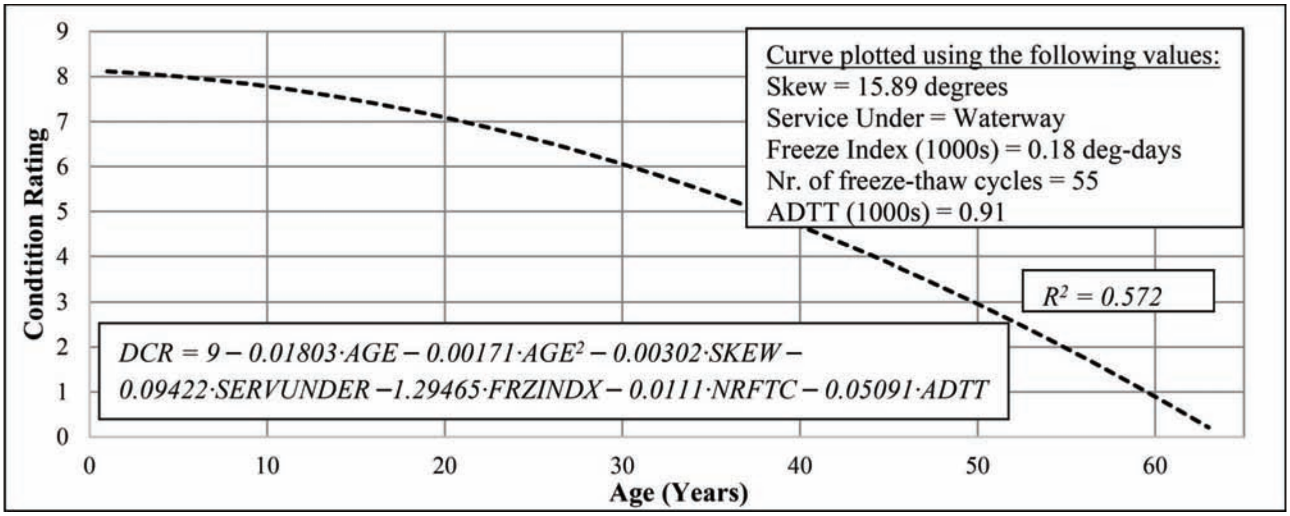

Figure B.5 Model for decks of bridges without prior repair—Southern districts, NHS.

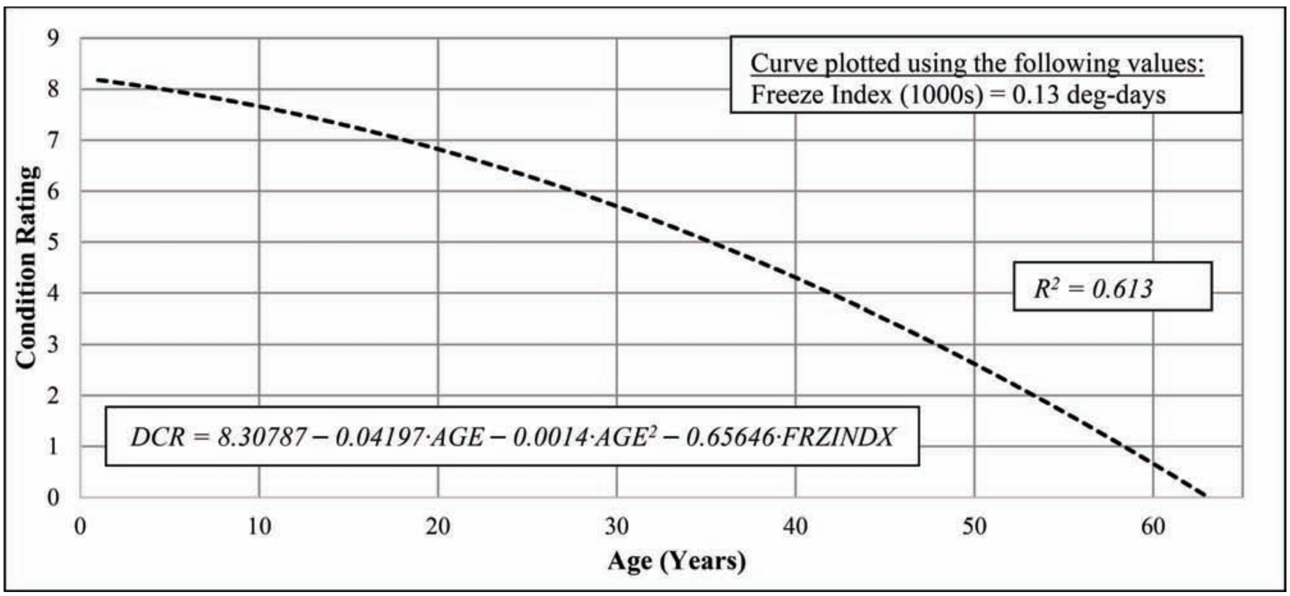

Figure B.6 Model for decks of bridges without prior repair—Southern districts, non-NHS.

superstructures in Indiana's Northern districts suggests that the superstructure age and freeze index were the most significant factors of the superstructure condition rating (Table B.8). Also, service under the bridge and number of spans in main unit, were significant. The signs for almost all the significant variables were negative, indicating that higher levels of these variables translated into lower condition ratings of the superstructures.

For the decks on non-NHS cast in-place concrete superstructures, the exponential deterioration model suggests that deck age and number of freeze-thaw cycles were the significant factors of deck condition. The variable representing service under the bridge was also significant, suggesting that bridges that cross waterways are generally associated with greater levels of deck deterioration.

In Figures B.13 and B.14, the plotted curves represent the superstructure condition rating corresponding to specific values of the independent variables (as shown in the upper right box of the general model presented in the lower left box. The deterioration curves shown in the figures suggest that NHS cast-in-place concrete superstructures deteriorate faster compared to their non-NHS counterparts. This implies that the higher design standards on NHS bridges compared to their non-NHS counterparts, was outweighed by the higher traffic loads carried on NHS superstructures compared to their non-NHS counterparts. The models accounted for about 67% and 48% of the variation in the superstructure condition ratings. The predictive efficiency of the models as determined by the RMSE for both NHS and non-NHS models in the Northern districts was found to be 0.68.

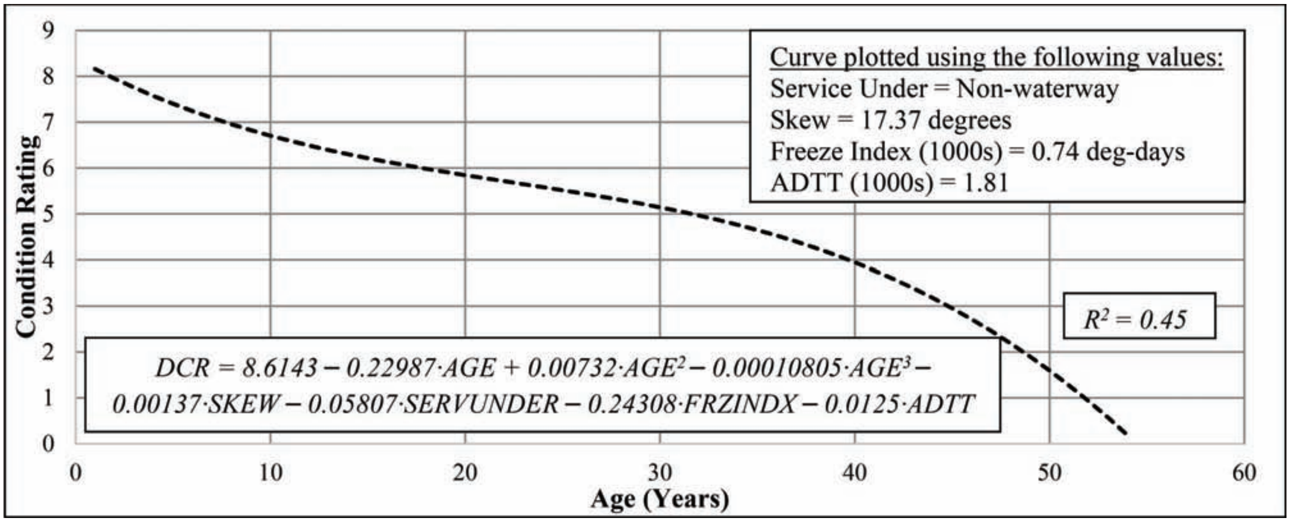

Figure B.7 Model for decks of bridges with prior repair—Northern districts, NHS.

(b) Models for Cast-in-Place Concrete Superstructure of Bridges without Prior Repair, Central Districts. The model results for NHS cast in-place concrete superstructures in Indiana's Central districts suggest that the age and skew were the significant factors affecting the condition of the superstructures. For their non-NHS counterparts, the variables found to be significant were age, skew, and service under the bridge (Table B.8). The polynomial and exponential models (Figures B.15 and B.16), which were verified and chosen for the two deterioration models accounted for approximately 57% and 62% of the variations in the superstructure condition ratings. The plotted curves in the figures represent the deck condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The RMSE for cast-in-place concrete superstructures on the NHS was found to be 0.60 and 0.63 for models of superstructures on the non-NHS roads.

(c) Models for Cast-in-Place Concrete Superstructure of Bridges without Prior Repair, Southern Districts. For NHS cast-in-place concrete superstructures in this family of bridges, the models suggest that age and freeze index were the significant factors of deterioration, and the polynomial function explained 58% of the variation in the superstructure condition rating (Table B.8). For their non-NHS counterparts, the significant factors were age, skew, and freeze index; and the exponential model accounted for 61% of the variation in the superstructure condition rating. In Figures B.17 and B.18, the plotted curves represent the cast-in-place concrete superstructure condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The predictive efficiency of the models as determined by the RMSE was 0.51 for cast-in-place concrete superstructures on the NHS. The RMSE for models of the non-NHS cast-in-place concrete superstructures was 0.65.

B.2.2 Cast-in-Place Superstructures of Bridges with Prior Repair

(a) Models for Cast In-Place Concrete Superstructure of Bridges with Prior Repair, Northern Districts. The model for this family of bridges suggests that the polynomial form offered the best fit for NHS bridges located in Indiana's Northern districts. The model also suggests that the age, service under the bridge, and number of freeze-thaw cycles were the most significant variables (Table B.9). Specifically, a lower physical condition of the superstructure was observed when the service under the bridge was a waterway rather than a highway, railway, or other feature. Also, a high number of freeze-thaw cycles was associated with a lower condition rating of the cast in-place concrete superstructure. For their non-NHS counterparts, age, number of spans in main unit, and number of freeze-thaw cycles were significant. In Figures B.19 and B.20 below, the plotted curves represent the superstructure condition rating corresponding to specific values of the independent variables, as shown in the upper right box) of the general model presented in the lower left box. The RMSEs were found to be 0.56 and 0.60 for cast-in-place concrete superstructures on the NHS and non-NHS, respectively.

(b) Models for Cast-in-Place Concrete Superstructure of Bridges with Prior Repair, Central Districts. The results of the analysis showed that age, number of freeze thaw-cycles, and ADTT (Table B.9) were significant factors in the deterioration of NHS cast-in-place concrete bridge superstructures in Indiana's Central districts. For their non-NHS counterparts, the superstructure age, ADTT and service under the bridge were found to be significant factors (Table B.9). The directions of the

TABLE B.5
Modeling Results for Decks of Bridges with Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	8.6143	90.66	8.82	90.77	8.402	93.26	9.000	–	8.1469	60.22	7.6985	202.03
Operational Factors												
ADTT(1000)	-0.0125	-4.83	–	–	–	–	–	–	-0.04037	-10.24	-0.13994	-7.75
Design Factors												
Age	-0.22987	-23.13	-0.24361	-19.94	-0.16855	-24.21	-0.19984	-24.01	-0.05332	-15.05	-0.03433	-8.62
Age-Squared	0.00732	9.53	0.01051	12.25	0.00638	11.94	0.00928	15.67	-0.00063	-5.14	-0.00099	-8.40
Age-Cubed	-0.00011	-6.26	-0.00019	-10.78	-0.00014	-11.40	-0.00019	-15.16	–	–	–	–
Interstate (1 if on Interstate, 0 otherwise)	–	–	–	–	-0.05922	-4.08	–	–	–	–	–	–
Skew	-0.00137	-3.02	–	–	–	–	-0.00138	-3.41	–	–	-0.00199	-3.72
Service Under (1 if waterway, 0 other)	-0.0581	-3.46	–	–	-0.08571	-7.32	-0.07713	-5.10	–	–	–	–
Number of Spans in Main Unit	–	–	-0.0276	-4.90	–	–	-0.03905	-7.23	–	–	-0.03765	-6.84
Climate Factors												
Freeze Index (1000s)	-0.2431	-2.13	-0.67943	-5.91	–	–	–	–	-0.21593	-3.90	-0.52647	-7.40
Number of Freeze-Thaw Cycles	–	–	–	–	-0.00677	-4.67	-0.01401	-21.59	-0.00822	-3.40	–	–
Model Fit Statistics												
Observations	8869		5969		15043		8985		8011		7031	
R-Squared	0.453		0.395		0.394		0.371		0.385		0.613	

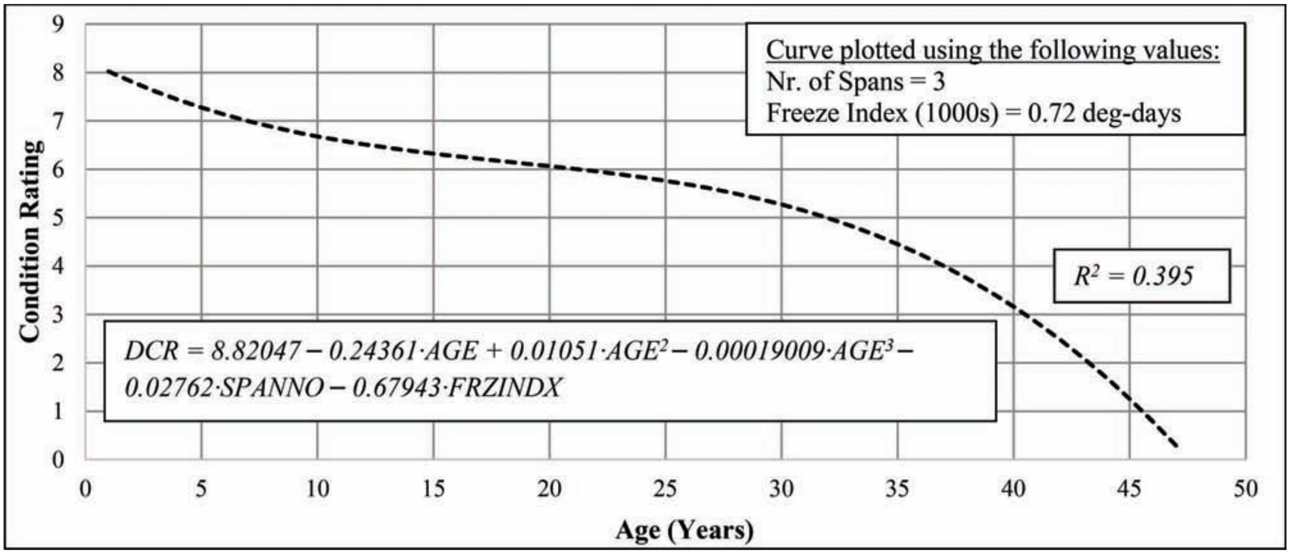

Figure B.8 Model for decks of bridges with prior repair—Northern districts, non-NHS.

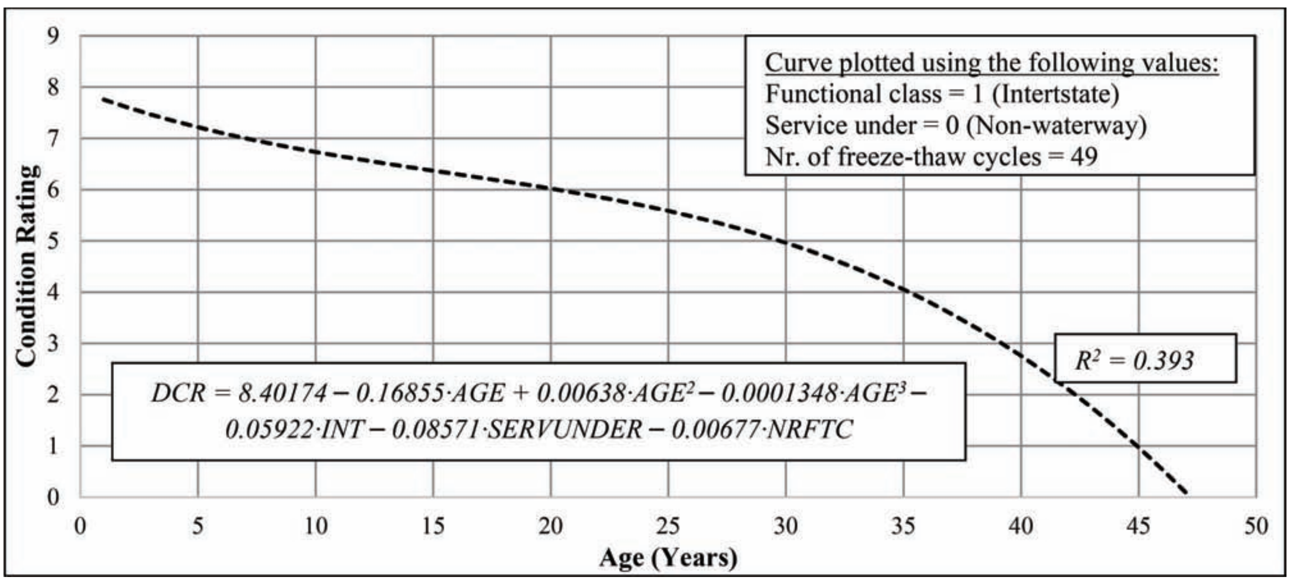

Figure B.9 Model for decks of bridges with prior repair—Central districts, NHS.

signs of these variables suggested that a higher level of these variables was associated with lower ratings of the superstructure condition. The polynomial curve of the second degree and the exponential curves were found to be most appropriate functional forms to fit the data for both models. The models shown in Figures B.21 and B.22 accounted for about 46% and 54% of the variation of the condition rating observations for the NHS and non-NHS superstructure, respectively. The predictive efficiency of the models as determined by the RMSE was found to be 0.51 for the NHS models and 0.59 for the non-NHS models.

(c) Models for Cast-in-Place Concrete Superstructure of Bridges with Prior Repair, Southern Districts. For NHS cast-in-place concrete superstructures, the data analysis suggested that the significant variables were age, bridge skew, freeze index, number of freeze-thaw cycles, and ADTT (Table B.9). The exponential model accounted for about 50% of the variation in the superstructure condition ratings. For its non-NHS counterparts, age, skew, service under the bridge, number of spans in main unit, freeze index, and ADTT were found to be significant (Table B.9). The exponential functional form was found to be the most appropriate fit for the data and explained about 53% of the variation in the superstructure condition rating. The parameter signs for both models were intuitive and adequately explain the chosen models. In the figures below, the plotted curves represent the superstructure condition ratings corresponding to specific values of the independent variables, as shown in the upper right box of

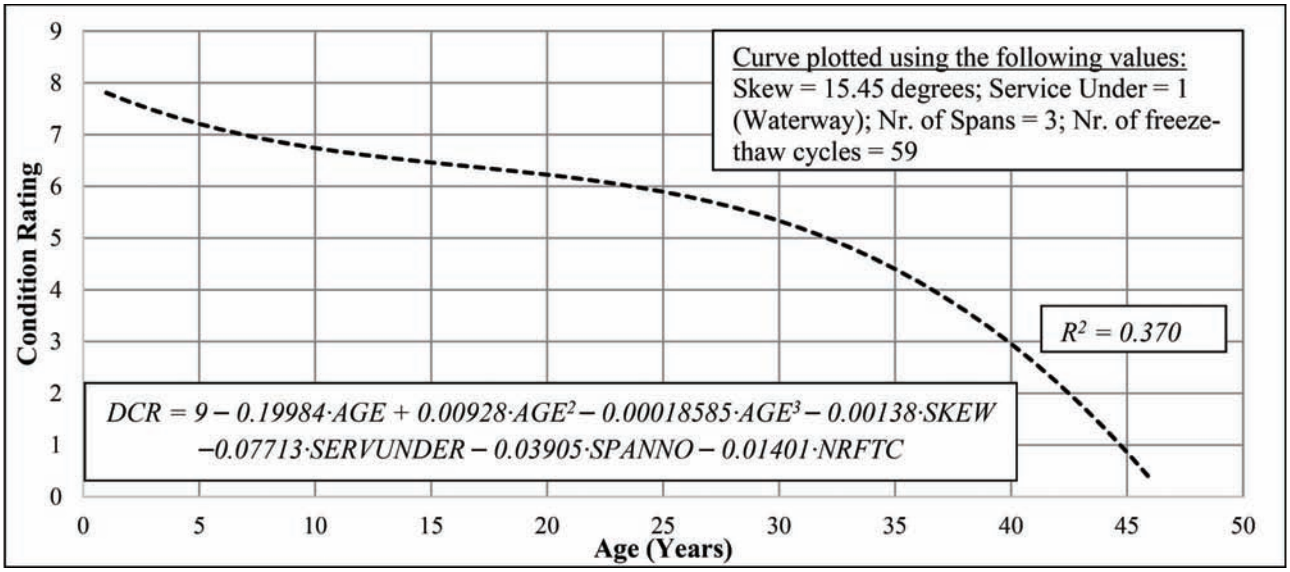

Figure B.10 Model for decks of bridges with prior repair—Central districts, non-NHS.

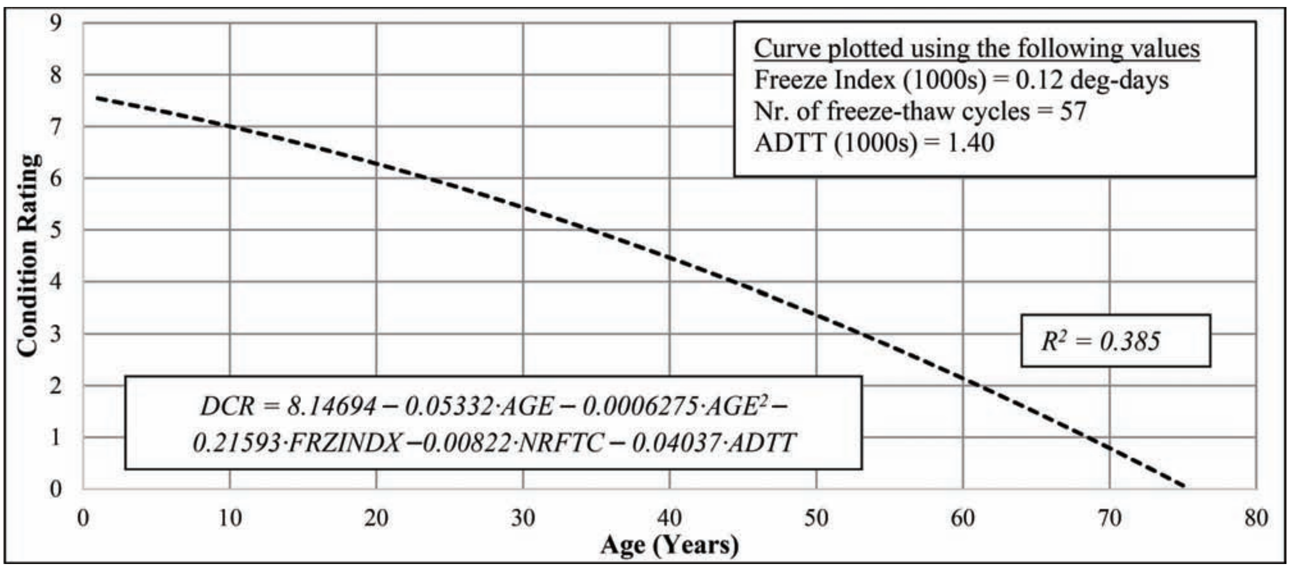

Figure B.11 Model for decks of bridges with prior repair—Southern districts, NHS.

the general model presented in the lower left box. The deterioration curves in Figures B.23 and B.24 show that cast-in-place concrete superstructures of bridges in this family generally deteriorate at a slower rate compared to those in the Northern and Central districts due to the milder climate condition of the former. The RMSE for cast-in-place concrete superstructure models in the Southern districts for the NHS and non-NHS were 0.56 and 0.62, respectively.

