Journal of Ethiopian Association of Civil Engineers (EACE Journal)
Vol.14, Issue 1 (2023)
www.eacecivil.org | ISSN 3005-6446 (Print)

Predicting Remaining Service Life of Reinforced Concrete bridge Superstructures by using Linear Regression-Based Deterioration Models

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Abstract

Aging infrastructure poses major maintenance challenges worldwide. In developed nations like the United States and Europe, bridges have often surpassed their intended design lives, resulting in significant structural deficiencies and staggering repair costs. Conversely, in developing countries such as Ethiopia, newer infrastructure also struggles with effective maintenance. Addressing these issues requires robust bridge management systems. This study developed deterministic polynomial regression models linking reinforced concrete bridge superstructure ages to condition ratings within the United States' National Bridge Inventory database. By creating separate deterioration curves for categories of Average Daily Truck Traffic (ADTT) volumes and span lengths, the models indirectly accounted for these influential factors, exhibiting strong correlations from 0.64 to 0.845 in R-squared values. Furthermore, applying the deterioration models allowed computation of remaining service life for bridges. On average, the remaining useful life was found to be 60 years, offering insight into maintenance prioritization. Overall, the proposed regression technique demonstrates potential for effective bridge management planning both internationally and domestically.

Key words: Infrastructure, Structural deficiencies, Bridges, ADTT, Deterioration models

1. Introduction

1.1 Background

In developed nations, key infrastructures such as highways, railways, bridges, and public buildings were primarily erected in the last century. Now, these crucial structures require extensive maintenance, repair, or rehabilitation (MR&R) due to aging. Among them, highway bridges play a pivotal role in facilitating smooth goods and services transportation. In the United States, where the bridge network exceeds 617,000, a pressing issue emerges: roughly 42% have surpassed the 50-year mark, and 7.5% exhibit structural deficiencies, demanding urgent attention with an estimated repair cost of $125 billion (ASCE, 2021). Similarly, in Europe, bridges constructed after 1945 were designed with lifespans of 50 to 100 years, implying many have reached their service limits (Gkoumas, 2019) posing critical safety concerns. Conversely, developing countries like Ethiopia generally boast lower percentages of structurally deficient bridges compared to the US and Europe, as much of their infrastructure was constructed within the past three decades. However, they grapple with challenging maintenance, repair, and rehabilitation tasks for their aging bridges as well.

To address the challenges faced by Department of Transportations (DOT) in allocating limited resources to aging highway bridges, implementing a bridge management system is crucial. Such a system enables DOT agencies to assess current and future bridge conditions, make informed decisions regarding the allocation of funds MR&R options across a diverse range of bridge structures (AASHTO, 2018).

In an effort to implement a data-centric approach to bridge management within the US, the establishment of a National Bridge Inventory system was initiated, mandated by Code of Federal Regulations, necessitating states to maintain comprehensive records of all bridge structures. Currently, the national inventory encompasses a comprehensive bridge inventory data spanning from 1992 to 2023. The Federal Highway Administration's (FHMA) oversight spurred the creation of computerized Bridge Management System (BMS) software, Bridget and Pontis, in 1998. Subsequently, Pontis was absorbed by AASHTO by 2009, leading to the evolution of AASHTOware as the upgraded iteration of BMS software (HURT & SCHROCK, 2016).



Figure 1 Deteriorated Plain Concrete ARC Bridge Along Awash-Mile Road

A crucial element within any contemporary bridge management system involves a deterioration modeling of bridge components, typically reliant on condition rating values. This facet holds immense importance in forecasting necessary maintenance actions in the future. Accurate deterioration modeling plays a pivotal role in conducting effective Bridge Life Cycle Cost Analysis (BLCCA). (HURT & SCHROCK, 2016).

Deterioration models commonly use inspection data from the National Bridge Inventory (NBI) in the United States. This database contains various bridge details like deck width, type, superstructure and substructure specifications, span numbers, Average Daily Truck Traffic (ADTT), Average Daily Traffic (ADT), structural

condition ratings (on a scale of 0-9), and Appraisal ratings (also on a 0-9 scale). A detailed breakdown of structural condition ratings can be found in Table 1. Visual inspections occur yearly or every two years and these records are pivotal in guiding MR&R strategies for the bridge inventory (FHWA-PD-96-001, 1995).

Precise estimation of a bridge's remaining service life necessitates the application of deterioration models specifically tailored to the bridge type. These models can be broadly categorized as deterministic or stochastic. Deterministic models presume a specific trend in the deterioration process, constructed through regression analysis of condition data. They rely on empirical relationships between variables, using linear or non-linear regression models to evaluate the influence of independent variables on the bridge condition. On the other hand, stochastic models introduce randomness and uncertainty into the deterioration process by considering random variables such as time and the condition state of bridge elements. These models can be further classified as state-based or time-based, with the Markov-chain method commonly employed as a stochastic approach (Srikanth & Arockiasamy, 2020). Additionally, although artificial intelligence deterioration models utilizing artificial neural networks (ANN) have gained recent popularity, comprehensive research is imperative before their integration into future Bridge Management System (BMS) software (Moomen et al., 2016).

Many US state DOTs have developed customized deterioration models. Both deterministic and stochastic techniques have been employed. For example, Agrawal and Kawaguchi (2009) developed bridge element deterioration rates for New York State Department of Transportation (NYSDOT) using Markov chains and a Weibull distribution-based approach. Their work demonstrated the value of combined predictive modeling methods tailored specifically for a DOT's needs. As analytics capabilities advance, transportation agencies can refine existing models or create new ones leveraging a range of techniques. Prior research established that individualized modeling, regardless of methodology, benefits infrastructure asset management at the organizational level.