(d) Models for Prestressed-Concrete Superstructure of Bridges without Prior Repair, Northern Districts. The model results (Table B.10) suggest that for prestressed-concrete bridge superstructures in Indiana's Northern districts without prior repair, the variables that significantly affected the condition rating of the superstructure were age, number of spans in main unit, freeze index, and ADTT. The t-value indicated that ADTT was the most significant variable after age. The polynomial functional form explained about 35% of the variation in the superstructure condition rating. For the non-NHS deterioration model, the variables found to be significant were age, skew, and number of freeze-thaw cycles. The second-order polynomial model accounted for approximately 43% of the variation in the condition rating. The deterioration curves in Figures B.25 and B.26 show that the non-NHS prestressed concrete superstructures had a slower rate of deterioration compared to its NHS counterparts, which suggests that for the NHS bridges, the damaging effect

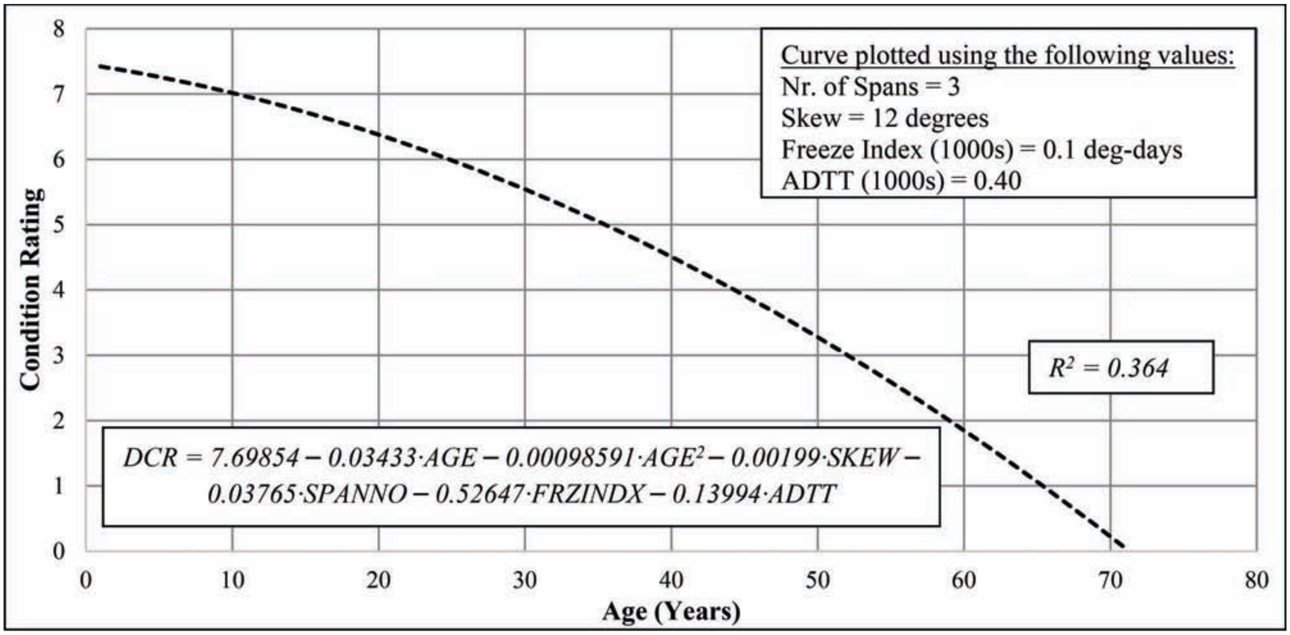

Figure B.12 Model for decks of bridges with prior repair—Southern districts, non-NHS.

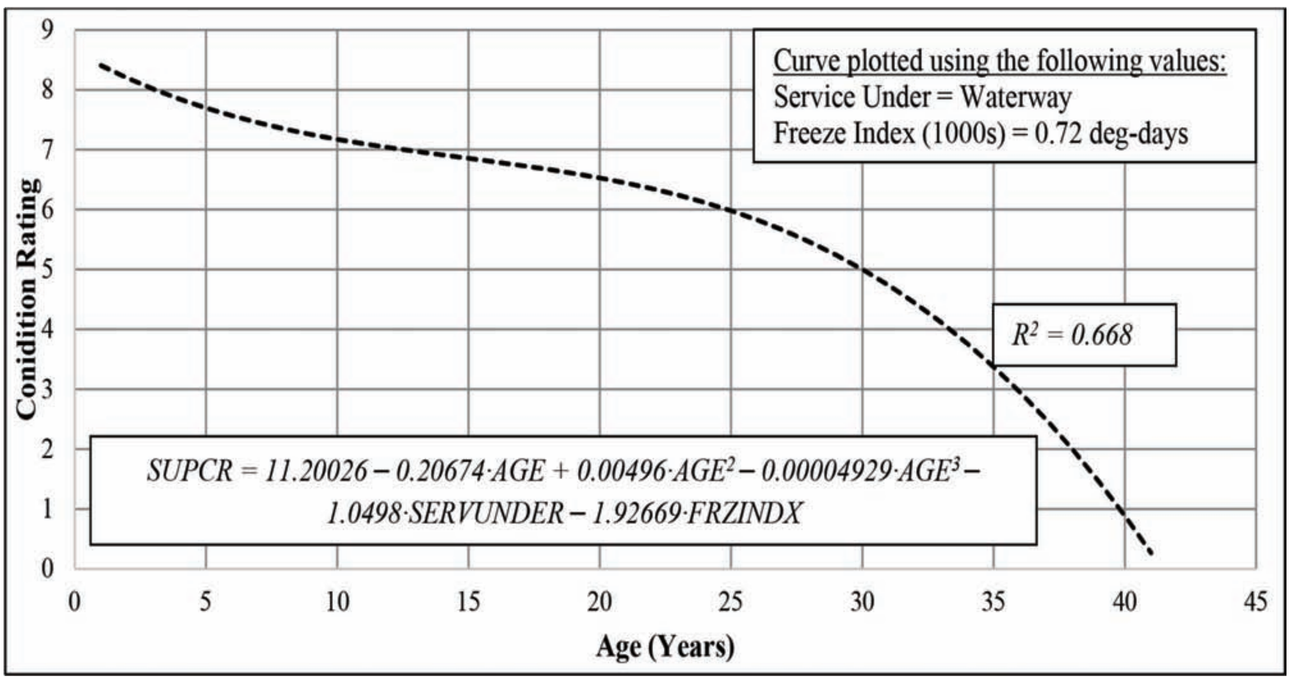

Figure B.13 Model for cast-in-place concrete superstructure of bridges without prior repair—Northern districts, NHS.

of the higher traffic loading outweighed the redeeming effect of higher design standards compared to the non-NHS bridges. In the figures below, the plotted curves represent the superstructure condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The models for prestressed concrete superstructures on the NHS and non-NHS had RMSE values of 0.58 and 0.53, respectively.

Prestressed-Concrete Superstructure

B.2.3 Prestressed-Concrete Superstructure of Bridges without Prior Repair

(a) Models for Prestressed-Concrete Superstructure of Bridges without Prior Repair, Central Districts. The superstructure condition rating for NHS prestressed concrete superstructures was explained by four variables: age, skew, service under the bridge, and freeze

TABLE B.6
Service Life of Bridge Decks at Condition Rating 4

Study	Component Description	Service Life (Years)
Bolukbasi et al., 2004	Reinforced Concrete Deck	50
	Steel Deck	50
	Prestressed Concrete Deck	45
Jiang and Sinha, 1989	Concrete Decks—Interstate	35
	Steel Decks Interstate	35
	Concrete Decks—Other Highways	55
	Steel Decks Other Highways	60

TABLE B.7
Variables for Superstructure Deterioration Modeling

Variable	Code
Superstructure Condition Rating	*SUPCR*
Superstructure Age (years)	*AGE*
Skew	*SKEW*
Type of Service Under Bridge (1 if waterway, 0 otherwise)	*SERVUNDER*
Number of Spans in Main Unit	*SPANNO*
Average Precipitation in a Year (inches)	*AVGPPN*
Freeze Index (1000's of degree-days)	*FRZINDX*
Number of Freeze-Thaw Cycles	*NRFTC*
Average Daily Truck Traffic (in 1,000s)	*ADTT*

index (Table B.10), which suggests that for this family of bridges, the design and climate variables were the main factors of bridge deterioration. The model accounted for about 40% of the variation in superstructure condition ratings. For their non-NHS counterparts, age, number of spans in main unit, and number of freeze-thaw cycles were found to be significant (Table B.10). The model explained about 52% of the variation in condition rating. Comparing the two models plotted in Figures B.27 and B.28, it can be seen that the NHS prestressed concrete superstructures deteriorated faster compared to their non-NHS counterparts. The figures also show that superstructures in the Central districts were generally in a far superior condition compared to those in the Northern districts, which is likely due to the harsher climate of the latter. The predictive efficiency of the models determined by the RMSE were 0.60 and 0.49 for the NHS and non-NHS, respectively.

(b) Models for Prestressed-Concrete Superstructure of Bridges without Prior Repair, Southern Districts. A detailed analysis of the NHS prestressed concrete superstructure deterioration model in the Southern districts showed that age, skew, and service under the bridge were the significant variables (Table B.10). This result seems to suggest that the operational and climate categories of factors were not significant. The second-order polynomial functional form chosen for the superstructure deterioration model accounts for approximately 58% of the variation in the superstructure condition rating for this bridge family. For the non-NHS bridges in this bridge family, an exponential model was found to be the best model, and this model suggests that superstructure age, number of spans in main unit, and ADTT were the significant factors. Again, no climatic variable was significant, suggesting that there was relatively little variation in the climate factors in the Southern districts compared to the Central and Northern districts. The model explained approximately 50% of the variation in the superstructure condition rating. In Figures B.29 and B.30, the plotted curves represent the superstructure condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The RMSE for the models were 0.88 and 0.52 for the NHS and non-NHS, respectively.

B.2.4 Prestressed Concrete Superstructure of Bridges with Prior Repair

(a) Models for Prestressed Concrete Superstructure of Bridges with Prior Repair, Northern Districts. Table B.11 presents the deterioration models developed for this family of bridges in the NHS and non-NHS systems. Superstructure age and number of freeze-thaw cycles were found to be the significant variables. The second-order polynomial functional form, which was found to be the best fit model, explained approximately 40% of the superstructure condition. The other design factors (skew, service under the bridge and number of spans in the main unit) and the operational factor (namely, the ADTT), were found to be statistically insignificant. A comparison of the trends in Figures B.31 and

TABLE B.8
Modeling Results for Cast-in-Place Concrete Superstructure of Bridges without Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	11.020062	32.79	2.21722	41.01	8.8491	51.69	2.33523	97.81	8.40296	94.11	2.20021	316.18
Operational Factors												
ADTT(1000)	–	–	–	–	–	–	–	–	–	–	–	–
Design Factors												
Age	-0.20674	-9.43	-0.01126	-37.59	-0.19572	-6.72	-0.01395	-52.84	-0.05096	-4.91	-0.01307	-50.35
Age-Squared	0.00496	4.73	–	–	0.00466	3.22	–	–	-0.00036	-1.71	–	–
Age-Cubed	-0.000049	-3.99	–	–	-4.589E-05	-2.23	–	–	–	–	–	–
Skew	–	–	–	–	-0.00736	-3.28	-0.00061	-3.97	–	–	-0.00045	-2.56
Service Under (1 if waterway, 0 otherwise)	-1.0498	-11.92	–	–	–	–	-0.18807	-8.46	–	–	–	–
Number of Spans in Main Unit	–	–	–	–	–	–	–	–	–	–	–	–
Climate Factors												
Freeze Index (1000s)	-1.92669	-4.58	–	–	–	–	–	–	-1.82996	-6.78	-0.13064	-6.45
Number of Freeze-Thaw Cycles	–	–	-0.00209	-2.19	–	–	–	–	–	–	–	–
Model Fit Statistics												
Observations	407		1568		357		1722		379		1624	
R-Squared	0.508		0.479		0.569		0.623		0.579		0.613	

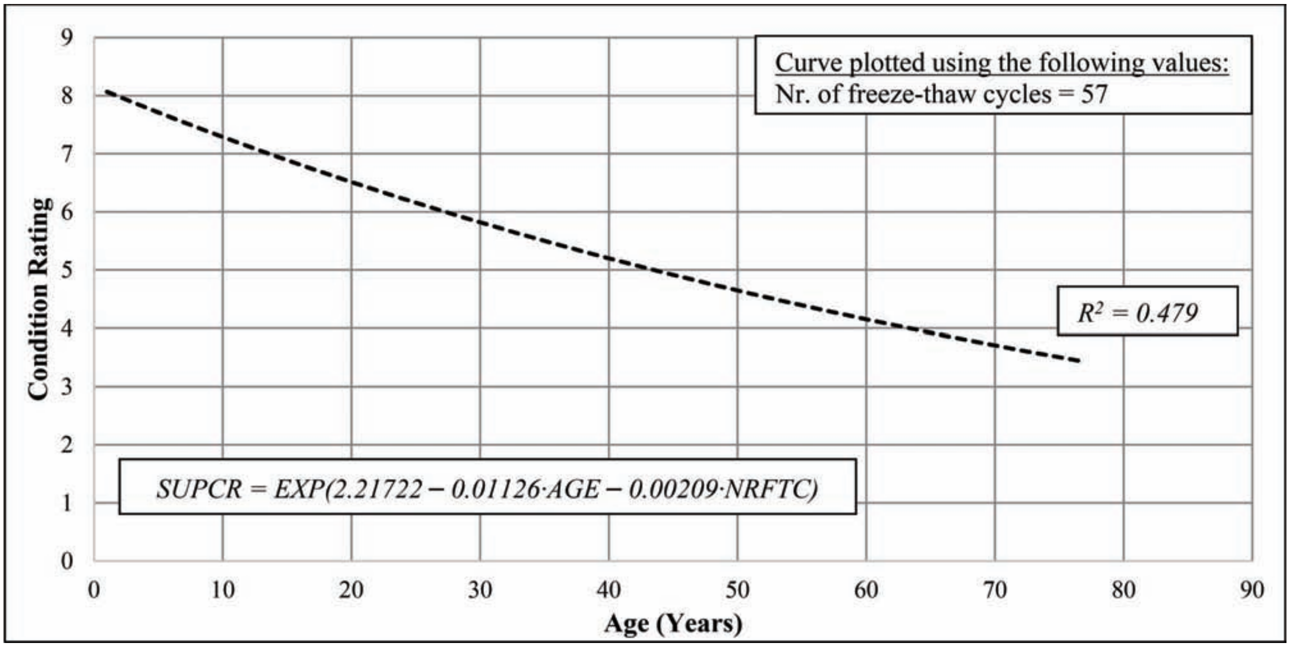

Figure B.14 Model for cast-in-place concrete superstructure of bridges without prior repair—Northern districts, non-NHS.

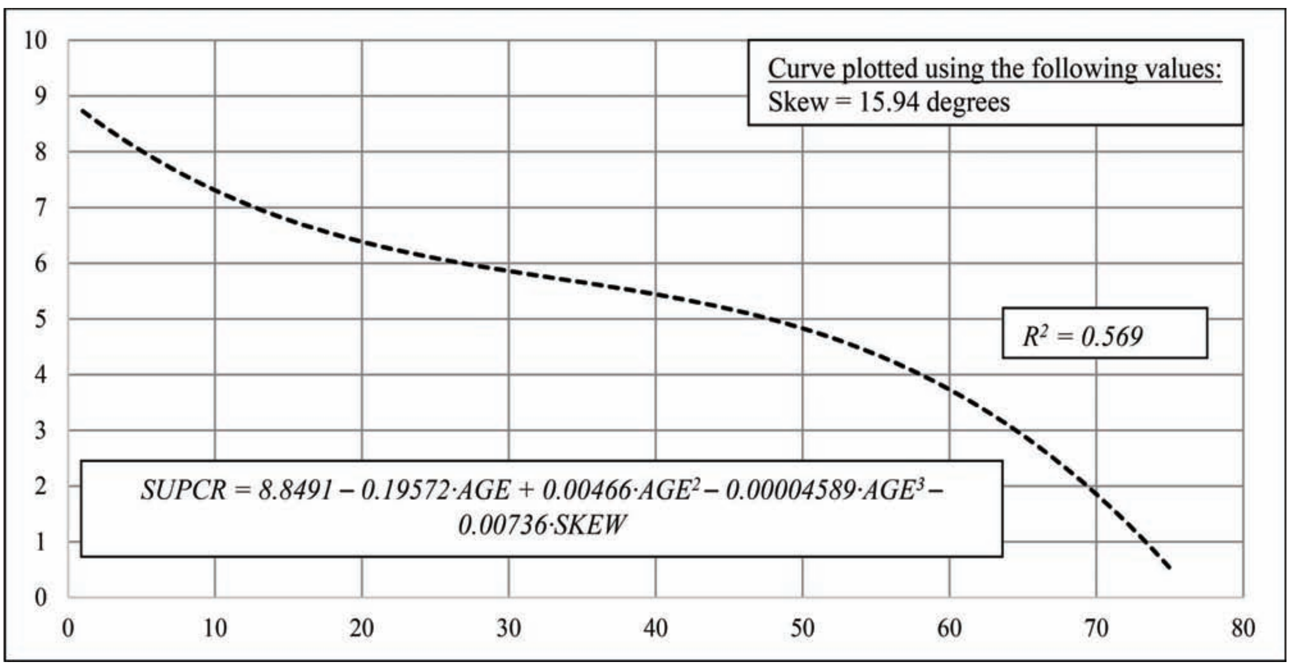

Figure B.15 Model for cast-in-place concrete superstructure of bridges without prior repair—Central districts, NHS.

B.32 suggest that the NHS prestressed concrete superstructures generally had a lower condition compared to the non-NHS prestressed concrete superstructures.

In Figures B.31 and B.32, the plotted curves represent the superstructure condition rating corresponding to specific values of the independent variable (number of freeze-thaw cycle), as shown in the upper right box of the general model presented in the lower left box. The RMSE for the models on the NHS and non-NHS were determined to be 0.67 and 0.66, respectively.

(b) Models for Prestressed-Concrete Superstructure of Bridges with Prior Repair, Central Districts. Table B.11 indicates that only superstructure age and number of freeze-thaw cycles were found to be significant for prestressed concrete superstructures on NHS roads in the Central districts. The third-order polynomial functional form provides the best fit for the data and explained about 34% of the variation in the superstructure condition rating. For its non-NHS counterparts, the exponential functional form was found to fit the data best; and the

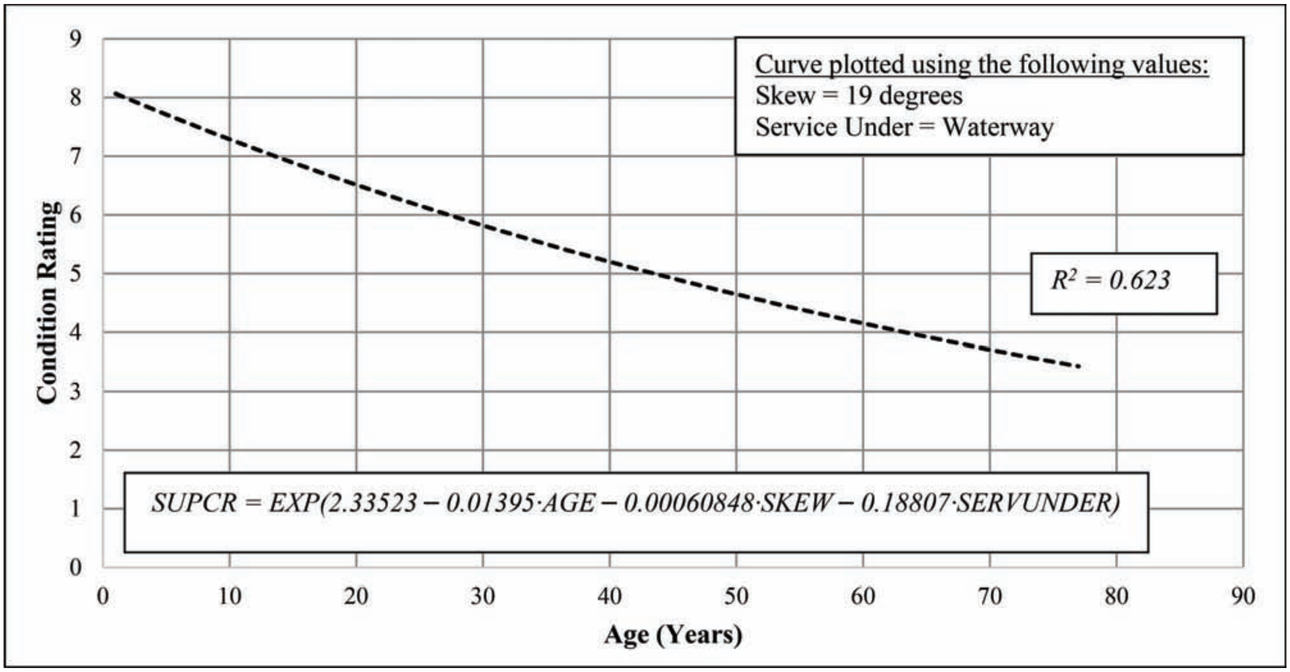

Figure B.16 Model for cast-in-place concrete superstructure of bridges without prior repair—Central districts, non-NHS.

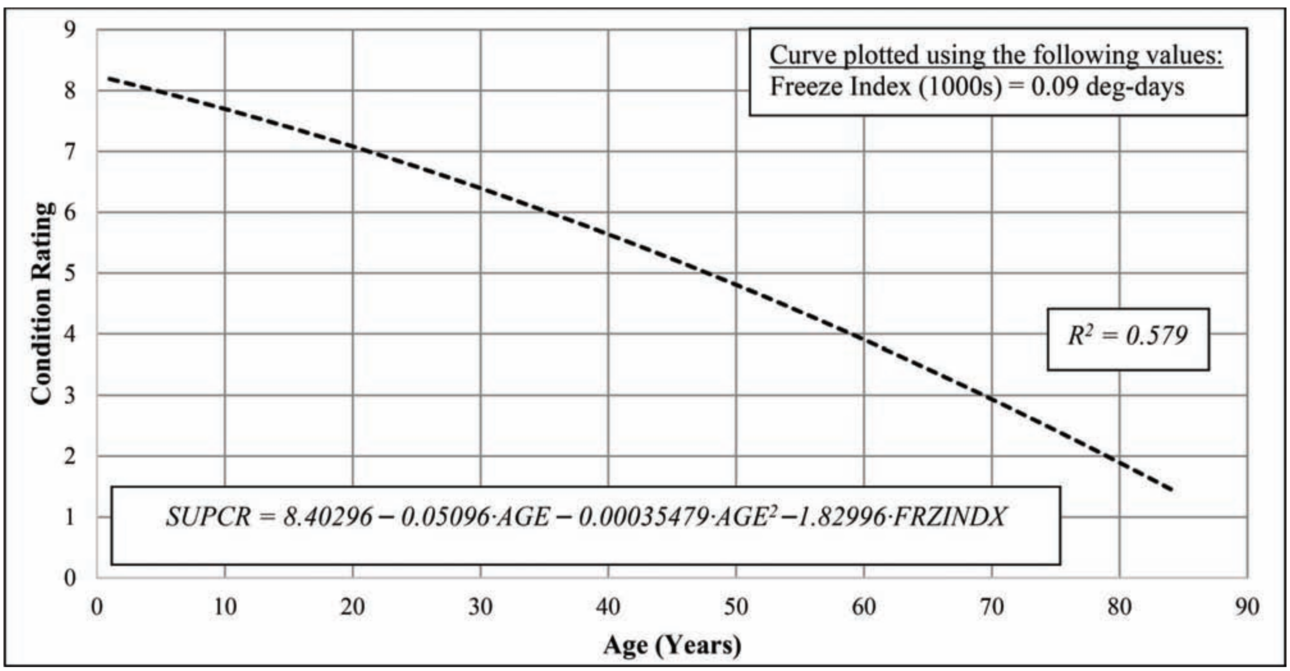

Figure B.17 Model for cast-in-place concrete superstructures of bridge without prior repair—Southern districts, NHS.

superstructure age, bridge skew, and number of freeze-thaw cycles were found to be significant at 95% confidence. In Figures B.33 and B.34, the plotted curves represent the superstructure condition rating corresponding to specific values of the number of freeze-thaw cycles, as shown in the upper right box of the general model presented in the lower left box. The model accounted for about 45% of the variation in the prestressed concrete superstructure condition ratings. It was also observed that the non-NHS prestressed concrete superstructures in the Central districts generally were in far superior condition compared to the NHS prestressed concrete superstructures. The RMSE for the models on the NHS and non-NHS were determined to be 0.60 and 0.65, respectively.

(c) Models for Prestressed-Concrete Superstructure of Bridges with Prior Repair, Southern Districts. For this family of bridges, only the superstructure age was

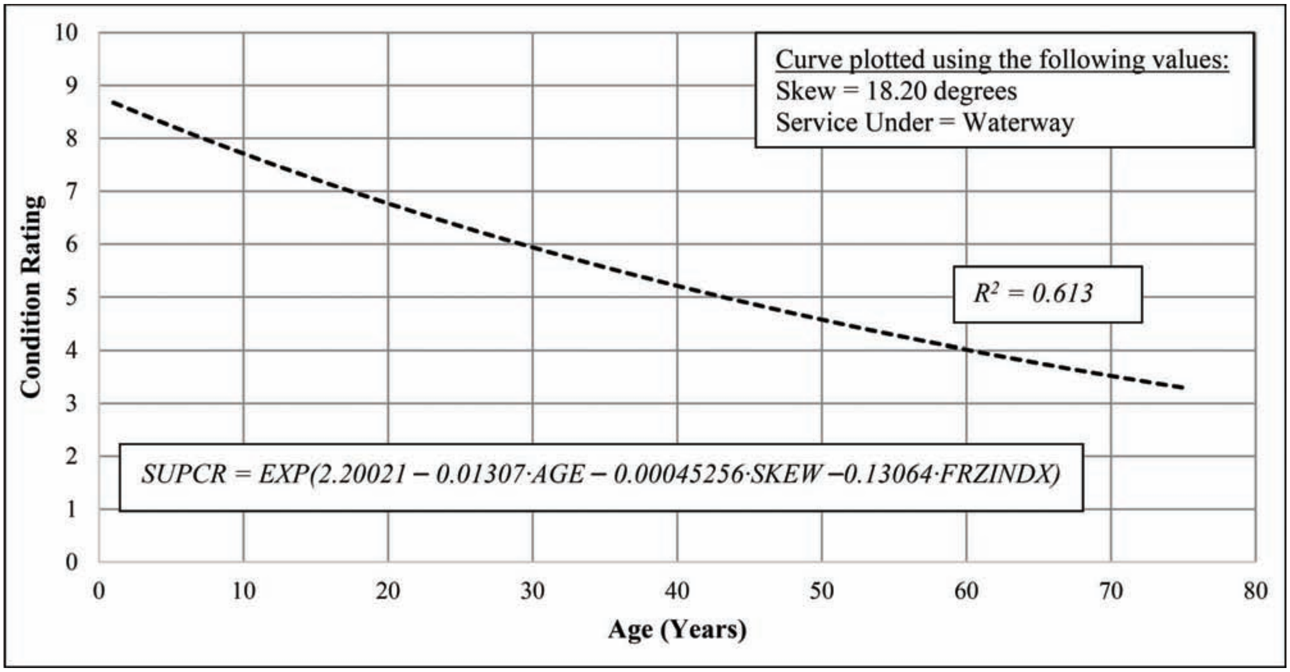

Figure B.18 Model for cast-in-place concrete superstructures of bridge without prior repair—Southern districts, non-NHS.

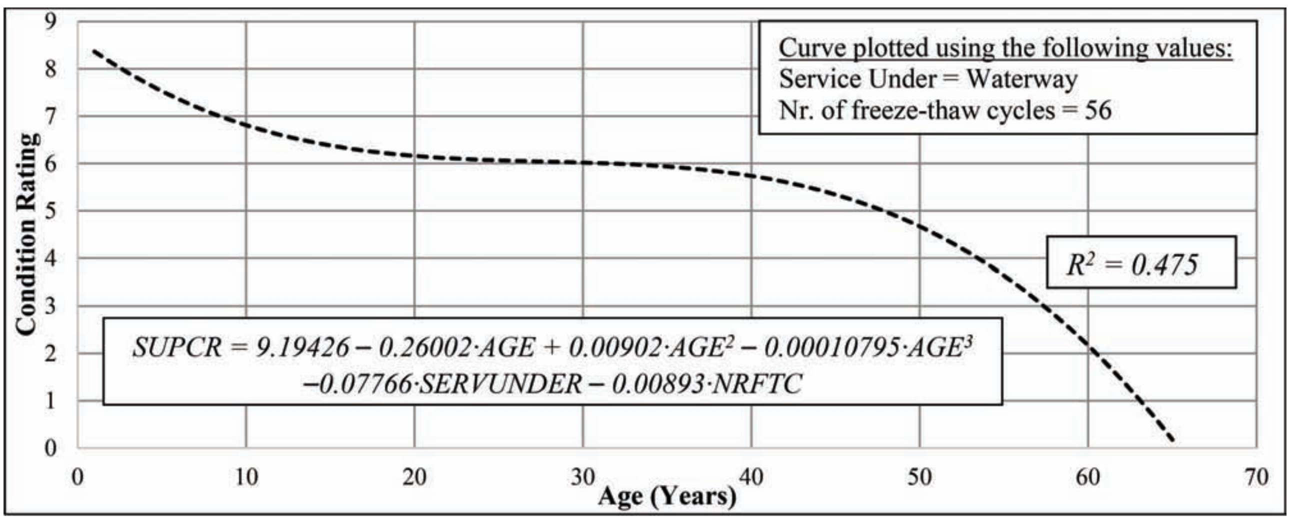

Figure B.19 Model for cast-in-place concrete superstructure of bridges with prior repair—Northern districts, NHS.

found to be significant at 95% confidence (Table B.11), which suggests that for this family, there was little variation in the operational, climatic, and most of the design-related factors of deterioration. The selected second-order polynomial functional form explained 41% of the variation in the superstructure condition rating. For its NHS counterpart, the only significant variables were the superstructure age and freeze index, and the model explained only 21% of the variation in superstructure condition rating. The model outcomes shown in Figures B.35 and B.36 also suggest that the prestressed concrete superstructures in the Southern districts generally deteriorate at a much slower rate compared to their counterparts in the Northern or Central regions, which could be due to the generally lower levels of traffic loading and the milder climatic conditions in the Southern districts. The predictive accuracy as determined by the RMSE was 0.61 and 0.59 for models on the NHS and non-NHS, respectively.

Steel Superstructures

B.2.5 Steel Superstructure of Bridges without Prior Repair

(a) Models for the Steel Superstructure of Bridges without Prior Repair, Northern Districts. The deterioration model developed for this bridge family was found to be best defined by an exponential functional

TABLE B.9
Modeling Results for Cast-in-place Concrete Superstructure of Bridges with Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.1943	49.63	8.7083	-60.31	8.2929	69.24	2.0952	390.18	2.14361	77.64	2.1324	151.39
Operational Factors												
ADTT(1000)	–	–	–	–	-0.01554	-2.94	-0.01394	-3.18	-0.00514	-5.11	-0.01336	-2.39
Design Factors												
Age	-0.26002	-23.46	-0.21532	-15.88	-0.09522	-12.16	-0.01123	-60.39	-0.00977	-45.78	-0.01024	-46.12
Age-Squared	0.00902	15.60	0.00724	11.65	0.00149	3.98	–	–	–	–	–	–
Age-Cubed	-0.00011	-12.77	-0.00009	-10.8	-0.000018	-3.62	–	–	–	–	–	–
Skew	–	–	–	–	–	–	–	–	-0.00104	-8.03	-0.00045	-2.72
Service Under (1 if waterway, 0 if other)	-0.07766	-2.49	–	–	–	–	-0.04685	-10.54	–	–	-0.03926	-4.14
Number of Spans in Main Unit	–	–	-0.0348	-2.91	–	–	–	–	–	–	-0.00659	-2.93
Climate Factors												
Freeze Index (1000s)	–	–	–	–	–	–	–	–	-0.03918	-2.88	-0.0701	-3.98
Number of Freeze-Thaw Cycles	-0.00893	-3.10	-0.33124	-2.06	-0.01066	-5.63	–	–	-0.00131	-2.59	–	–
Model Fit Statistics												
Observations	2271		1905		3715		1722		2433		2195	
R-Squared	0.475		0.396		0.461		0.548		0.497		0.53	

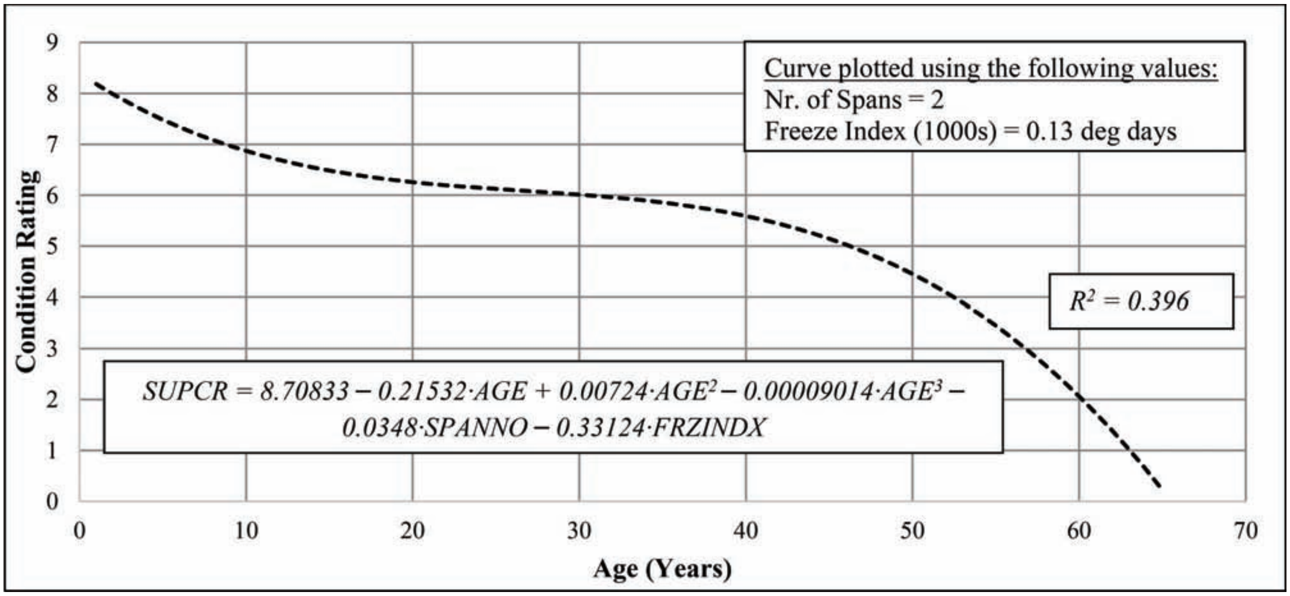

Figure B.20 Model for cast-in-place concrete superstructure of bridges with prior repair—Northern districts, non-NHS.

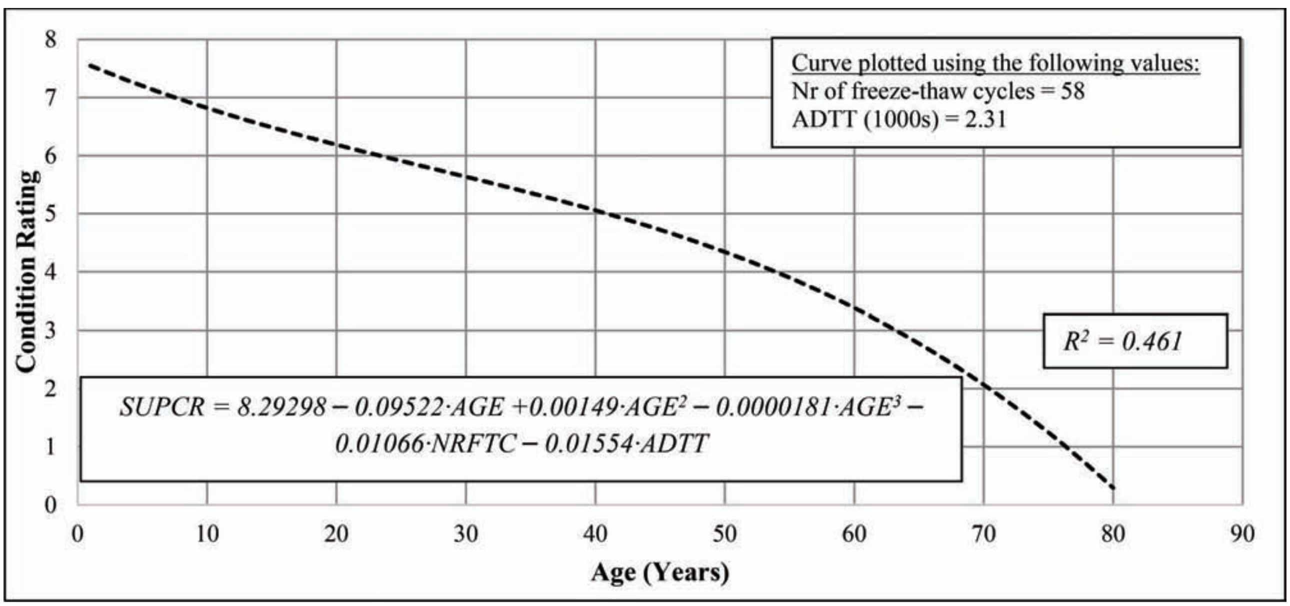

Figure B.21 Model for cast-in-place concrete superstructure of bridges with prior repair—Central districts, NHS.

form and had a coefficient of determination of 58%, which is relatively high compared to the other models. The model suggests that the superstructure age, freeze index, average precipitation, ADTT and number of freeze-thaw cycles were significant at 95% confidence (Table B.12). For the non-NHS bridges, the second-order polynomial functional form was found to provide the best fit to the observed data. The significant variables were superstructure age, average precipitation, freeze index, and number of freeze-thaw cycles; and the model accounted for 58% of the variation in steel superstructure condition ratings. In Figures B.37 and B.38, the plotted curves represent the superstructure condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. As the trends in the two figures suggest, for NHS steel superstructures in this bridge family, the condition deteriorated slowly compared to non-NHS bridges, which may be explained by the higher design standards of NHS bridge superstructures relative to their higher loads compared to non-NHS bridge superstructures. The predictive accuracy as determined by the RMSE was 0.47 and 0.55 for models on the NHS and non-NHS, respectively.

(b) Models for the Steel Superstructures of Bridges without Prior Repairs, Central Districts. For the steel superstructures of NHS bridges without prior repairs in

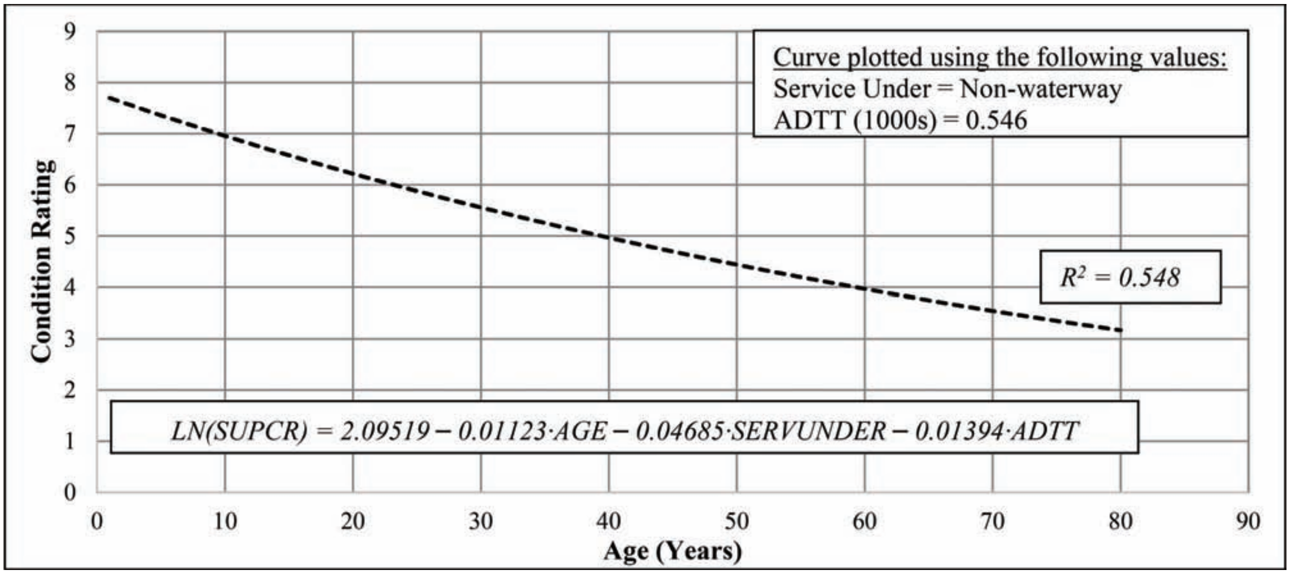

Figure B.22 Model for cast-in-place concrete superstructure of bridges with prior repair—Central districts, non-NHS.

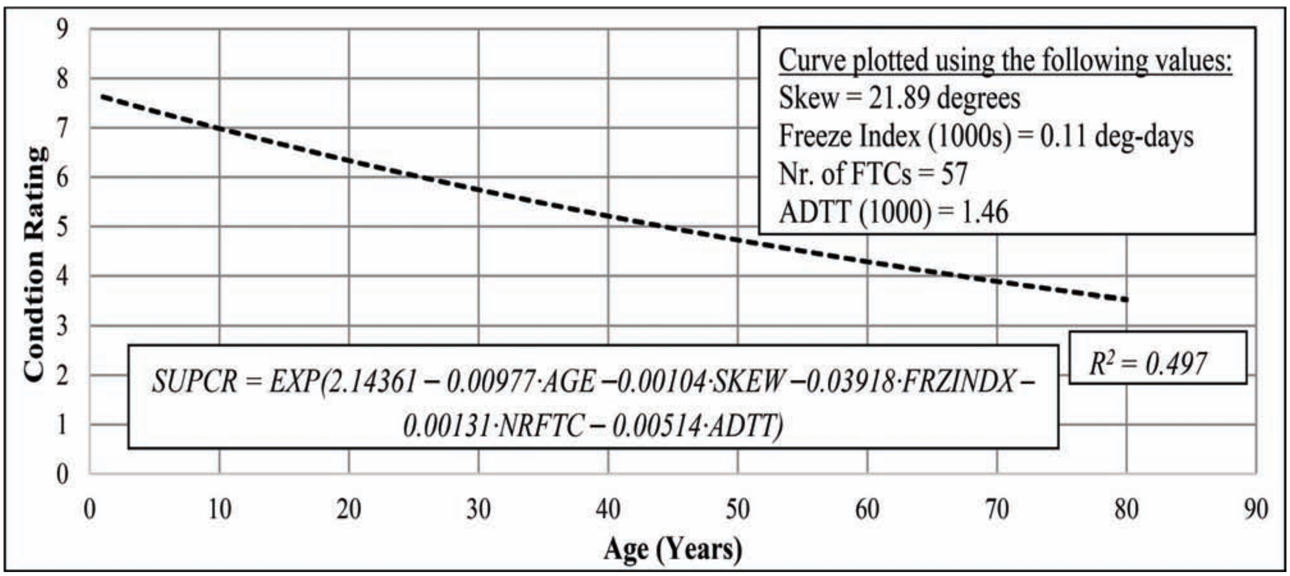

Figure B.23 Model for cast-in-place concrete superstructure of bridges with prior repair—Southern districts, NHS.

the Central districts, the model results suggest that the superstructure age and service under the bridge were significant at 95% confidence (Table B.12). The model's coefficient of determination was approximately 45%. A second-order polynomial functional form was found to provide the best fit to the data. For the non-NHS bridges, the exponential model was found to provide the best fit, and the significant variables were superstructure age, freeze index, and ADTT (Table B.12); and the model accounted for about 56% of the variation in the superstructure condition rating. The plots in Figures B.39 and B.40 suggest that non-NHS steel superstructures deteriorate more slowly compared to their NHS counterparts, which was possibly due to the lower traffic loads on the non-NHS bridges. The models for steel superstructures on the NHS and non-NHS had RMSEs of 0.45 and 0.42, respectively.

(c) Models for the Steel Superstructure of Bridges without Prior Repair, Southern Districts. For this bridge family, the polynomial functional form was found to suit the data best. The variables that were found to be statistically significant were superstructure age, bridge skew, service under the bridge, average precipitation, and freeze index. The model accounted for about 75% of the variation in the superstructure condition rating, and the signs of the parameter estimates were all intuitive. For the non-NHS bridges, the significant variables of the steel

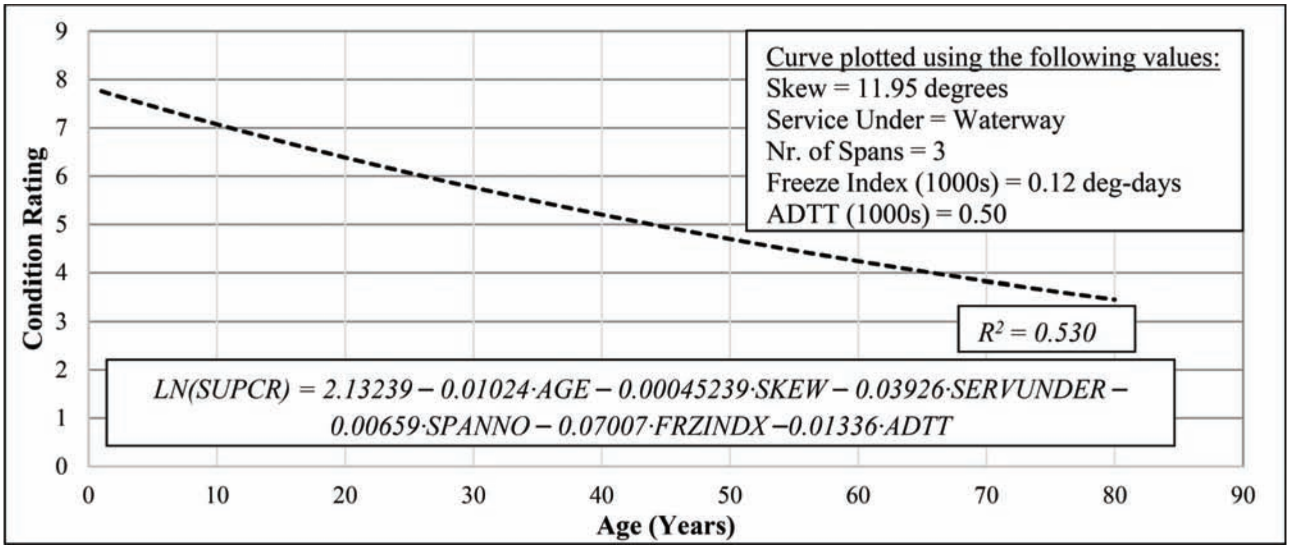

Figure B.24 Model for cast-in-place concrete superstructure of bridges with prior repair—Southern districts, non-NHS.

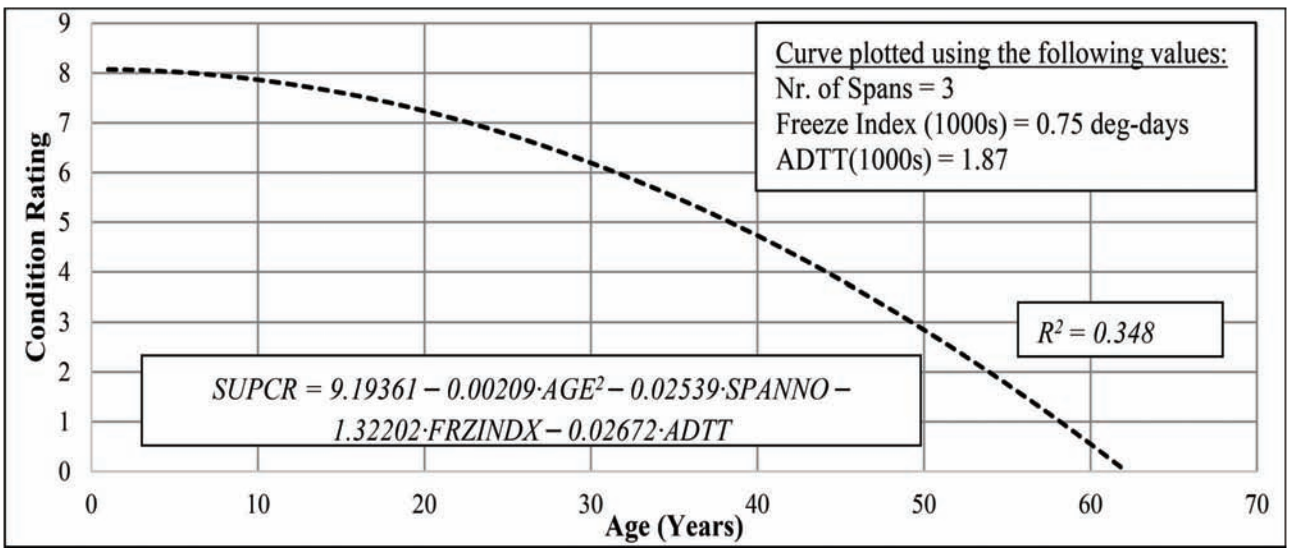

Figure B.25 Model for prestressed-concrete superstructure of bridges without prior repair—Northern districts, NHS.

superstructure deterioration were superstructure age, service under the bridge, and ADTT (Table B.12). The model explained about 54% of the variation in the steel superstructure condition rating. The plotted curves in Figures B.41 and B.42 represent the superstructure condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The trends exhibited by the curves suggest that steel superstructures in the Southern districts deteriorated at a slower rate compared to their counterparts in the Northern and Central districts. The predictive accuracy of the models as determined by the RMSE was found to be 0.28 and 0.64, respectively, for steel superstructures on the NHS and non-NHS, respectively.

B.2.6 Steel Superstructure of Bridges with Prior Repair

(a) Models for the Steel Superstructure of Bridges with Prior Repair, Northern Districts. For NHS steel superstructure with prior repair located in the Southern districts, the variables found to be significant at 95% confidence were superstructure age, bridge skew, number of spans in main unit, freeze index, number of freeze-thaw cycles, and ADTT (Table B.13). The coefficient of determination was approximately 51%. For the non-NHS steel superstructure in this family, the significant variables were superstructure age, bridge skew, service under the bridge, number of spans in the main unit, freeze index, and ADTT. The model accounted for about 55% of the variation in the superstructure condition rating. The plotted curves in

TABLE B.10
Modeling Results for Prestressed-Concrete Superstructure of Bridges without Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.19361	43.66	9.66	20.86	8.52923	82.06	2.40586	62.89	8.23375	311.55	2.16278	410.23
Operational Factors												
ADTT(1000)	-0.02672	-7.05	–	–	–	–	–	–	–	–	-0.01575	-2.83
Design Factors												
Age	–	–	-0.05087	-4.78	–	–	-0.01091	-31.64	–	–	-0.0083	-37.22
Age-Squared	-0.00209	-17.58	-0.00061	-1.7	-0.00179	-12.52	–	–	-0.00181	-33.14	–	–
Age-Cubed	–	–	–	–	–	–	–	–	–	–	–	–
Skew	–	–	-0.00387	-2.45	-0.00215	-2.48	–	–	-0.00365	-5.20	–	–
Service Under (1 if waterway, 0 other)	–	–	–	–	-0.38201	-6.31	–	–	-0.11058	-4.08	–	–
Number of Spans in Main Unit	-0.02539	-3.93	–	–	–	–	-0.01679	-5.89	–	–	-0.01575	-4.40
Climate Factors												
Freeze Index (1000s)	-1.32202	-4.55	–	–	-0.6489	-3.09	–	–	–	–	–	–
Number of Freeze-Thaw Cycles	–	–	-0.01721	-2.47	–	–	-0.00385	-6.28	–	–	–	–
Model Fit Statistics												
Observations	839		641		467		920		1029		1474	
R-Squared	0.348		0.426		0.395		0.521		0.579		0.497	

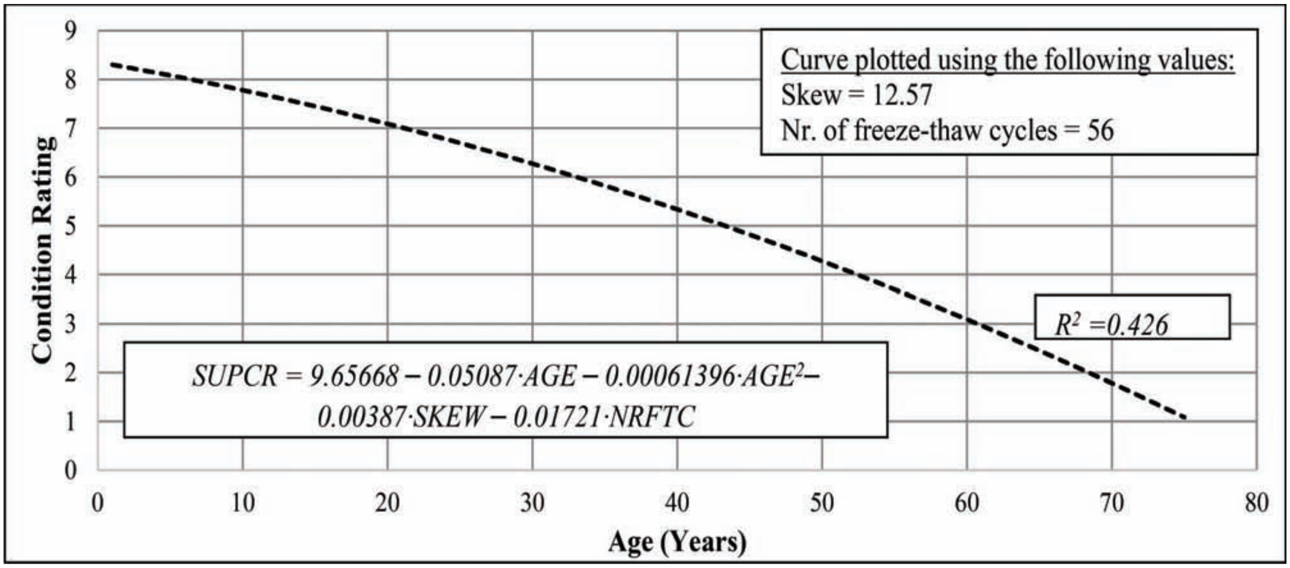

Figure B.26 Model for prestressed-concrete superstructure of bridges without prior repair—Northern districts, non-NHS.

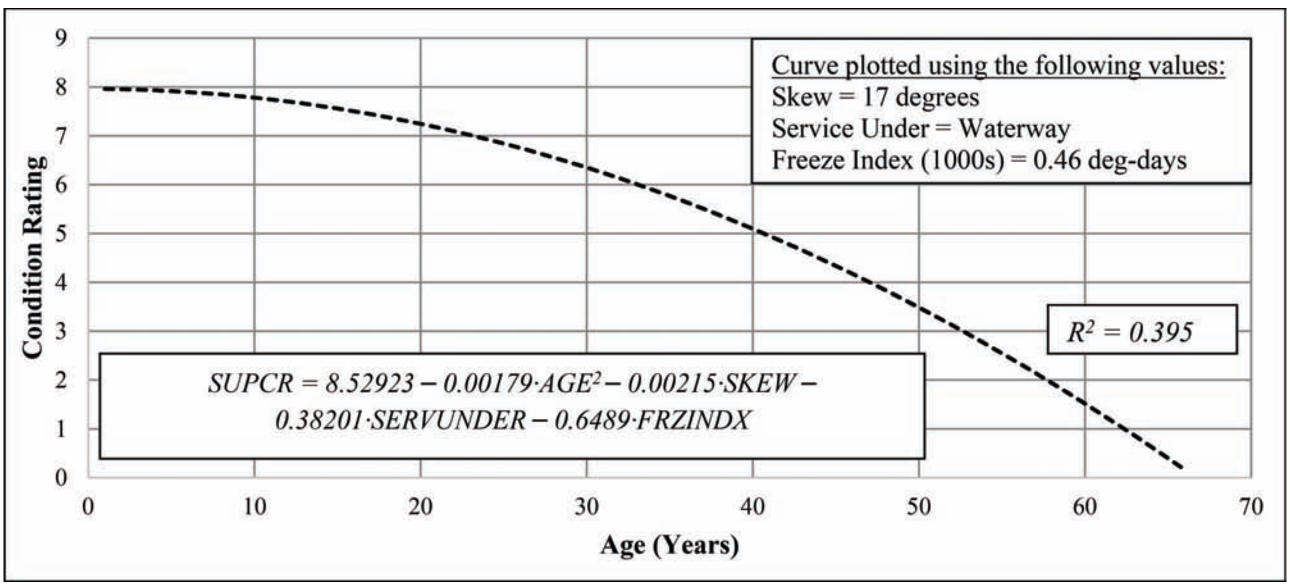

Figure B.27 Model for prestressed-concrete superstructure of bridges without prior repair—Central districts, NHS.

Figures B.43 and B.44 represent the superstructure condition rating corresponding to specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The models for steel superstructures on the NHS and non-NHS had RMSEs of 0.52 and 0.65, respectively.

(b) Models for the Steel Superstructure of Bridges with Prior Repair, Central Districts. As shown in Table B.13, for NHS bridges with prior repair located in Indiana's Central districts, the model outcomes suggest that the steel superstructure condition was significantly influenced by the following independent variables: age, service under the bridge, and freeze index. The model explained only 23% of the variation in the superstructure condition rating. For non-NHS superstructures in the Central districts, the significant variables, at 95% confidence, were age, service under the bridge, average precipitation, and the number of freeze-thaw cycles. An exponential curve was found to provide the best fit to the data. The model had a coefficient of determination of about 33%. Figures B.45 and B.46 illustrate the relationship between the superstructure condition rating and the superstructure age in the Central districts, and the plotted curves show the superstructure condition rating corresponding to specific values of the independent variables, as shown in the upper right box

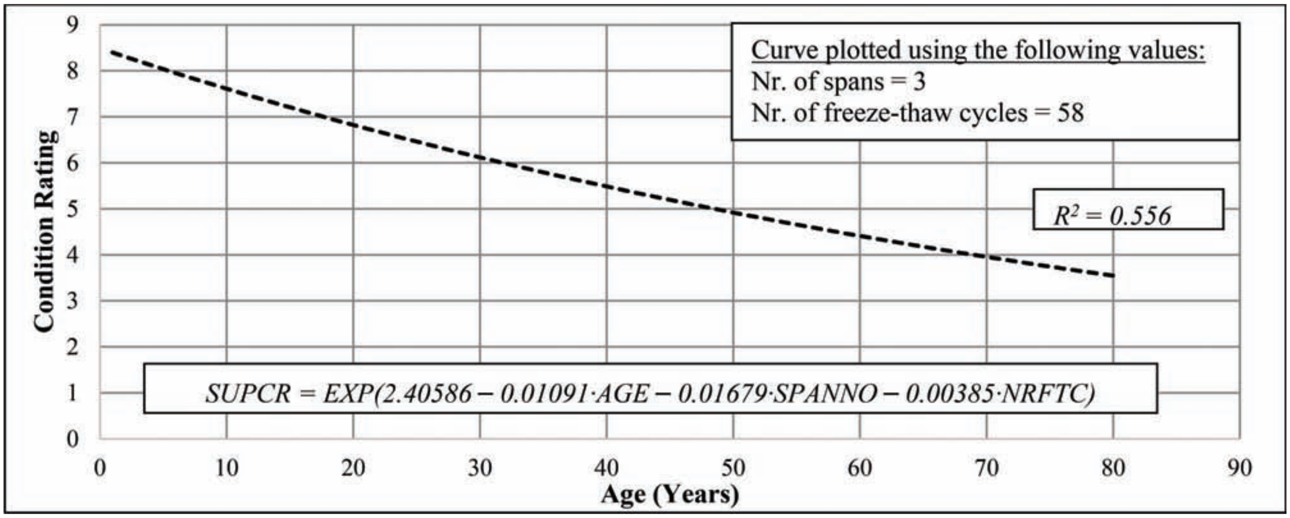

Figure B.28 Model for prestressed-concrete superstructure of bridges without prior repair—Central districts, non-NHS.

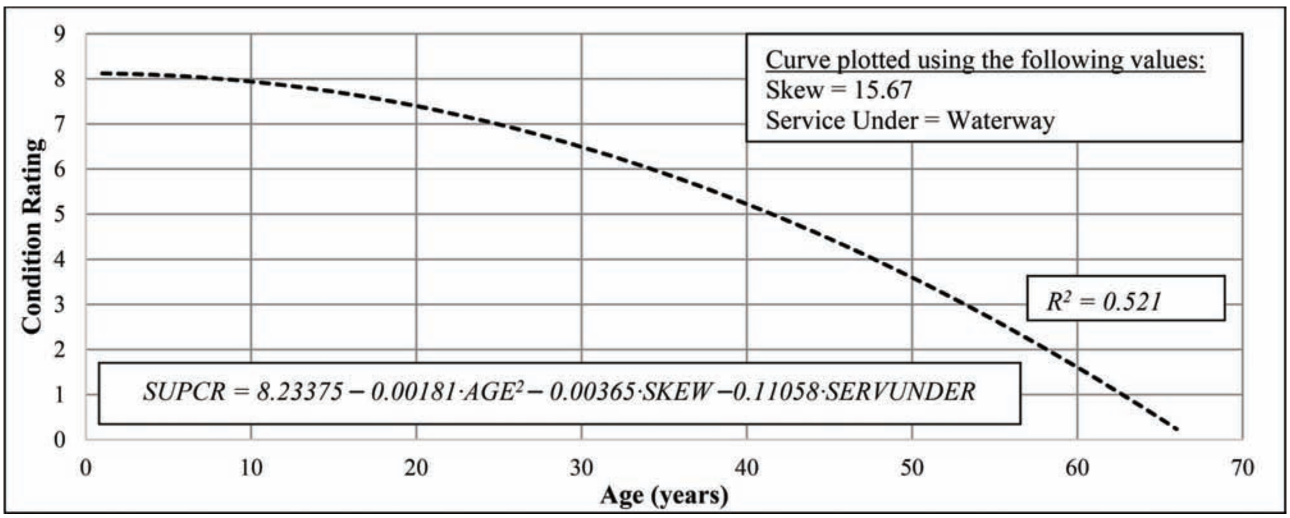

Figure B.29 Model for prestressed-concrete superstructure without prior repair—Southern districts, NHS.

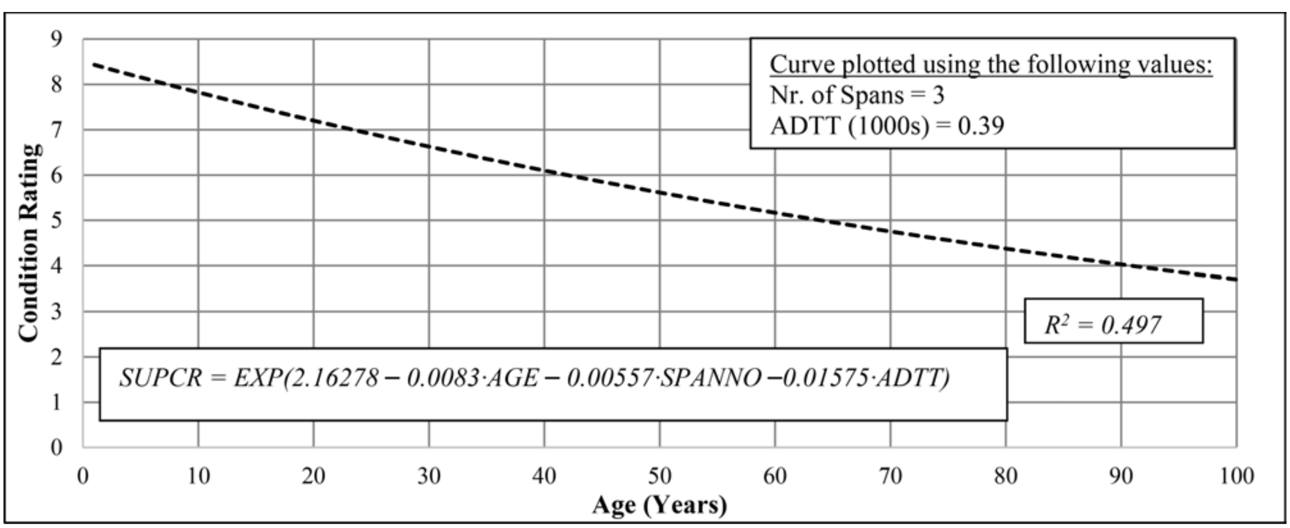

Figure B.30 Model for prestressed-concrete superstructure of bridges without prior repair—Southern districts, non-NHS.

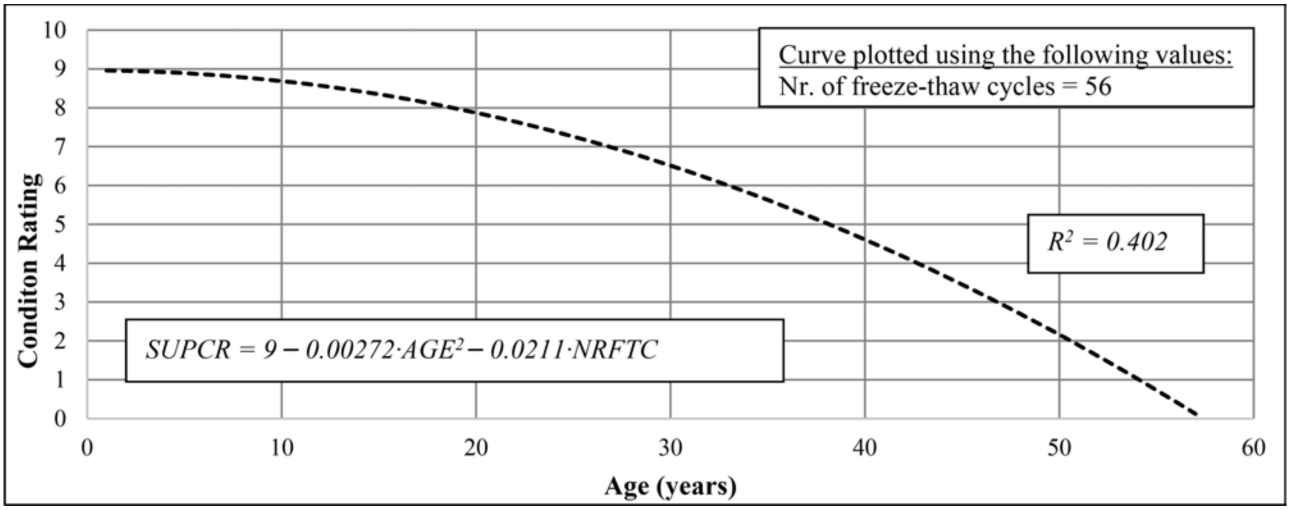

Figure B.31 Model for prestressed-concrete superstructure of bridges with prior repair—Northern districts, NHS.

of the general model presented in the lower left box. The predictive efficiency of the models determined by the RMSE were 0.42 and 0.72, respectively, for steel superstructures on the NHS and non-NHS.

(c) Model for Steel Superstructure of Bridges with Prior Repair, Southern Districts. The model results in Table B.13 suggest that the superstructure age, average precipitation, freeze index, and ADTT are significant variables for the superstructure of bridges in this family. The significant variables at 95% confidence were precipitation, freeze index, and ADTT. A second-order polynomial curve, which was found to be the most appropriate for the data, accounted for only 18% of the variation in the superstructure condition rating. For the non-NHS bridges, the significant factors were superstructure age, service under the bridge, freeze index, and ADTT. Of the several possible functional forms investigated, the exponential form, which explained only 26% of the variation in the superstructure condition rating, was found to provide the closest fit to the data. Figures B.47 and B.48 below illustrate the trends in the superstructure condition rating vs. the superstructure age plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. Also, the models suggest that generally speaking, steel superstructures in the Southern districts deteriorated at a slower pace compared to their counterparts in the Northern and Central districts. The models had RMSEs of 0.48 and 0.60, respectively, for steel superstructures on the NHS and non-NHS roads in Indiana's Southern districts.

B.3 Substructure Deterioration Models

Table B.14 presents the variables investigated for substructure deterioration modeling. The substructures were classified according to whether they had received repairs. Further classification was done by using the highway district on which the substructures were located as well as the reference in terms of the highway system. A total of 12 models were developed for bridge substructures. Two main functional forms were investigated for the best fit: exponential and polynomial. Second- and third-order polynomial functional forms were considered for developing the best models for the substructure models. Tables B.15 and B.16 present the modeling results for steel superstructure of bridges without and with prior repair, respectively.

B.3.1 Substructures of Bridges without Prior Repair

(a) Models for Substructures of Bridges without Prior Repair, Northern Districts. For NHS substructures in the Northern districts, the results indicated that the condition rating could be explained by four variables: age, freeze index, number of freeze-thaw cycles, and ADTT. As shown in the model results (Table B.15), the signs of all the variables were intuitive; for each of these variables, higher levels were found to be associated with a lower substructure condition rating. The model explained approximately 28% of the variability of the substructure condition rating. For the non-NHS substructures in the Southern districts, the results suggest that the following variables were significant in the substructure models: age, service under the bridge, freeze index, and number of freeze-thaw cycles; and the model explained about 53% of the variability of the substructure condition rating. Figures B.49 and B.50 illustrate the trends in the substructure condition rating vs. the substructure age, plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The RMSE for the deterioration models on the NHS and non-NHS were 0.53 and 0.55, respectively.

TABLE B.11
Modeling Results for Prestressed-Concrete Superstructure of Bridges with Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.00	37.01	8.63	31.44	10.3840	28.32	2.15446	70.48	8.0548	106.2	7.3685	114.79
Operational Factors												
ADTT(1000)	–	–	–	–	–	–	–	–	–	–	–	–
Design Factors												
Age	–	–	-0.06584	-6.73	-0.19175	-6.24	-0.01209	-37.55	-0.04641	-4.20	-0.02417	-3.63
Age-Squared	-0.00272	-26.67	-0.00001	-0.03	0.00837	3.22	–	–	-0.00077	-2.17	-0.00036	-2.21
Age-Cubed	–	–	–	–	-0.00015	-2.31	–	–	–	–	–	–
Skew	–	–	–	–	–	–	-0.00047	-3.25	–	–	–	–
Service Under (1 if waterway, 0 other)	–	–	–	–	–	–	–	–	–	–	–	–
Number of Spans in Main Unit	–	–	–	–	–	–	–	–	–	–	–	–
Climate Factors												
Freeze Index (1000s)	–	–	–	–	–	–	–	–	–	–	-0.39259	-3.10
Number of Freeze-Thaw Cycles	-0.02111	-8.00	-0.01191	-2.47	-0.03152	-5.35	-0.00106	-2.09	–	–	–	–
Model Fit Statistics												
Observations	1096		1456		637		1745		737		2669	
R-Squared	0.402		0.336		0.337		0.451		0.412		0.205	

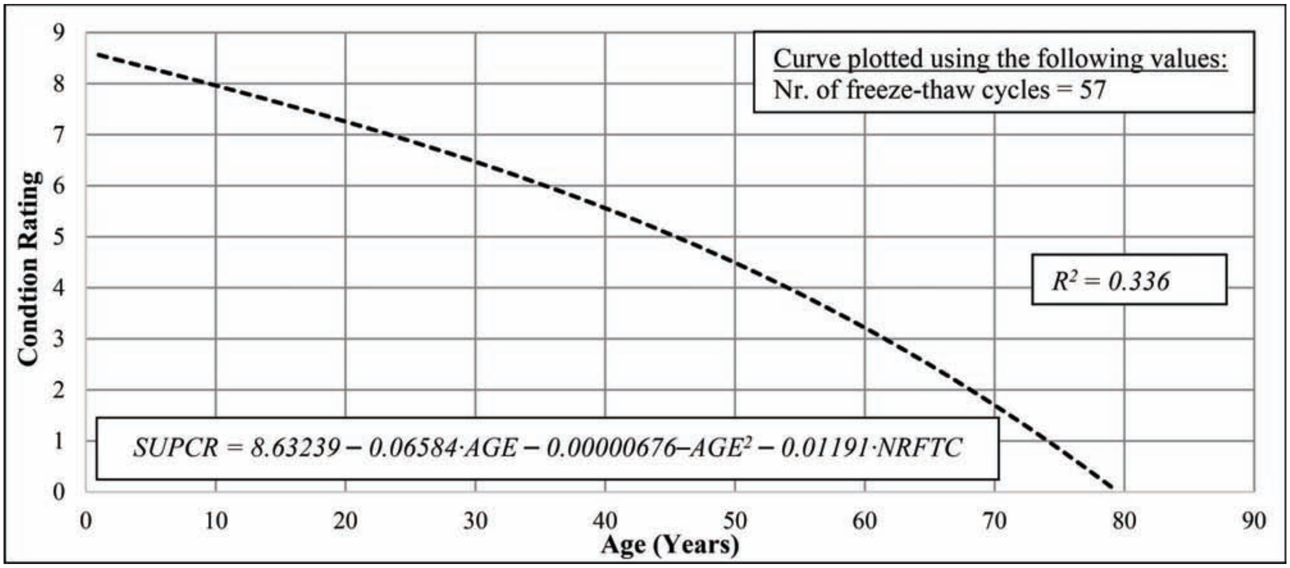

Figure B.32 Model for prestressed-concrete superstructure of bridges with prior repair—Northern districts, non-NHS.

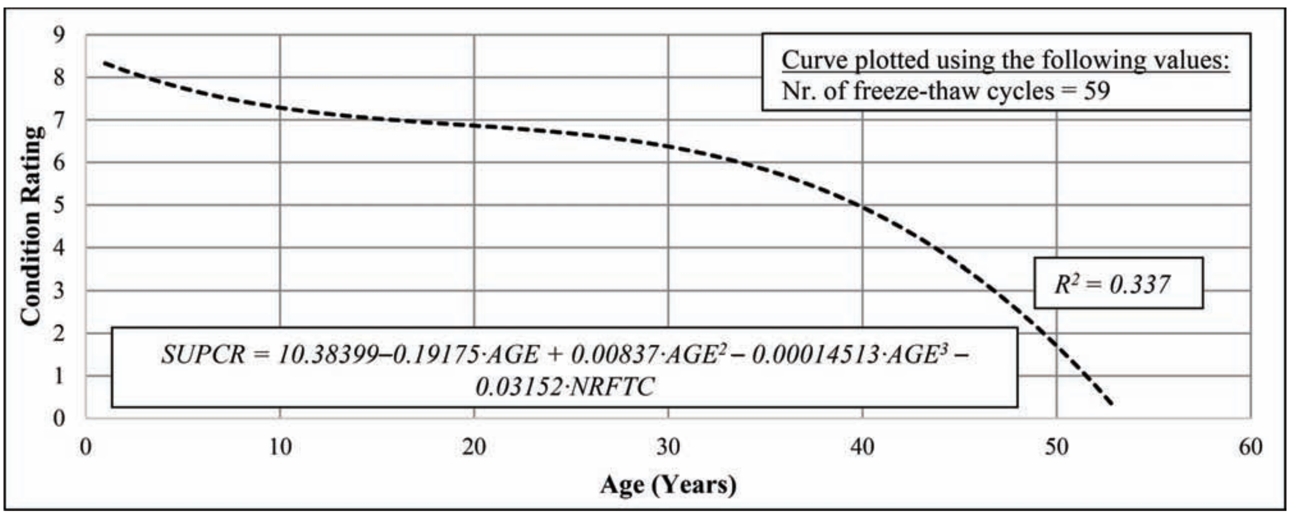

Figure B.33 Model for prestressed-concrete superstructure of bridges with prior repair—Central districts, NHS.

(b) Models for Substructure of Bridges without Prior Repair, Central Districts. The results of the analysis for substructure condition rating for NHS bridges in the Central districts indicate that age, service under the bridge, freeze index, and ADTT were significant (Table B.15), which suggests that operational, design, and climatic factors all play a role in the deterioration of the substructures of this bridge family. The second-order polynomial functional form, which was found to provide the best fit to the data, accounted for approximately 55% of the variation in the substructure condition rating. For the non-NHS, the significant variables were age, number of freeze-thaw cycles, and ADTT; and the model accounted for 63% of the variation in substructure condition rating. Each of the two charts (Figures B.51 and B.52), which illustrate the trends in the substructure condition rating vs. the substructure age, was plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The figures suggest that the non-NHS substructures generally deteriorated more slowly compared to the NHS substructures. The predictive efficiencies of the models determined by the RMSEs were 0.45 and 0.72 for substructures in Indiana's Central districts.

(c) Models for Substructure of Bridges without Prior Repair, Southern Districts. From the analysis results (Table B.15), it was concluded that, for NHS bridges in the Southern districts, the age, service under the bridge, freeze index, number of freeze-thaw cycles and ADTT were the most significant variables that affected substructure deterioration. The results suggest that climate plays a very significant role in the deterioration of this bridge component. The model explained approximately 58% of the variation in the substructure condition. For

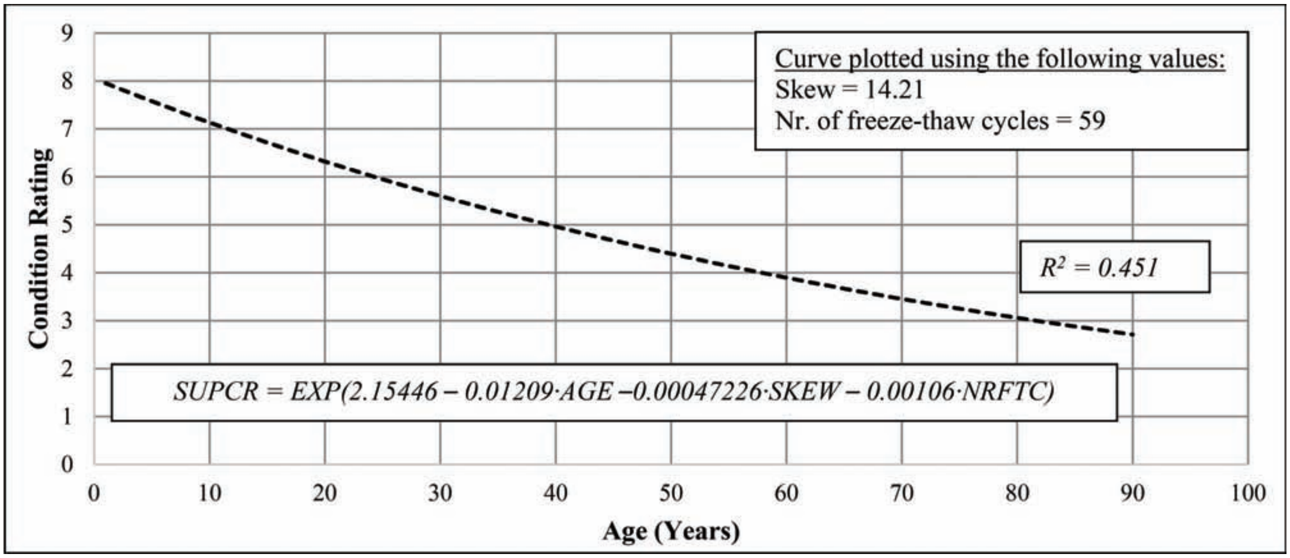

Figure B.34 Model for prestressed-concrete superstructure of bridges with prior repair—Central districts, non-NHS.

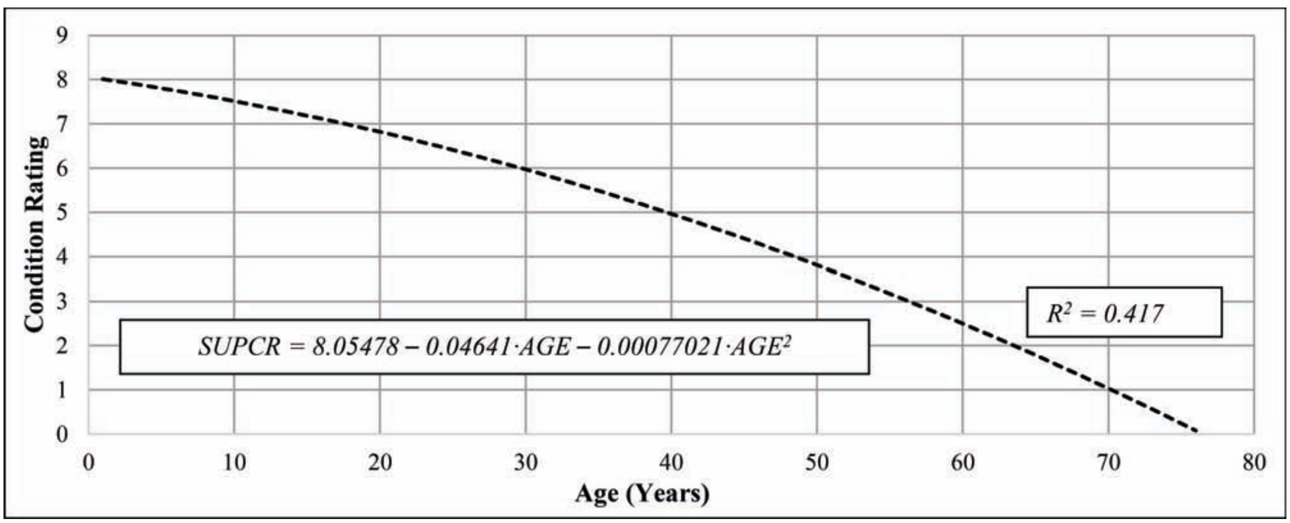

Figure B.35 Model for prestressed-concrete superstructure of bridges with prior repair—Southern districts, NHS.

the non-NHS bridges, it was found that the significant variables affecting substructure deterioration were age, service under the bridge, and freeze index. The exponential model was found to provide the best fit for the data and explained about 57% of the variation in the substructure condition rating. The substructures in the Southern districts were generally observed to deteriorate at a slower rate compared to those in the Northern and Central districts. Figures B.53 and B.54 illustrate the relationship between the substructure condition rating vs. the age of the substructure, which were plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The models had RMSEs of 0.30 and 0.56 for substructures on the NHS and non-NHS, respectively.

B.3.2 Substructures of Bridges with Prior Repair

(a) Models for Substructures of Bridges with Prior Repair, Northern Districts. For NHS bridge substructures with prior repair that were located in Indiana's Northern districts, the best model suggested that the condition rating can be explained by three variables: age, freeze index, and number of freeze-thaw cycles (Table B.16). Interestingly, the factor related to traffic operations (ADTT) and most of the design factors were not significant at a 95% level of confidence. The polynomial curve to the third degree explains about 28% of the variation in the substructure condition. For the non-NHS bridges in this family, their ages, service under the bridge, and freeze index were the significant variables explaining the substructure

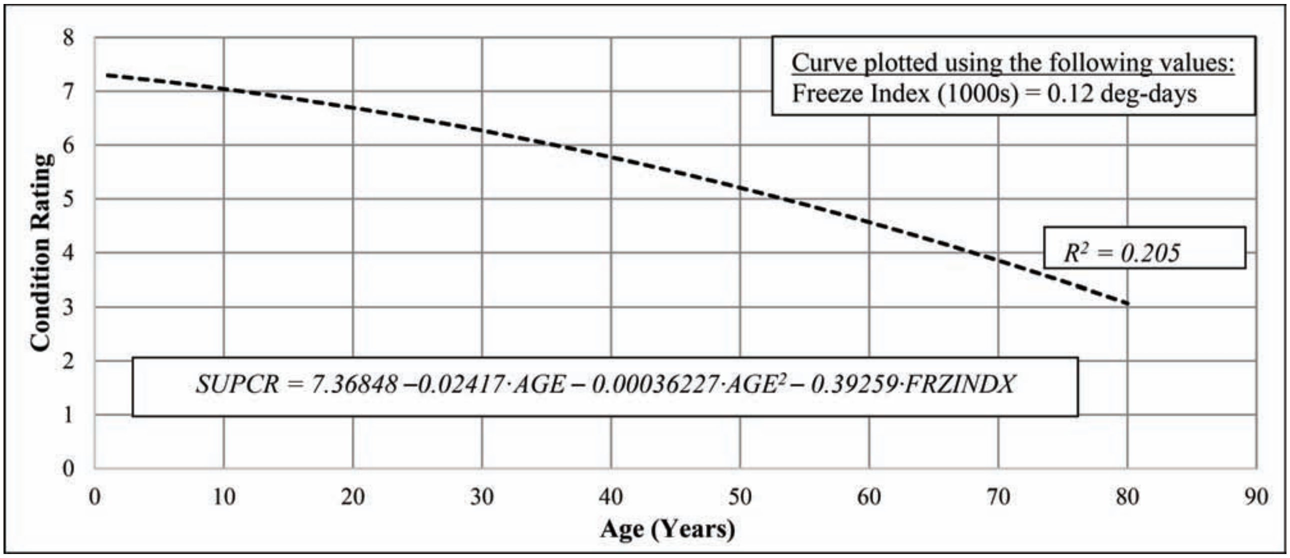

Figure B.36 Model for prestressed-concrete superstructure of bridges with prior repair—Southern districts, non-NHS.

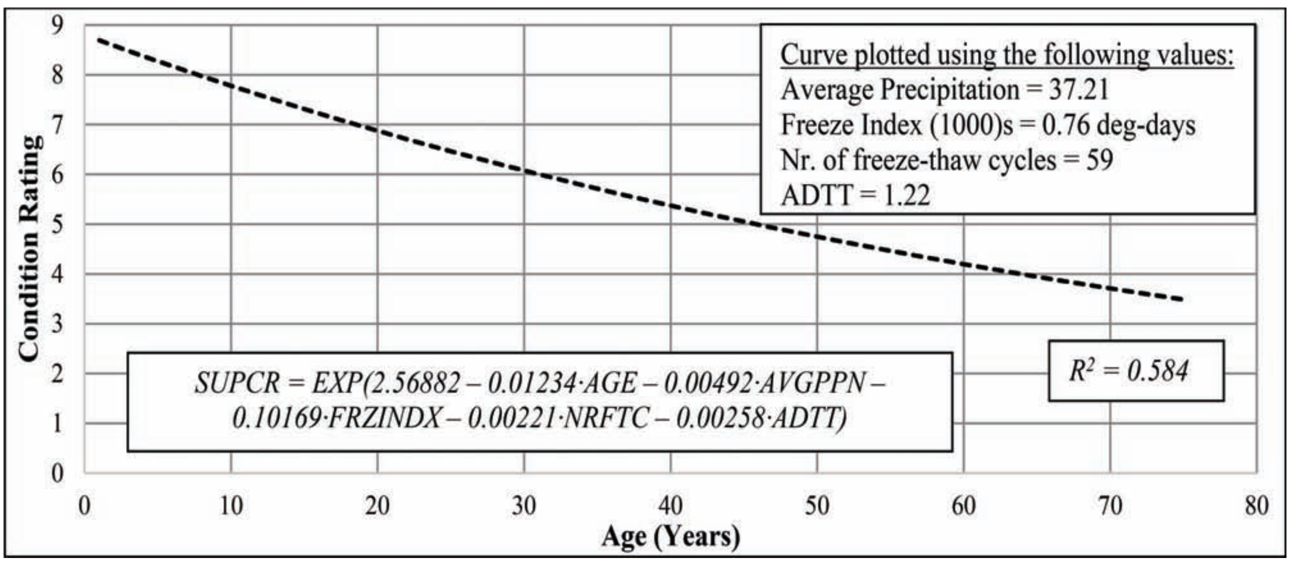

Figure B.37 Model for steel superstructure of bridges without prior repair—Northern districts, NHS.

condition rating. The model accounted for about 37% of the variation in the substructure condition. For the NHS and non-NHS bridges in this family, Figures B.55 and B.56 illustrate the relationship between the substructure condition rating vs. the age of the substructure, which were plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The predictive efficiency for the NHS and non-NHS models, as determined by the RMSE were 0.55 and 0.61, respectively.

(b) Models for Substructure of Bridges with Prior Repair, Central, Districts. The model developed using substructure-related data for bridges with prior repair in the Central districts of Indiana was established after multiple attempts with a large number of potential functional forms. The significant variables were found to be: age, route type (Interstate or otherwise), service under the bridge, and the number of freeze-thaw cycles. The signs of these significant variables were consistent with engineering expectation: higher levels of age and freeze-thaw cycles were found to be associated with lower condition rating of the substructure. The substructures of Interstate bridges were found to be associated with lower condition rating, possibly due to the higher levels of truck traffic; also, the substructures of bridges that cross waterways were found to be associated with higher deterioration rates. The second-order polynomial curve explained about 28% of the

TABLE B.12
Modeling Results for Steel Superstructure of Bridges without Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	2.56882	41.50	2.585	42.1	7.79797	144.03	2.19722	–	9.000	–	2.21129	208.80
Operational Factors												
ADTT(1000)	-0.00258	-2.37	–	–	–	–	-0.05009	-3.50	–	–	-0.02094	-3.19
Design Factors												
Age	-0.01243	-35.86	-0.01234	-36.41	–	–	-0.00929	-23.52	–	–	-0.01068	-26.02
Age-Squared	–	–	–	–	-0.00157	-16.1	–	–	-0.00172	-29.60	–	–
Age-Cubed	–	–	–	–	–	–	–	–	–	–	–	–
Skew	–	–	–	–	–	–	–	–	-0.00325	-3.21	–	–
Service Under (1 if waterway, 0 other)	–	–	–	–	-0.28086	-4.03	–	–	-0.30314	-3.56	-0.03279	-4.61
Number of Spans in Main Unit	–	–	–	–	–	–	–	–	–	–	–	–
Climate Factors												
Average Precipitation	-0.00492	-3.49	-0.0052	-3.78	–	–	–	–	-0.01474	-24.17	–	–
Freeze Index (1000s)	-0.10169	-1.95	-0.1034	-2.02	–	–	-0.12848	-4.46	-0.99109	-6.82	–	–
Number of Freeze-Thaw Cycles	-0.00221	-2.77	-0.00232	-3.03	–	–	–	–	–	–	–	–
Model Fit Statistics												
Observations	963		963		313		447		542		612	
R-Squared	0.58		0.584		0.454		0.557		0.750		0.540	

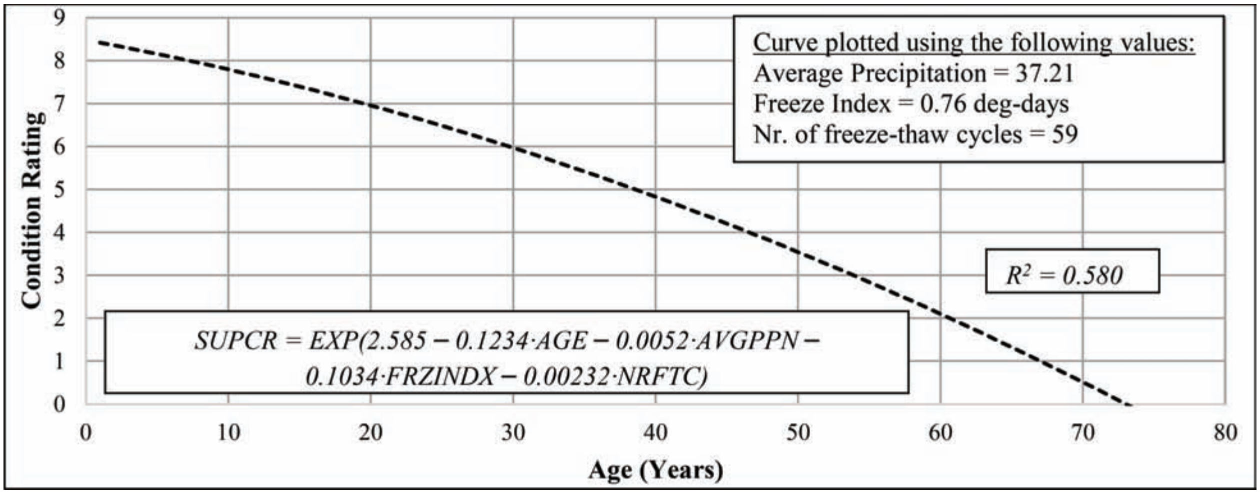

Figure B.38 Model for steel superstructure of bridges without prior repair—Northern districts, non-NHS.

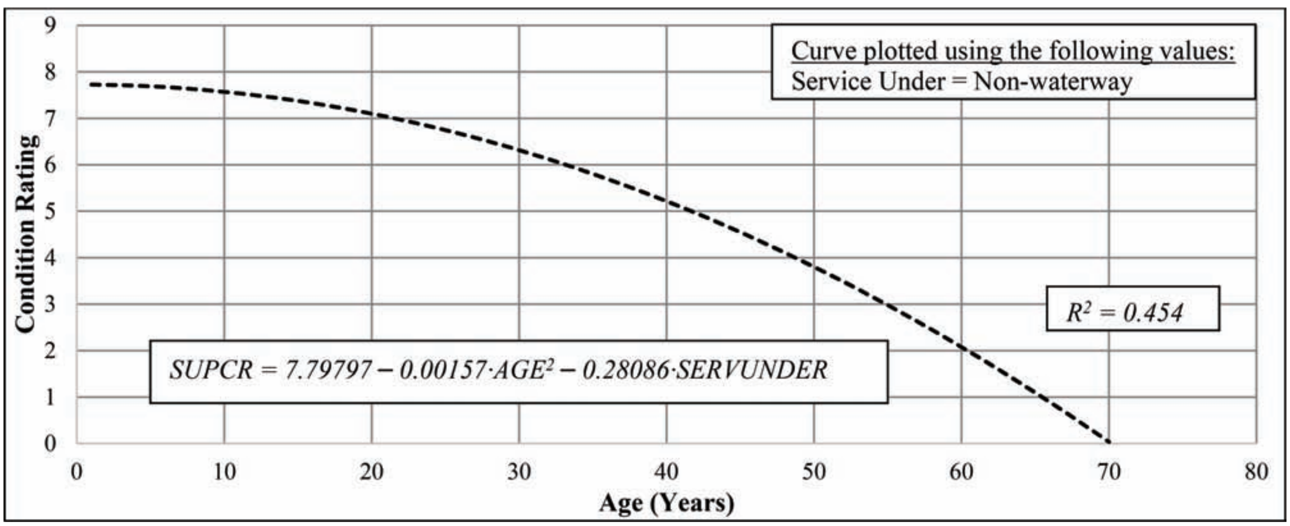

Figure B.39 Model for steel superstructure of bridges without prior repair—Central districts, NHS.

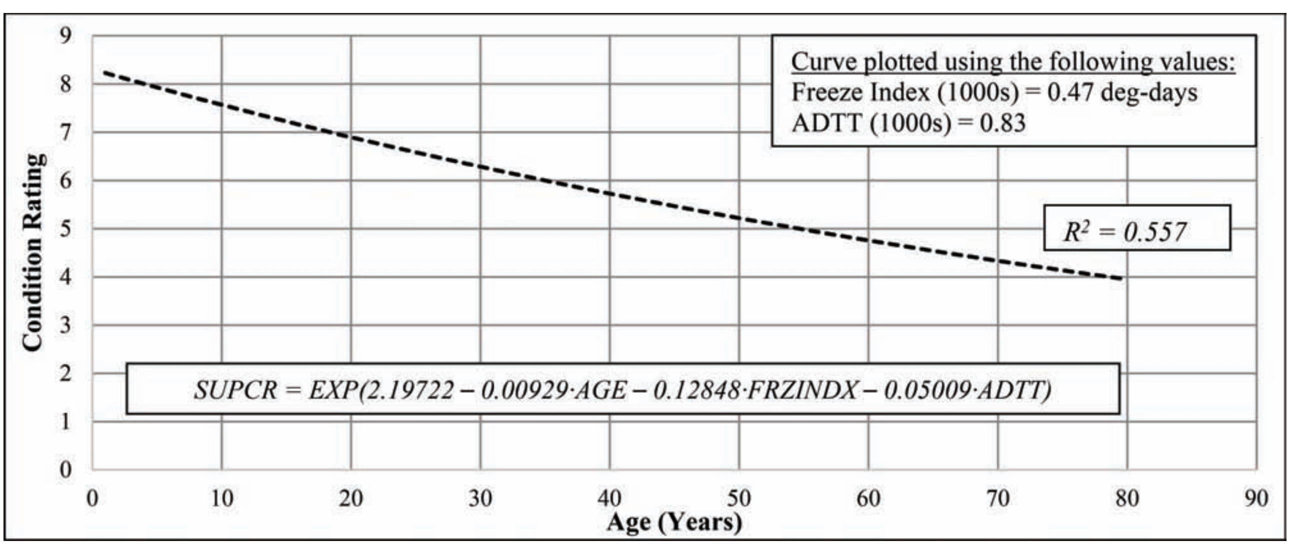

Figure B.40 Model for steel superstructure of bridges without prior repair—Central districts, non-NHS.

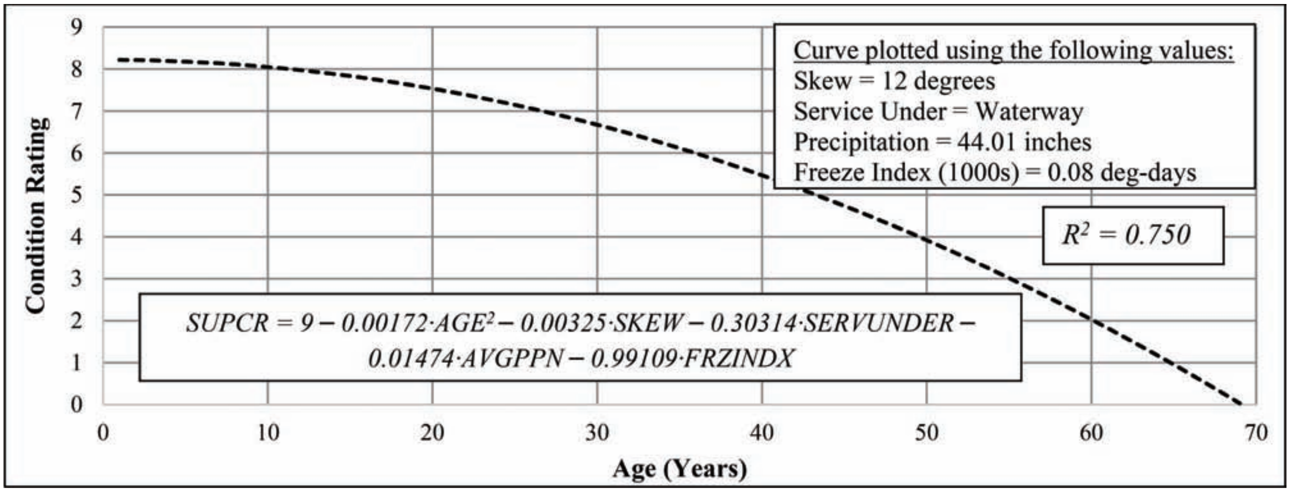

Figure B.41 Model for steel superstructure of bridges without prior repair—Southern districts, NHS.

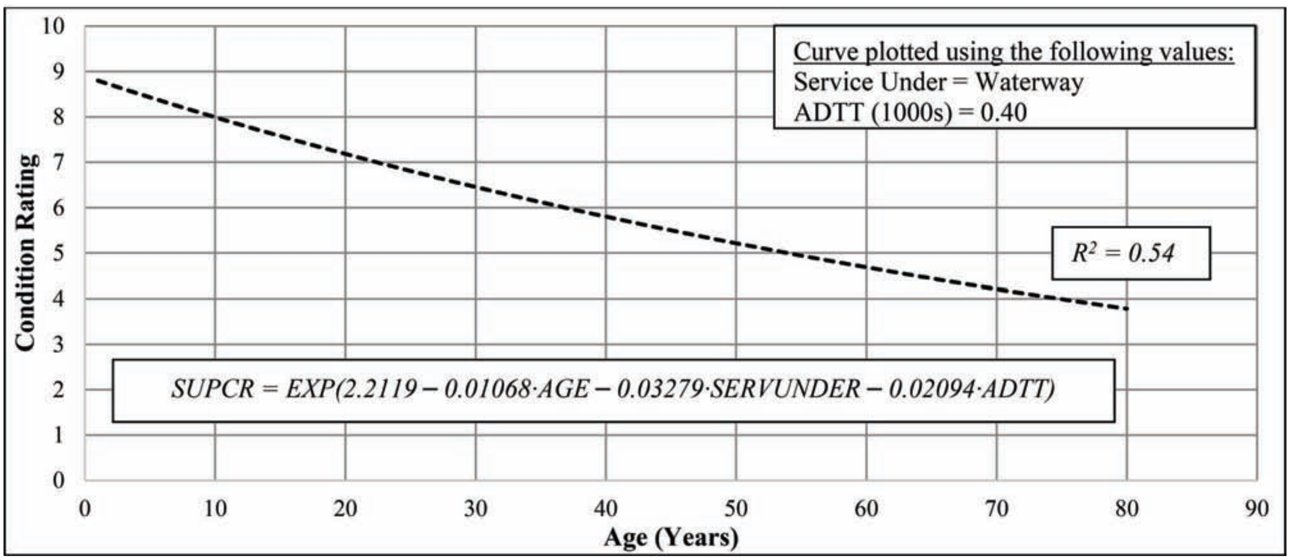

Figure B.42 Model for steel superstructure of bridges without prior repair—Southern districts, non-NHS.

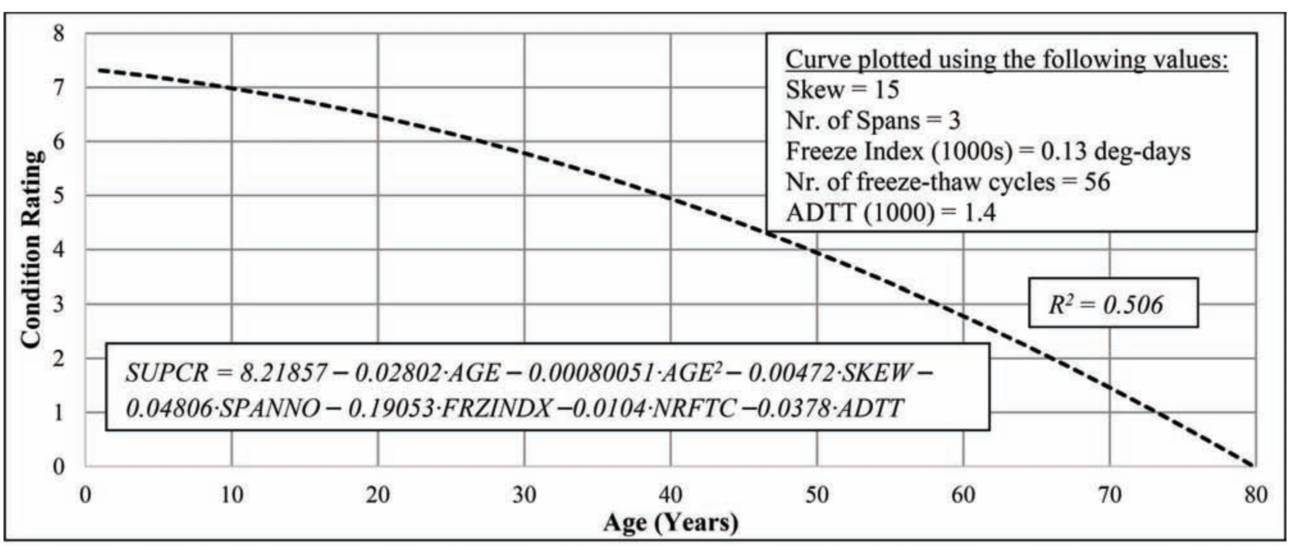

Figure B.43 Model for steel superstructure of bridges with prior repair—Northern districts, NHS.

TABLE B.13
Modeling Results for Steel Superstructure of Bridges with Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	8.2186	46.54	7.979	86.93	7.38503	86.34	2.19722	–	9.025	36.67	2.04373	347.60
Operational Factors												
ADTT(1000)	-0.0378	-6.13	-0.07858	-2.52	–	–	–	–	-0.00878	-2.29	-0.02072	-5.51
Design Factors												
Age	-0.02802	-6.25	-0.0444	-9.09	-0.01763	-5.38	-0.0088	-39.98	-0.01203	-2.83	-0.00713	-27.85
Age-Squared	-0.00081	-7.31	-0.00031	-3.3	-0.00067	-6.46	–	–	-0.00057	-4.63	–	–
Age-Cubed	–	–	–	–	–	–	–	–	–	–	–	–
Skew	-0.00472	-6.03	-0.00408	-4.33	–	–	–	–	–	–	–	–
Service Under (1 if waterway, 0 otherwise)	–	–	-0.22323	-4.21	-0.03158	-2.99	-0.01953	-6.28	–	–	-0.01782	-4.15
Number of Spans in Main Unit	-0.04806	-3.64	-0.04812	-3.74	–	–	–	–	–	–	–	–
Climate Factors												
Average Precipitation	–	–	–	–	–	–	-0.00269	-6.39	-0.03952	-7.37	–	–
Freeze Index (1000s)	-0.19053	-2.36	-0.4950	-5.08	–	–	–	–	-0.8398	-8.96	-0.04835	-2.95
Number of Freeze-Thaw Cycles	-0.0104	-3.41	–	–	-0.00301	-2.15	-0.00069	-2.48	–	–	–	–
Model Fit Statistics												
Observations	2433		2195		7949		3513		3784		2636	
R-Squared	0.506		0.553		0.225		0.333		0.180		0.259	

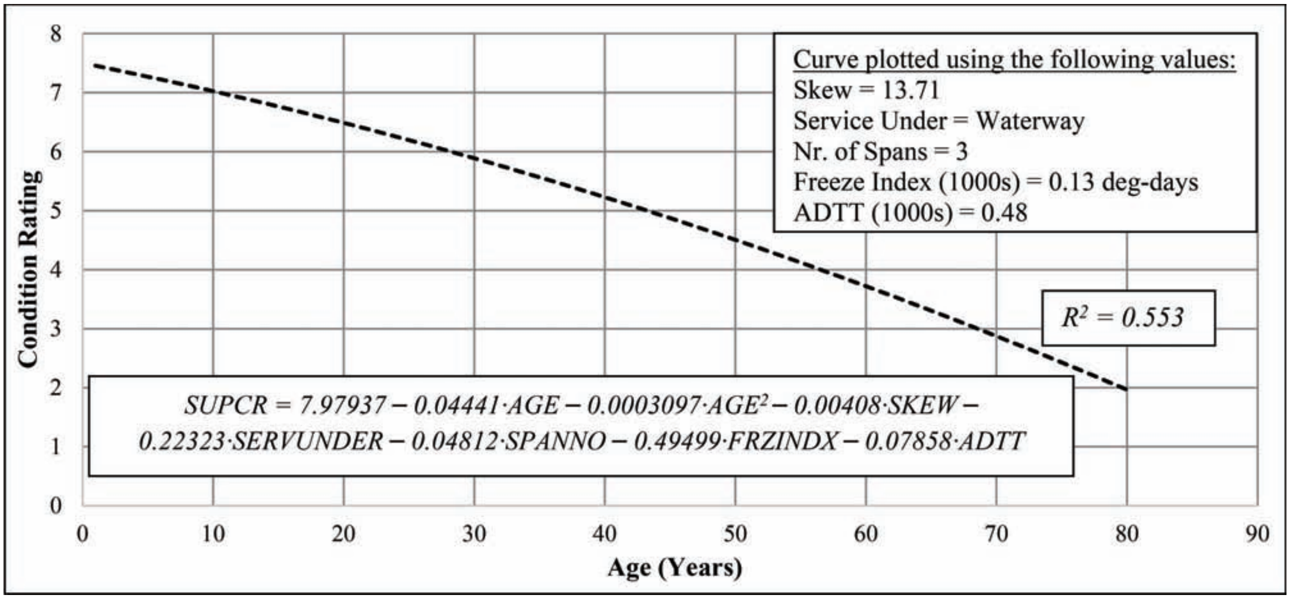

Figure B.44 Model for steel superstructure of bridges with prior repair—Northern districts, non-NHS.

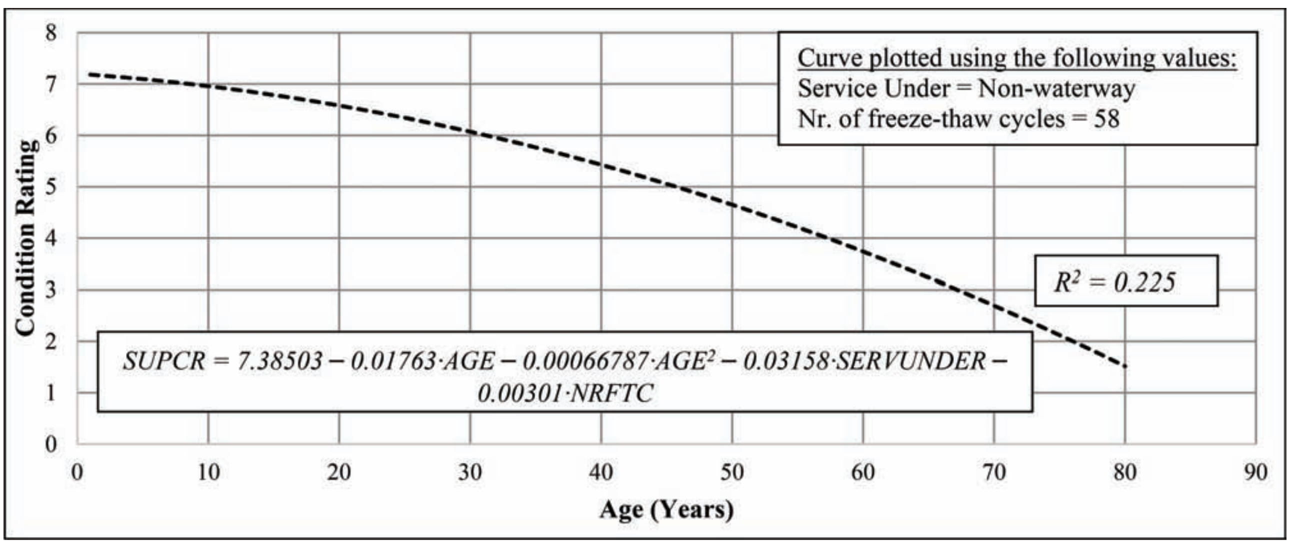

Figure B.45 Model for steel superstructure of bridges with prior repair—Central districts, NHS.

variation in the substructure condition rating (Figure B.57). For non-NHS bridges, the substructure condition rating was found to be explained by age, service under the bridge, the number of freeze-thaw cycles, and ADTT; and the exponential curve was found to be a good fit for the data and accounted for about 44% of the variation in the substructure condition rating (Figure B.58). The RMSE for the models were found to be 0.43 and 0.52 for the models representing substructures on the NHS and non-NHS, respectively.

(c) Models for Substructures of Bridges with Prior Repair, Southern Districts. The analysis for the substructure of NHS bridges with prior repair in the Southern district showed that age, service under the bridge, freeze index, number of freeze-thaw cycles, and ADTT were significant factors in substructure deterioration (Table B.16). The model accounted for about 29% of the variation in the substructure condition rating. For the non-NHS bridges, the significant factors were age, service under the bridge and freeze index, and the coefficient of determination was found to be 37%. As shown in Figures B.59 and B.60, the bridges in the Southern district had the slowest deterioration. The figures, which present the relationship between the substructure condition rating and age, were plotted using specific values of the independent variables, as shown in the upper right box of the general model presented in the lower left box. The predictive efficiency of the models as determined by the RMSE were 0.43 and 0.58 for substructures on the NHS and non-NHS roads, respectively.

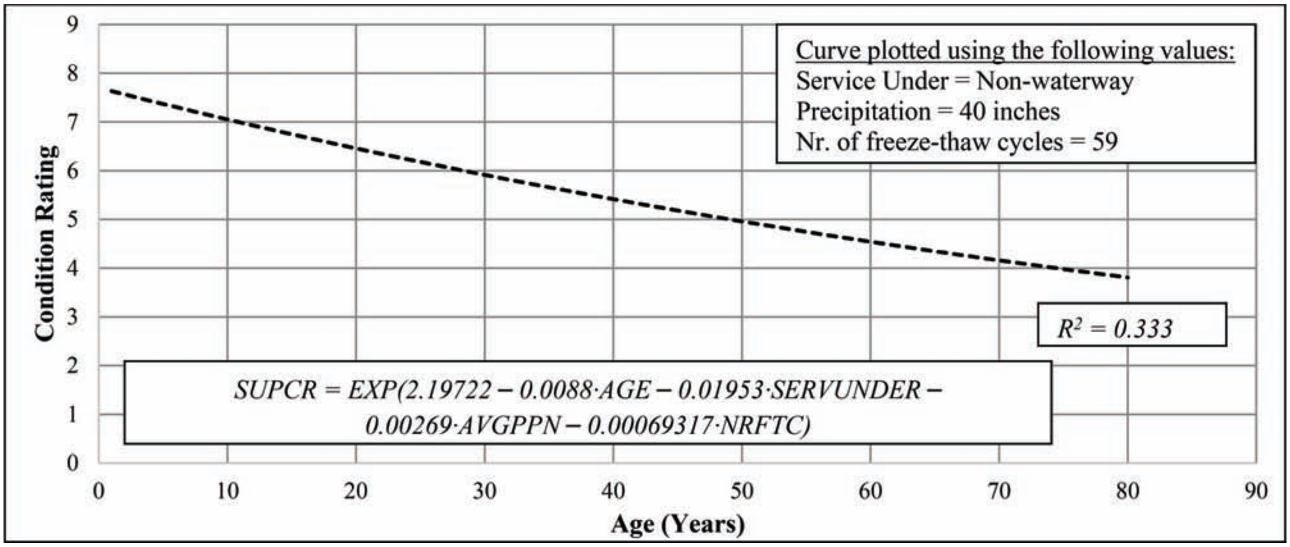

Figure B.46 Model for steel superstructure of bridges with prior repair—Central districts, non-NHS.

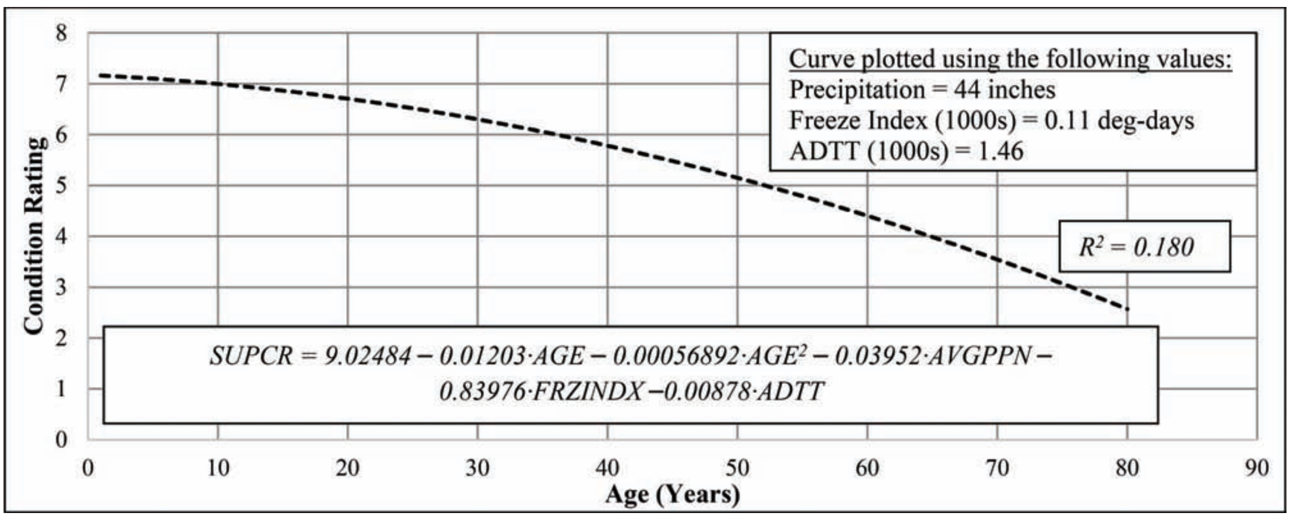

Figure B.47 Model for steel superstructure of bridges with prior repair—Southern districts, NHS.

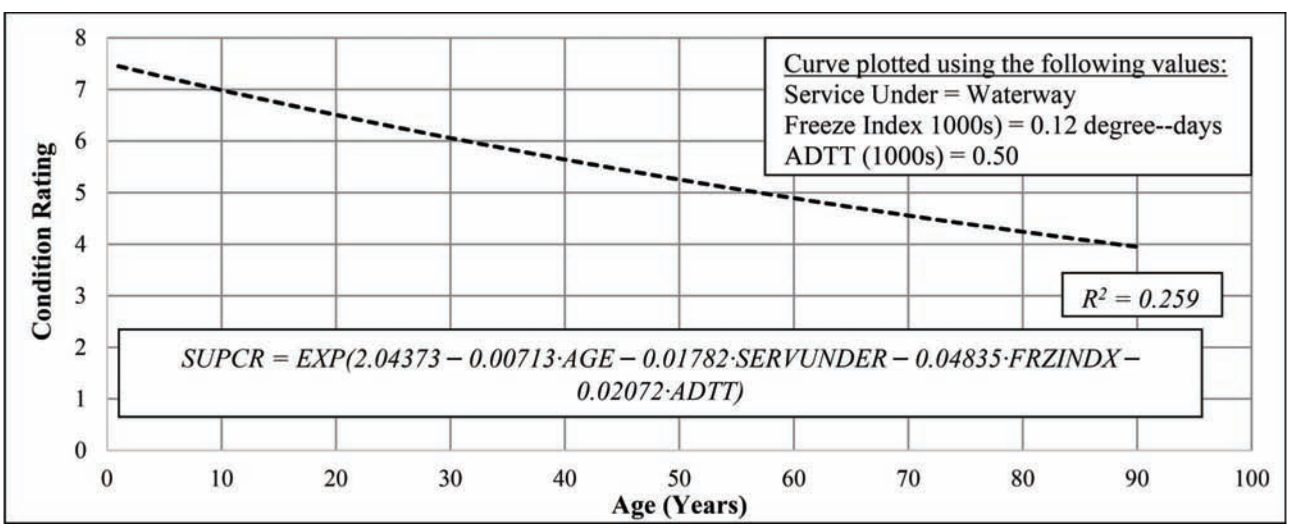

Figure B.48 Model for steel superstructure of bridges with prior repair—Southern districts, non-NHS.

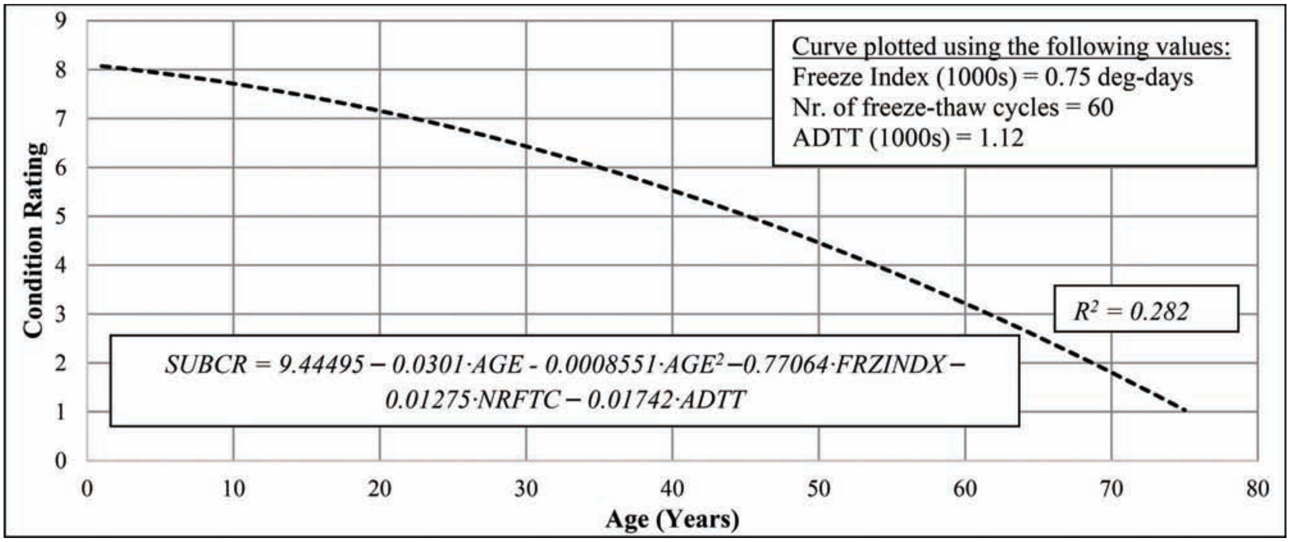

Figure B.49 Model for substructure of bridges without prior repair—Northern districts, NHS.

TABLE B.14
Variables for Substructure Deterioration Modeling

Variable	**Code**
Deck Condition Rating	*DCR*
Substructure Age (years)	*AGE*
Skew	*SKEW*
Type of Service Under Bridge	*SERVUNDER*
Number of Spans in Main Unit	*SPANNO*
Freeze Index (1000s of degree-days)	*FRZINDX*
Number of Freeze-Thaw Cycles	*NRFTC*
Average Daily Truck Traffic (1000s)	*ADTT*
Interstate (1 if located on an Interstate, 0 otherwise)	*INT*

TABLE B.15
Modeling Results for Substructure of Bridges without Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.44495	42.99	2.33	69.00	8.7113	106.46	2.23878	100.86	9.000	–	2.19417	518
Operational Factors												
ADTT(1000)	-0.01742	-4.30	–	–	-0.03907	-4.02	-0.01924	-4.67	-0.01417	-1.100	–	–
Design Factors												
Age	-0.0301	-6.85	-0.01013	-53.94	-0.144459	-12.60	-0.01255	-72.41	-0.00158	-42.35	-0.01037	-66.41
Age-Squared	-0.00086	-6.54	–	–	0.00472	7.48	–	–	–	–	–	–
Age-Cubed	–	–	–	–	-0.00007	-7.06	–	–	–	–	–	–
Skew	–	–	–	–	–	–	–	–	–	–	–	–
Service Under (1 if waterway, 0 other)	–	–	-0.02856	-6.52	-0.1744	-5.02	–	–	-0.05531	-2.98	-0.02081	-5.27
Number of Spans in Main Unit	–	–	–	–	–	–	–	–	–	–	–	–
Climate Factors												
Freeze Index (1000)	-0.77064	-3.93	-0.06893	-3.82	-0.27713	-2.07	–	–	-1.02942	-11.64	-0.04876	-4.32
Number of Freeze-Thaw Cycles	-0.01275	-3.44	-0.00192	-2.47	–	–	-0.00138	-3.69	-0.01298	-32.90	–	–
Model Fit Statistics												
Observations	2249		2771		1184		3079		1786		3512	
R-Squared	0.368		0.336		0.554		0.63		0.577		0.567	

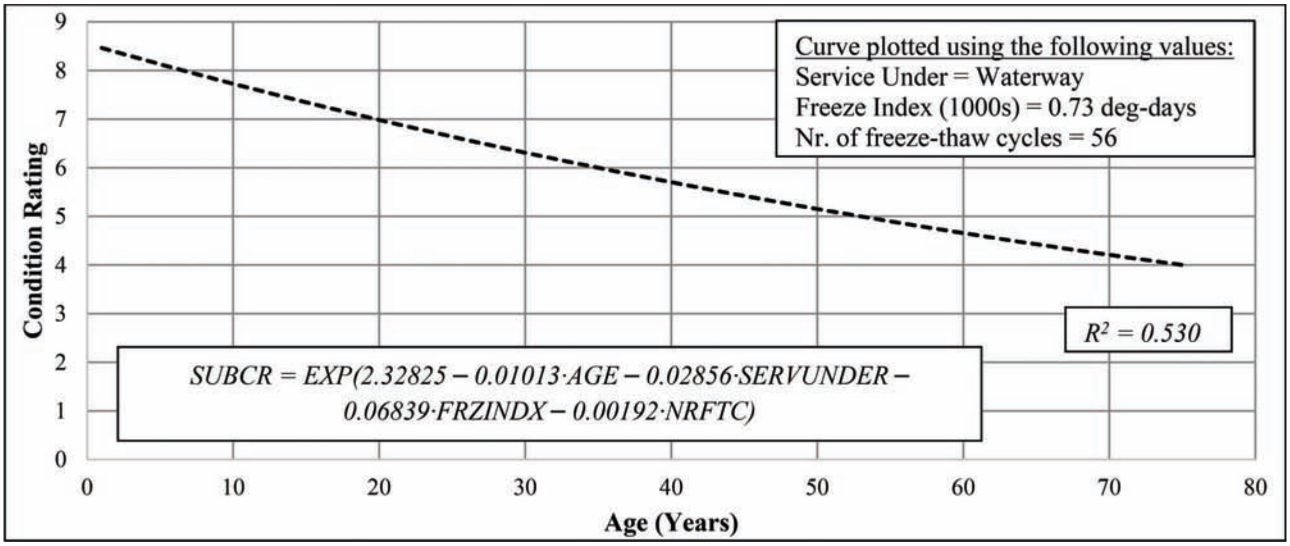

Figure B.50 Model for substructure of bridges without prior repair—Northern districts, non-NHS.

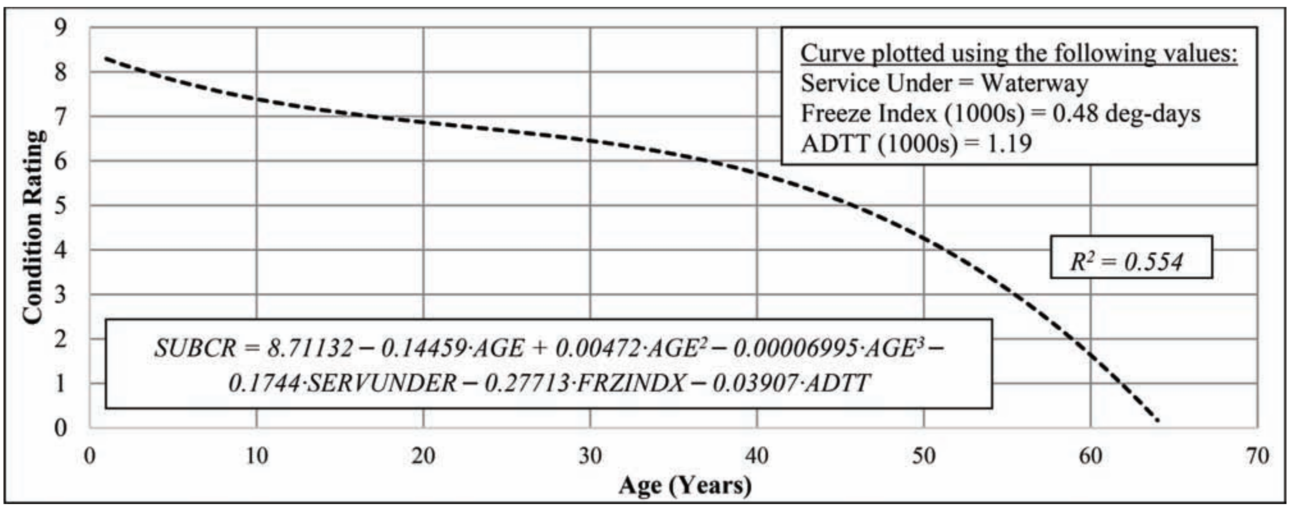

Figure B.51 Model for substructure of bridges without prior repair—Central districts, NHS.

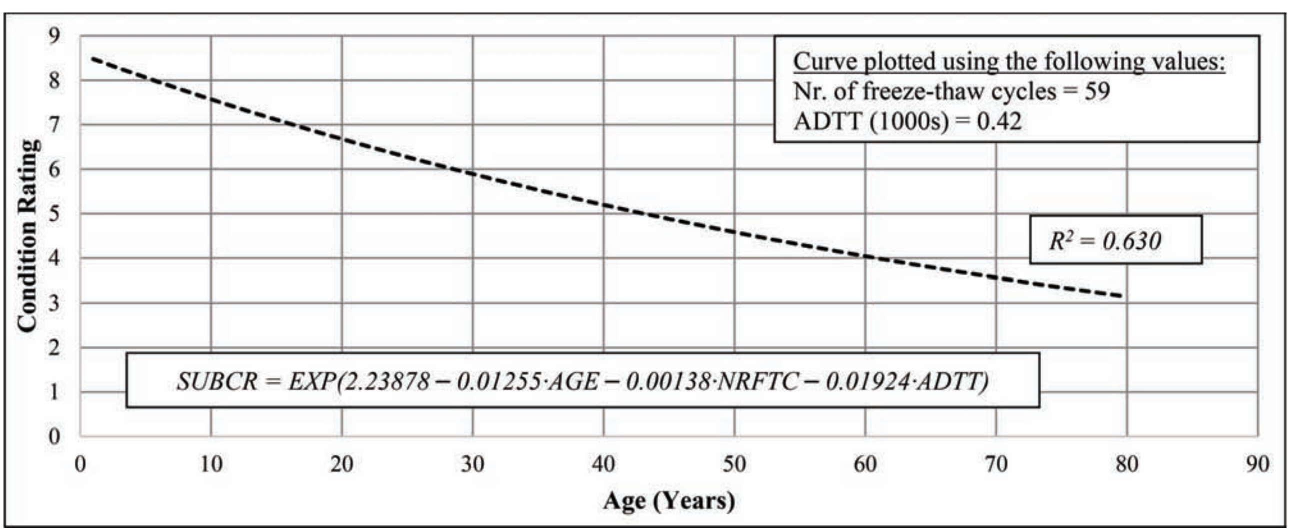

Figure B.52 Model for substructure of bridges without prior repair—Central districts, non-NHS.

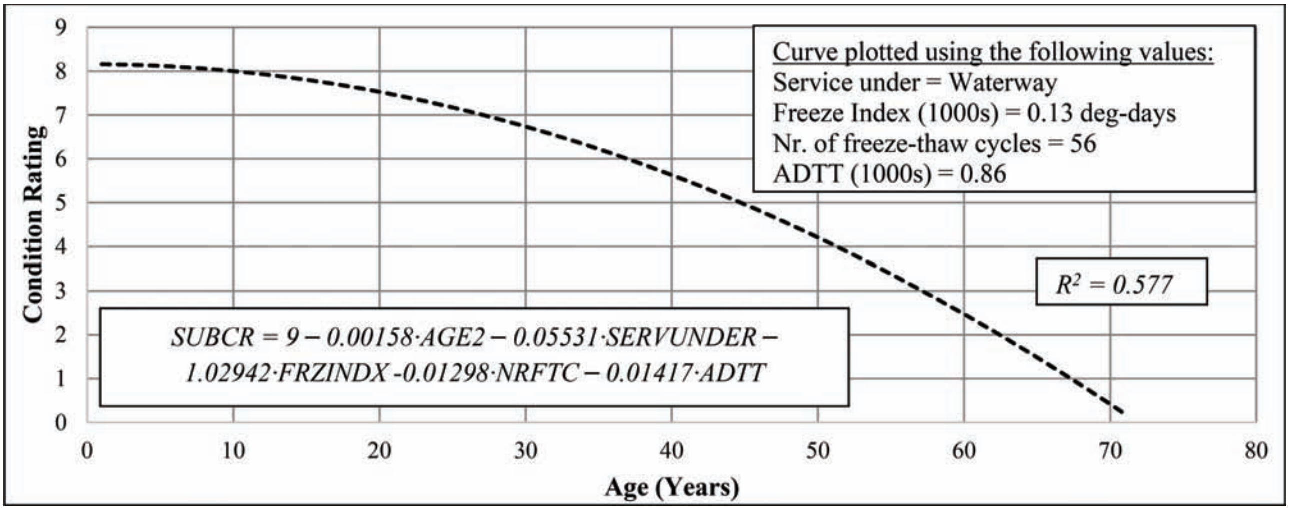

Figure B.53 Model for substructure of bridges without prior repair—Southern districts, NHS.

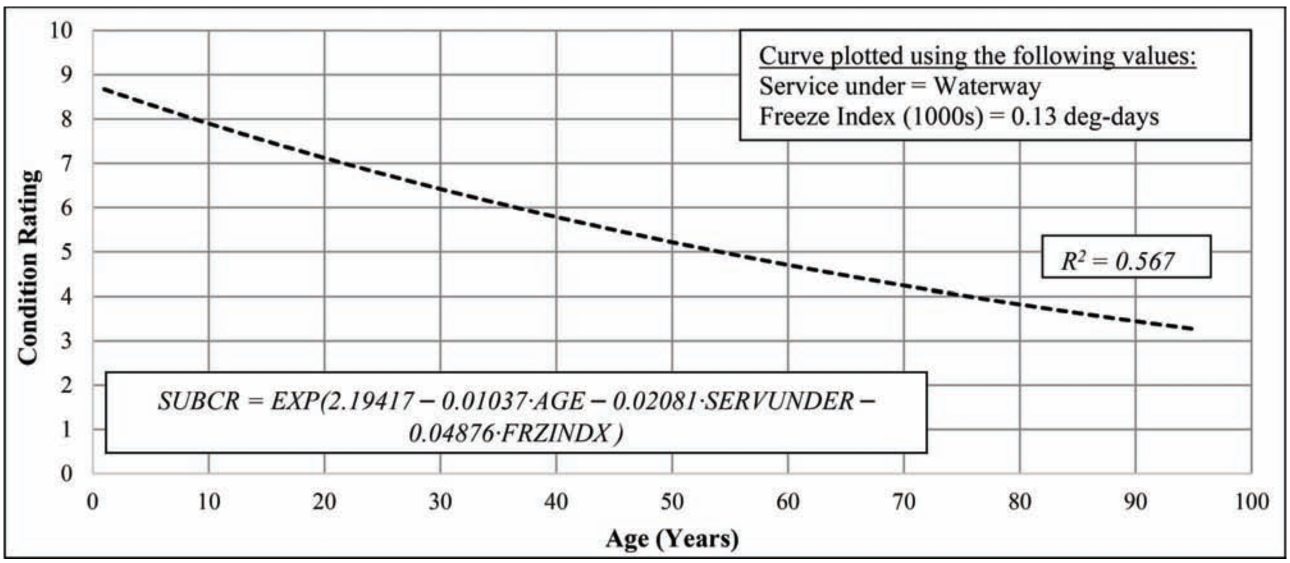

Figure B.54 Model for substructure of bridges without prior repair—Southern districts, non-NHS.

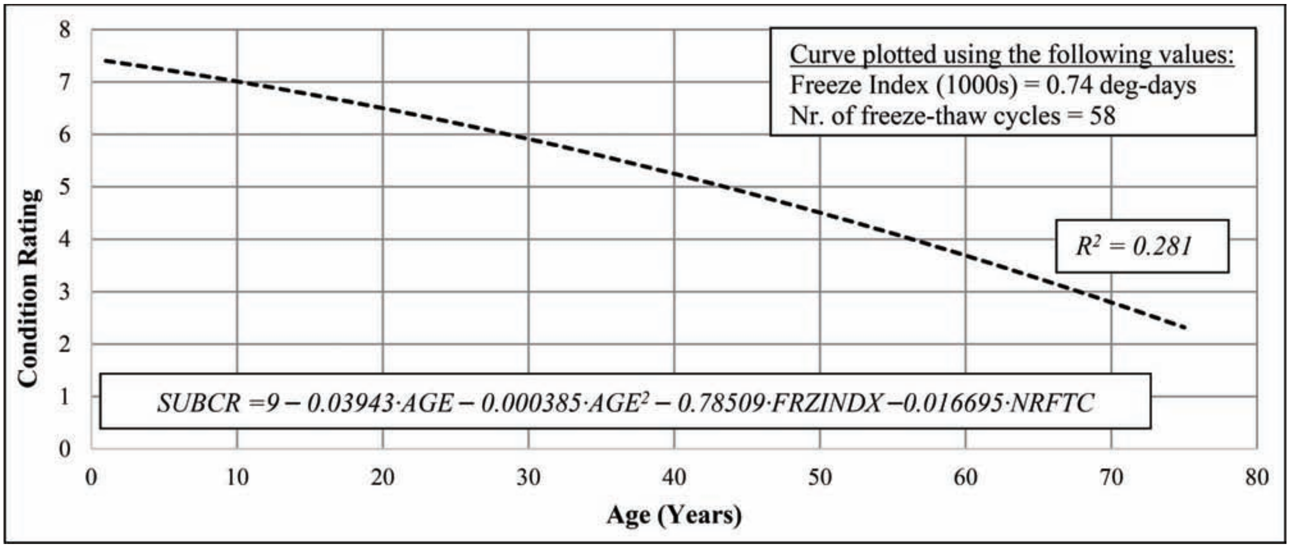

Figure B.55 Model for substructure of bridges with prior repair—Northern districts, NHS.

TABLE B.16
Modeling Results for Substructure of Bridges with Prior Repair

	North				Central				South			
	NHS		Non-NHS		NHS		Non-NHS		NHS		Non-NHS	
Variable	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**	**Parameter Estimate**	**t-stat**
Constant	9.000	–	2.07	185.08	9.000	–	2.19722	–	9.000	–	2.03824	573.4
Operational Factors												
ADTT(1000)	–	–	–	–			-0.00932	-4.81	-0.03017	-8.59	–	–
Design Factors												
Age	-0.03943	-16.70	-0.00844	-59.42	-0.01446	-9.21	-0.00894	-81.81	–	–	-0.008	-64.79
Age-Squared	-0.00039	-5.18	–	–	-0.00085	-15.97	–	–	-0.00104	-51.61	–	–
Age-Cubed	–	–	–	–	–	–	–	–	–	–	–	–
Interstate(1 if on Interstate, 0 otherwise)	–	–	–	–	-0.02948	-3.26	–	–	–	–	–	–
Skew	–	–	–	–	–	–	–	–	–	–	–	–
Service Under (1 if waterway, 0 other)	–	–	-0.0142	-5.31	-0.0839	-11.59	-0.03062	-15.61	-0.04217	-3.94	-0.02444	-7.46
Number of Spans in Main Unit	–	–	–	–	–	–	–	–	–	–	–	–
Climate Factors												
Freeze Index (1000)	-0.78509	-11.54	-0.06222	-4.35	–	–	–	–	-0.09126	-2.37	-0.0319	-3.19
Number of Freeze-Thaw Cycles	-0.01695	-18.90	–	–	-0.03028	-13.15	-0.00264	-62.61	-0.03192	-15.82	–	–
Model Fit Statistics												
Observations	8391		6302		14541		8922		7928		7899	
R-Squared	0.281		0.366		0.284		0.4364		0.256		0.372	

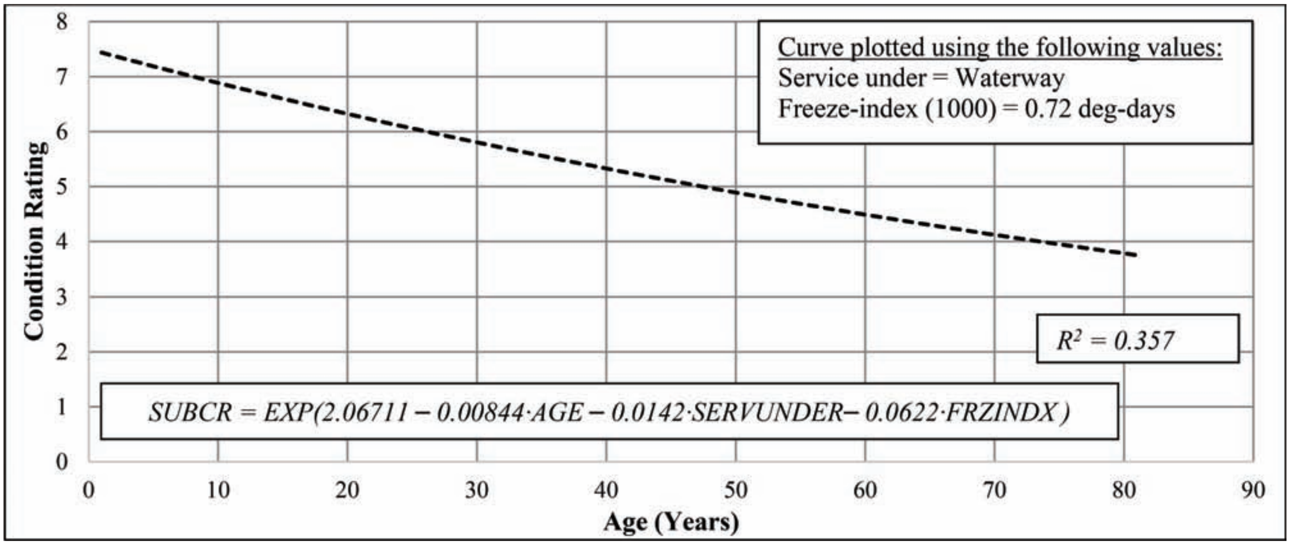

Figure B.56 Model for substructure of bridges with prior repair—Northern districts, non-NHS.

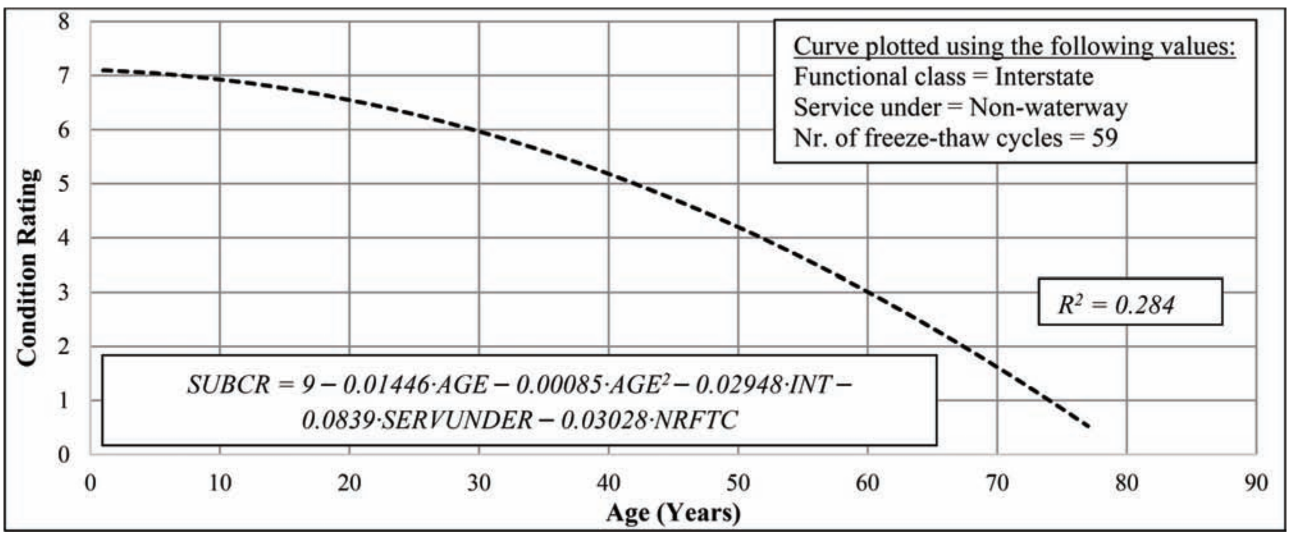

Figure B.57 Model for substructure of bridges with prior repair—Central districts, NHS.

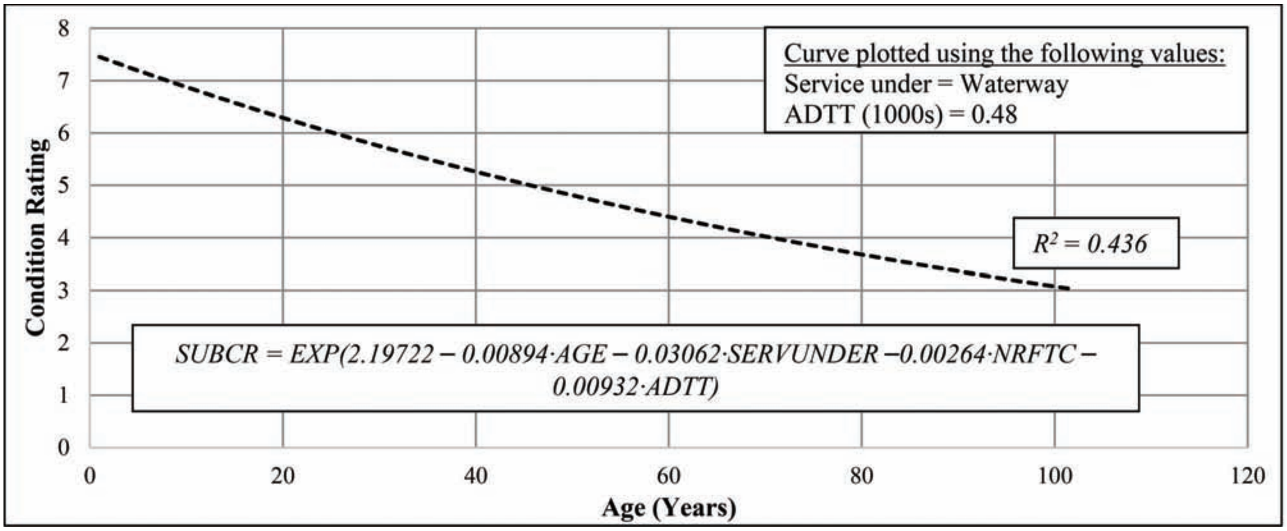

Figure B.58 Model for substructure of bridges with prior repair—Central districts, non-NHS.

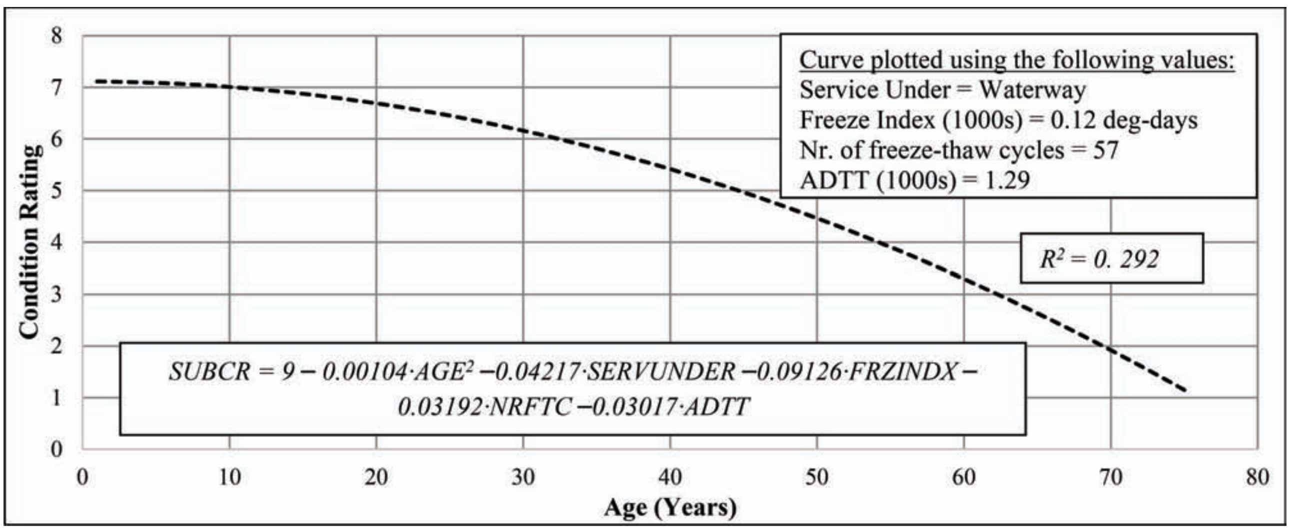

Figure B.59 Model for substructure of bridges with prior repair—Southern districts, NHS.

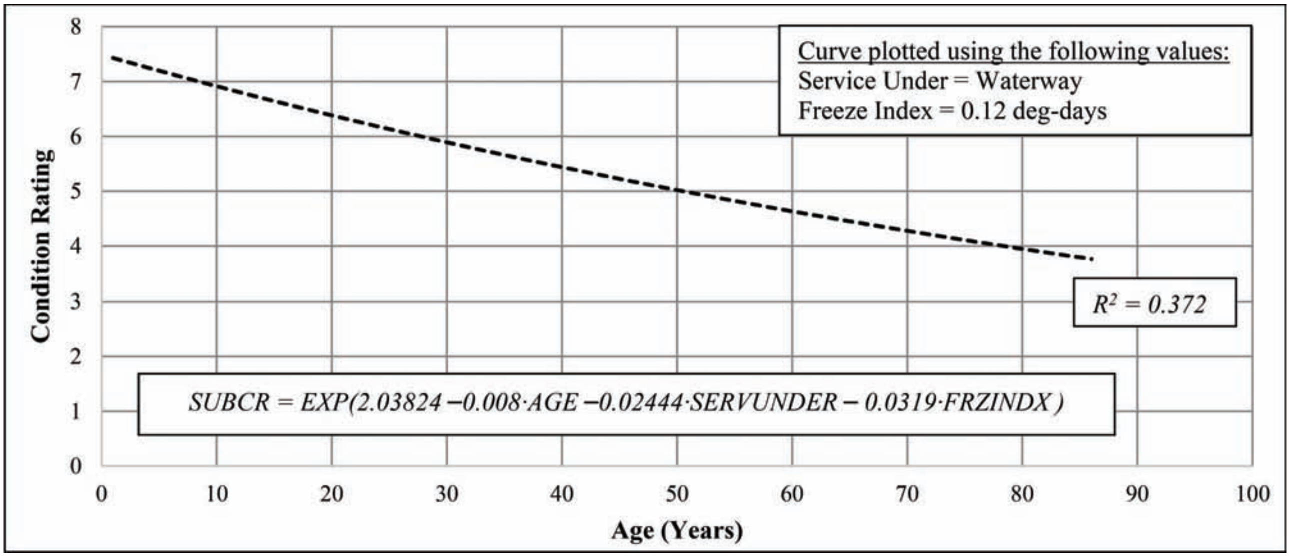

Figure B.60 Model for substructure of bridges with prior repair—Southern districts, non-NHS.

APPENDIX C: ESTABLISHMENT OF AGE RESTRICTIONS FOR DATA FILTERING

C.1 Calculation of Minimum Age Restrictions

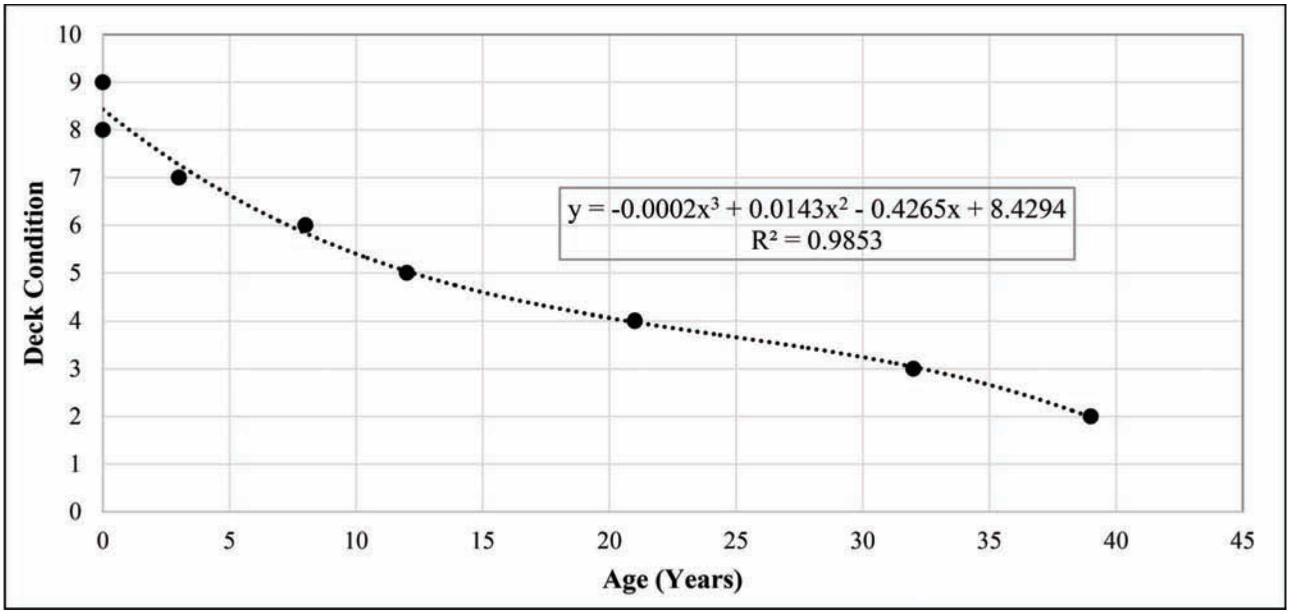

Figure C.1 Deck condition versus minimum age.

TABLE C.1
Calculation of Deck Minimum Age Restrictions

Condition Rating	Minimum Age	Predicted Minimum Age	Approximate Minimum Age
9	0		0
8	0	1.01	0
7	3	3.37	0
6	8	5.71	5
5	12	8.02	10
4	21	10.23	20
3	32		30
2	39		40
1			50

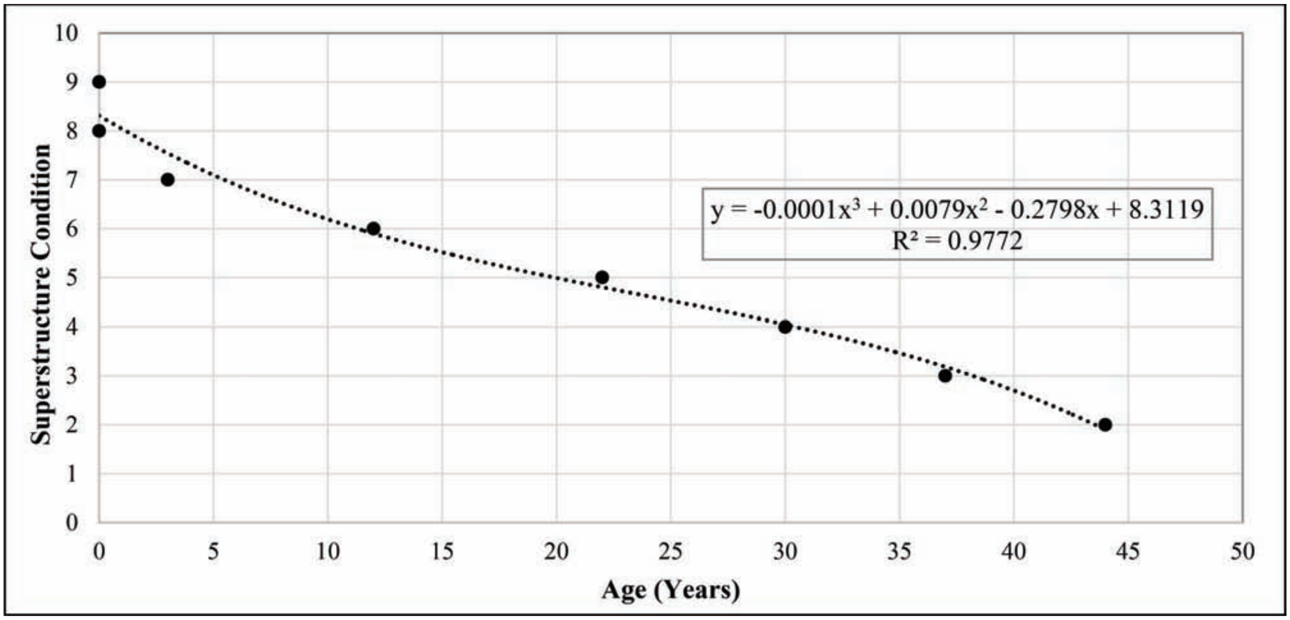

Figure C.2 Superstructure condition versus minimum age.

TABLE C.2
Calculation of Superstructure Minimum Age Restrictions

Condition Rating	Minimum Age	Predicted Minimum Age	Approximate Minimum Age
9	0	0	0
8	0	1.15	0
7	3	5.47	5
6	12	11.41	10
5	22	20.92	20
4	30	34.01	30
3	37	42.59	40
2	44	48.11	50
1		52.23	60

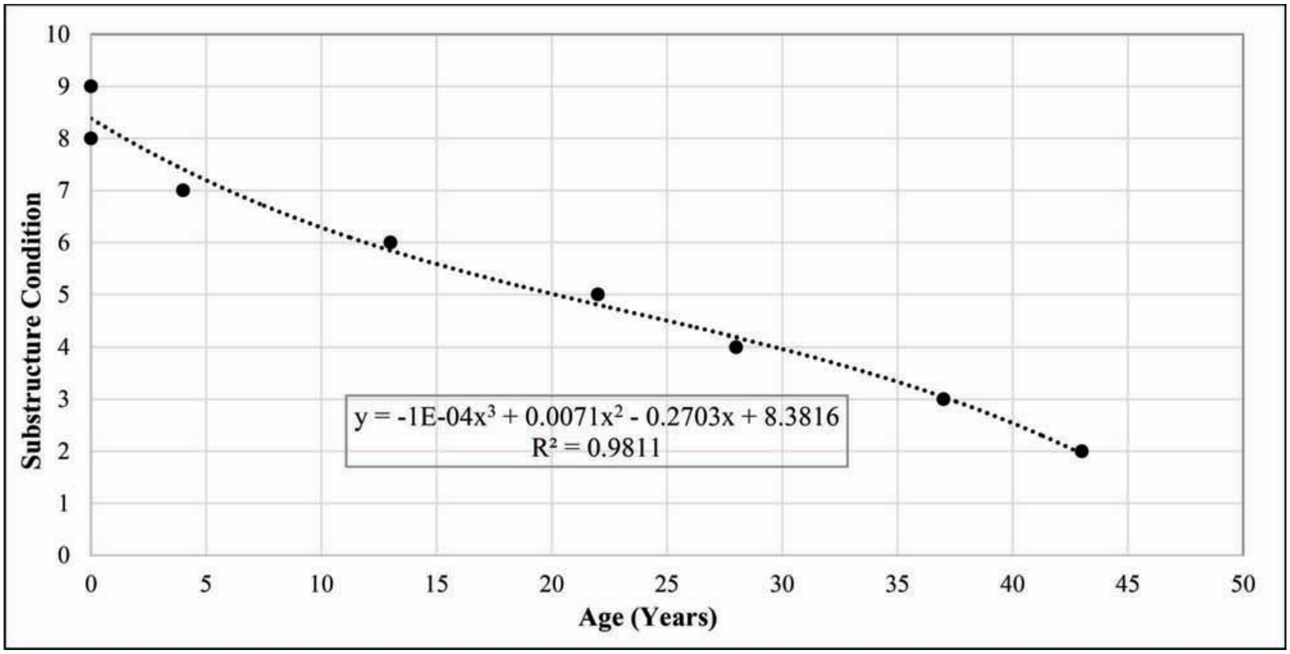

Figure C.3 Substructure condition rating versus minimum age.

TABLE C.3
Calculation of Substructure Minimum Age Restrictions

Condition Rating	Minimum Age	Predicted Minimum Age	Approximate Minimum Age
9	0		0
8	0	1.46	0
7	4	5.96	5
6	13	11.90	10
5	22	20.13	20
4	28	29.65	30
3	37	37.21	40
2	43	42.69	50
1		46.91	

C.2 Calculation of Maximum Age Restrictions

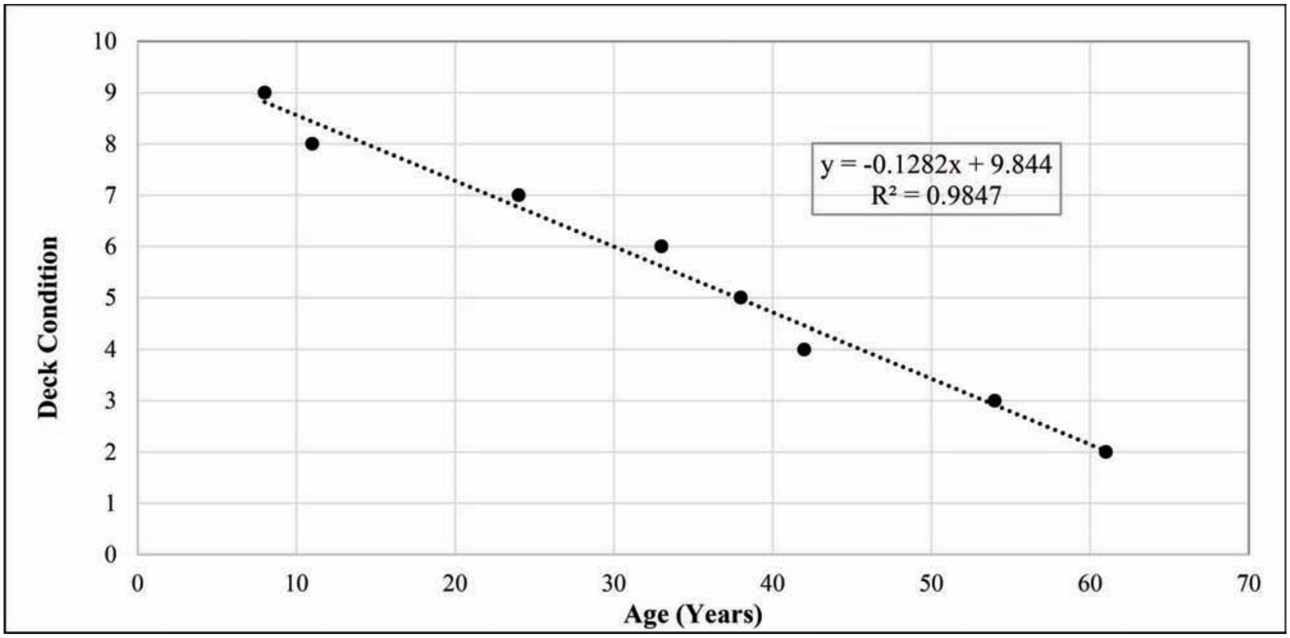

Figure C.4 Deck condition versus maximum age.

TABLE C.4
Calculation of Deck Maximum Age Restrictions

Condition Rating	Maximum Age	Predicted Maximum Age	Approximate Maximum Age
9	8	6.58	10
8	11	14.58	15
7	24	22.18	25
6	33	29.98	30
5	38	36.78	35
4	42	45.59	45
3	54	53.39	50
2	61	61.19	60
1			70

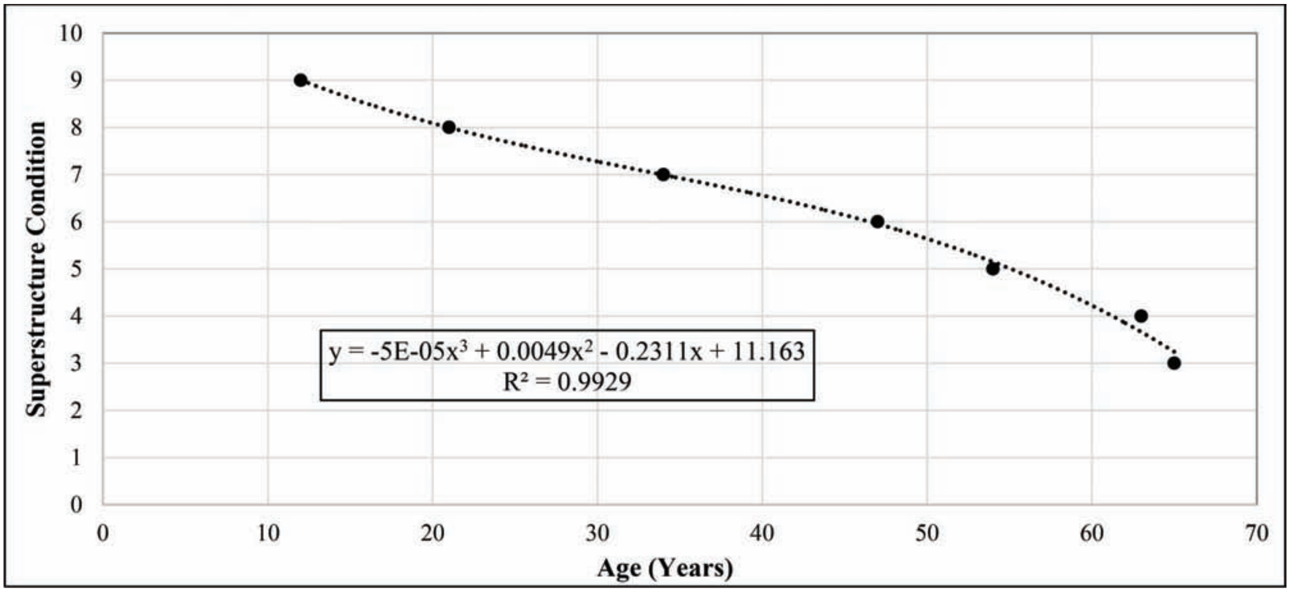

Figure C.5 Superstructure condition versus maximum age.

TABLE C.5
Calculation of Superstructure Maximum Age Restrictions

Condition Rating	Maximum Age	Predicted Maximum Age	Approximate Maximum Age
9	12	12.07	10
8	21	21.08	20
7	34	31.96	30
6	43	46.35	45
5	54	54.69	50
4	61	60.73	60
3	63	65.49	65
2		69.44	70
1		72.85	75

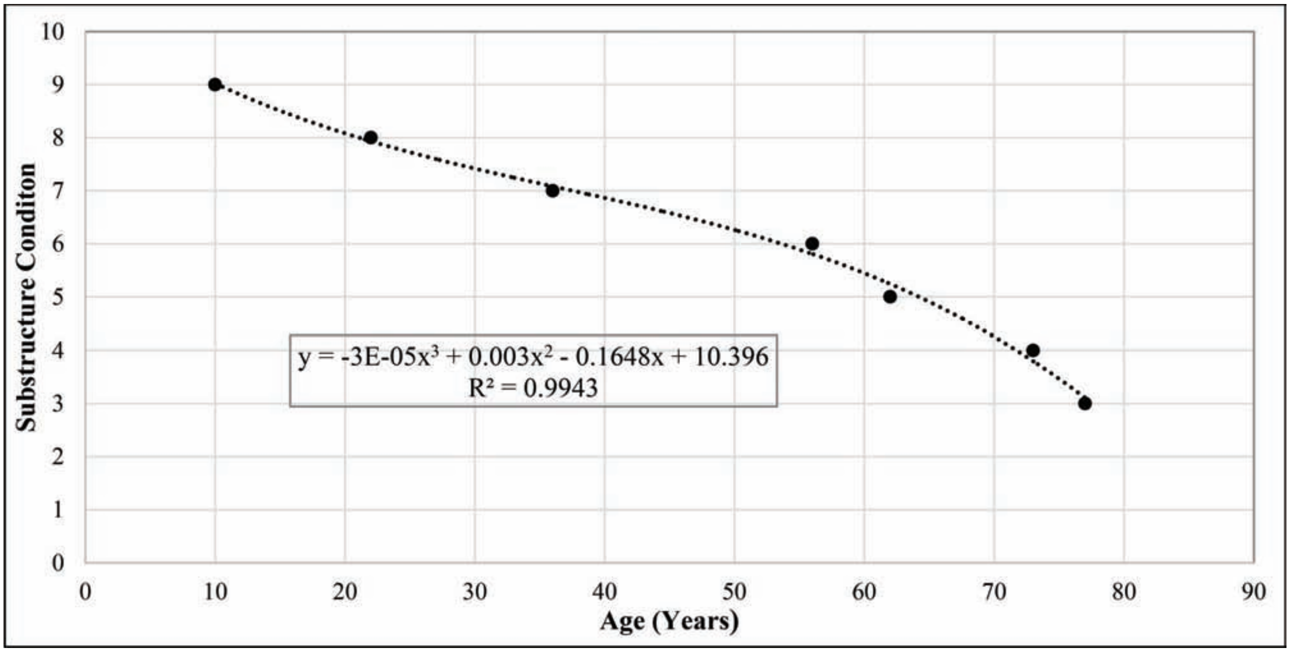

Figure C.6 Substructure condition rating versus maximum age.

TABLE C.6
Calculation of Substructure Maximum Age Restrictions

Condition Rating	Maximum Age	Predicted Maximum Age	Approximate Maximum Age
9	10	10.16	10
8	22	20.75	20
7	31	35.26	35
6	39	48.93	50
5	52	58.63	60
4	60	65.76	65
3	68	71.41	70
2	70	76.13	80
1		80.19	90

APPENDIX D: COUNTY CLIMATE TABLE

WEATHER ID	COUNTY	AVG PPN	WET DAYS	AVG TEMP	AVG WINTEMP	AVG SUMTEMP	HOT DAYS	WARM DAYS	COL DAYS	FRZ NDX	NR FTT	NR FTC	SF FZINT	MAX TEMP	MIN TEMP	FRZ MOD	WSL
1	Adams	35.47	128	50.7	27.1	72.0	16	81	86	612	104	52	174.02	53.05	46.29	2331	0.72
2	Allen	34.58	128	49.9	25.8	72.1	16	77	92	723	114	57	174.02	53.05	46.29	2374	0.78
3	Bartholomew	41.00	124	52.3	29.8	72.9	18	87	68	263	110	55	177.00	54.77	48.33	2026	0.63
4	Benton	38.83	134	50.2	25.2	71.9	13	81	80	557	124	62	171.89	52.30	46.58	2016	0.77
5	Blackford	37.31	116	48.9	25.4	70.2	15	59	91	593	114	57	172.76	53.04	47.75	2311	0.75
6	Boone	41.00	124	51.7	28.2	72.6	18	85	75	511	110	55	177.00	54.77	48.33	2115	0.73
7	Brown	47.95	113	52.0	29.4	72.4	37	83	70	260	122	61	173.53	57.82	50.97	2058	0.70
8	Carroll	37.03	113	51.3	27.6	72.3	16	82	78	570	108	54	174.72	53.63	47.21	2153	0.72
9	Cass	37.59	113	49.8	25.6	71.3	16	75	92	661	110	55	174.72	53.63	47.21	2355	0.77
10	Clark	45.84	124	56.0	34.6	75.5	35	106	25	30	120	60	176.92	57.04	49.43	865	0.59
11	Clay	43.01	106	52.1	28.7	73.1	31	88	72	326	122	61	175.70	55.53	48.43	2066	0.70
12	Clinton	39.09	124	51.6	27.9	72.5	18	85	78	520	102	51	177.00	54.77	48.33	2176	0.70
13	Crawford	47.95	113	54.5	31.2	74.4	37	98	48	0	124	62	173.53	57.82	50.97	1498	0.61
14	Daviess	43.99	95	55.7	33.3	75.7	49	109	41	115	104	52	188.03	57.80	51.22	1365	0.58
15	Dearborn	44.97	124	50.8	28.9	73.2	35	89	60	113	112	56	176.92	57.04	49.43	1734	0.60
16	Decatur	41.87	124	51.6	28.7	72.0	18	81	73	365	102	51	177.00	54.77	48.33	2095	0.66
17	Dekalb	38.45	128	48.4	24.6	70.2	16	60	97	841	110	55	174.02	53.05	46.29	2386	0.84
18	Delaware	37.63	116	50.8	26.7	72.4	15	82	87	566	130	65	172.76	53.04	47.75	2323	0.78
19	Dubois	45.44	95	53.4	30.9	73.5	49	89	61	53	116	58	188.03	57.80	51.22	1885	0.59
20	Elkhart	35.30	113	49.6	25.9	71.0	16	69	92	829	116	58	174.72	53.63	47.21	2383	0.83
21	Fayette	38.16	116	50.6	27.3	71.6	15	76	80	408	114	57	172.76	53.04	47.75	2184	0.68
22	Floyd	47.95	113	55.8	34.2	75.5	37	106	30	0	112	56	173.53	57.82	50.97	1026	0.58
23	Fountain	38.97	106	50.9	26.5	72.4	31	81	82	427	114	57	175.70	55.53	48.43	2173	0.69
24	Franklin	41.79	124	51.3	29.0	71.9	35	78	74	396	120	60	176.92	57.04	49.43	2146	0.71
25	Fulton	37.66	113	48.7	24.6	70.6	16	64	94	700	114	57	174.72	53.63	47.21	2312	0.79
26	Gibson	45.99	95	54.7	32.0	75.3	49	105	52	38	116	58	188.03	57.80	51.22	1664	0.59
27	Grant	37.56	124	49.8	26.0	71.3	18	72	88	624	118	59	177.00	54.77	48.33	2288	0.77
28	Greene	43.65	95	52.9	29.8	73.7	49	92	67	183	106	53	188.03	57.80	51.22	1997	0.61
29	Hamilton	37.27	124	51.2	27.8	72.1	18	82	76	556	108	54	177.00	54.77	48.33	2113	0.72
30	Hancock	42.40	124	51.3	27.5	72.8	18	87	80	531	114	57	177.00	54.77	48.33	2200	0.76
31	Harrison	47.95	113	54.7	32.5	73.5	37	101	45	0	102	51	173.53	57.82	50.97	1463	0.55
32	Hendricks	40.05	124	52.1	28.3	73.4	18	93	73	443	126	63	177.00	54.77	48.33	2066	0.74

(Continued)

COUNTY CLIMATE TABLE
(Continued)

WEATHER ID	COUNTY	AVG PPN	WET DAYS	AVG TEMP	AVG WINTEMP	AVG SUMTEMP	HOT DAYS	WARM DAYS	COL DAYS	FRZ NDX	NR FTT	NR FTC	SF FZINT	MAX TEMP	MIN TEMP	FRZ MOD	WSL
33	Henry	40.63	116	49.9	26.8	71.2	15	70	85	540	112	56	172.76	53.04	47.75	2278	0.74
34	Howard	39.89	124	49.4	25.2	71.1	18	69	91	615	118	59	177.00	54.77	48.33	2293	0.78
35	Huntington	38.45	128	49.1	25.3	70.6	16	64	91	697	124	62	174.02	53.05	46.29	2302	0.82
36	Jackson	42.51	113	52.3	30.1	72.5	37	84	66	191	120	60	173.53	57.82	50.97	1987	0.64
37	Jasper	36.72	134	49.1	24.1	71.2	13	75	91	618	102	51	171.89	52.30	46.58	2193	0.72
38	Jay	36.90	116	49.3	25.9	70.6	15	65	89	589	118	59	172.76	53.04	47.75	2305	0.75
39	Jefferson	43.85	124	54.6	32.8	74.4	35	99	46	85	116	58	176.92	57.04	49.43	1509	0.59
40	Jennings	43.44	124	54.3	32.5	73.7	35	96	48	174	116	58	176.92	57.04	49.43	1560	0.63
41	Johnson	40.05	124	51.5	28.4	72.5	18	83	75	422	116	58	177.00	54.77	48.33	2130	0.70
42	Knox	41.93	95	53.3	30.1	74.2	49	96	66	98	112	56	188.03	57.80	51.22	1987	0.58
43	Koscuisko	34.88	113	48.6	24.9	70.0	16	57	93	791	112	56	174.72	53.63	47.21	2316	0.81
44	Lagrange	36.33	128	47.3	23.3	67.4	16	50	102	813	114	57	174.02	53.05	46.29	2377	0.83
45	Lake	38.44	134	49.7	26.8	72.1	13	49	84	783	126	63	171.89	52.30	46.58	2251	0.86
46	LaPorte	40.03	134	49.6	25.0	71.0	13	67	93	800	98	49	171.89	52.30	46.58	2325	0.81
47	Lawrence	43.96	113	52.2	29.6	72.7	37	86	68	173	120	60	173.53	57.82	50.97	2013	0.64
48	Madison	38.28	124	50.2	27.0	71.2	18	76	78	760	126	63	177.00	54.77	48.33	2106	0.85
49	Marion	40.32	124	51.7	28.2	73.0	18	91	73	519	118	59	177.00	54.77	48.33	2059	0.75
50	Marshall	38.52	113	50.3	26.2	71.9	16	78	87	763	112	56	174.72	53.63	47.21	2279	0.82
51	Martin	46.68	95	54.3	31.9	74.3	49	106	44	135	122	61	188.03	57.80	51.22	1404	0.65
52	Miami	41.06	113	49.4	25.4	70.7	16	69	92	681	118	59	174.72	53.63	47.21	2337	0.82
53	Monroe	43.14	113	53.3	30.3	73.8	37	94	64	154	106	53	173.53	57.82	50.97	1939	0.59
54	Montgomery	38.97	106	51.3	27.4	72.5	31	83	79	462	142	71	175.70	55.53	48.43	2165	0.78
55	Morgan	40.87	124	51.6	28.7	72.3	18	81	73	400	122	61	177.00	54.77	48.33	2095	0.71
56	Newton	37.43	134	49.9	24.6	72.2	13	81	92	611	126	63	171.89	52.30	46.58	2263	0.79
57	Noble	38.45	128	47.9	24.1	68.8	16	55	98	826	114	57	174.02	53.05	46.29	2362	0.85
58	Ohio	44.97	124	50.8	28.9	73.2	35	89	60	93	112	56	176.92	57.04	49.43	1734	0.59
59	Orange	47.28	113	53.4	31.4	73.2	37	90	57	87	122	61	173.53	57.82	50.97	1790	0.63
60	Owen	44.32	106	51.7	28.8	72.6	31	84	72	233	130	65	175.70	55.53	48.43	2074	0.69
61	Parke	43.31	106	53.1	29.5	73.8	31	90	68	403	114	57	175.70	55.53	48.43	2006	0.71
62	Perry	47.53	113	55.5	33.5	75.5	37	106	39	0	98	49	173.53	57.82	50.97	1307	0.54
63	Pike	44.79	95	54.3	31.5	75.2	49	102	57	54	116	58	188.03	57.80	51.22	1796	0.59
64	Porter	38.21	134	49.6	25.7	70.9	13	79	86	764	104	52	171.89	52.30	46.58	2210	0.80
65	Posey	43.78	95	55.5	32.8	76.0	49	109	46	0	112	56	188.03	57.80	51.22	1509	0.55

(Continued)

COUNTY CLIMATE TABLE

(Continued)

WEATHER ID	COUNTY	AVG PPN	WET DAYS	AVG TEMP	AVG WINTEMP	AVG SUMTEMP	HOT DAYS	WARM DAYS	COL DAYS	FRZ NDX	NR FTT	NR FTC	SF FZINT	MAX TEMP	MIN TEMP	FRZ MOD	WSL
66	Pulaski	36.94	134	49.8	24.8	70.8	13	68	95	649	110	55	171.89	52.30	46.58	2356	0.76
67	Putnam	43.63	106	52.4	28.4	73.7	31	94	74	404	134	67	175.70	55.53	48.43	2102	0.76
68	Randolph	37.06	116	49.6	25.8	70.6	15	64	92	559	130	65	172.76	53.04	47.75	2374	0.77
69	Ripley	44.97	124	54.3	32.5	73.7	35	96	48	138	116	58	176.92	57.04	49.43	1560	0.62
70	Rush	41.89	124	50.6	27.3	71.6	18	76	80	414	114	57	177.00	54.77	48.33	2184	0.71
71	St Joseph	39.14	113	49.5	24.5	70.4	16	50	106	823	114	57	174.72	53.63	47.21	2597	0.85
72	Scott	43.99	124	53.8	31.5	74.1	35	96	56	79	120	60	176.92	57.04	49.43	1764	0.60
73	Shelby	39.87	124	51.5	28.1	72.6	18	84	77	451	114	57	177.00	54.77	48.33	2164	0.71
74	Spencer	45.46	95	56.1	34.6	75.8	49	107	25	0	104	52	188.03	57.80	51.22	865	0.54
75	Starke	38.83	134	49.3	25.6	71.5	13	73	90	725	106	53	171.89	52.30	46.58	2304	0.79
76	Steuben	35.53	128	47.3	23.4	69.3	16	50	103	889	114	57	174.02	53.05	46.29	2410	0.85
77	Sullivan	45.56	95	52.9	29.4	73.9	49	94	69	161	114	57	188.03	57.80	51.22	2029	0.63
78	Switzerland	43.26	124	50.8	28.9	73.2	35	89	60	83	112	56	176.92	57.04	49.43	1734	0.58
79	Tippecanoe	36.01	106	50.4	25.7	71.6	31	80	68	536	106	53	175.70	55.53	48.43	1748	0.70
80	Tipton	45.56	124	50.9	27.5	71.9	18	81	78	643	114	57	177.00	54.77	48.33	2145	0.82
81	Union	41.20	116	50.6	27.3	71.6	15	76	80	407	114	57	172.76	53.04	47.75	2184	0.70
82	Vanderburg	44.44	95	56.6	35.3	77.2	49	117	12	0	110	55	188.03	57.80	51.22	424	0.55
83	Vermillion	39.36	106	50.9	26.5	72.4	31	81	82	386	114	57	175.70	55.53	48.43	2173	0.68
84	Vigo	41.19	106	52.4	28.6	73.6	31	92	71	212	114	57	175.70	55.53	48.43	2031	0.62
85	Wabas h	38.46	113	48.9	25.1	70.3	16	61	92	714	126	63	174.72	53.63	47.21	2309	0.83
86	Warren	38.97	106	50.4	25.7	71.6	31	80	68	527	106	53	175.70	55.53	48.43	1748	0.71
87	Warrick	44.55	95	56.7	35.9	76.5	49	112	18	0	106	53	188.03	57.80	51.22	646	0.54
88	Washington	45.42	113	54.4	32.7	74.1	37	96	47	53	122	61	173.53	57.82	50.97	1537	0.61
89	Wayne	41.07	116	50.2	26.8	70.7	15	66	88	533	108	54	172.76	53.04	47.75	2358	0.73
90	Wells	38.45	128	49.9	26.2	71.3	16	73	89	643	122	61	174.02	53.05	46.29	2332	0.79
91	White	37.17	134	49.8	25.3	71.2	13	74	82	571	108	54	171.89	52.30	46.58	2075	0.72
92	Whitley	37.50	128	48.6	24.9	70.1	16	59	94	757	114	57	174.02	53.05	46.29	2341	0.81
MAXIMUM	47.95	134.00	56.70	35.90	77.20	49.00	117.00	106.00	889.00	142.00	71.00	188.03	57.82	51.22	2597.00	0.86	
MINIMUM	34.58	95.00	47.30	23.30	67.40	13.00	49.00	12.00	0.00	98.00	49.00	171.89	52.30	46.29	423.60	0.54	
AVERAGE	41.03	116.66	51.50	28.22	72.47	26.04	82.23	72.87	418.53	114.80	57.40	176.53	55.13	48.58	1998.86	0.70	
STANDARD	3.57	11.60	2.24	3.02	1.76	12.34	15.32	19.95	272.04	7.98	3.99	4.78	1.99	1.67	411.38	0.09	

About the Joint Transportation Research Program (JTRP)

On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1—evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,500 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at: http://docs.lib.purdue.edu/jtrp

Further information about JTRP and its current research program is available at: http://www.purdue.edu/jtrp

About This Report

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The recommended citation for this publication is:

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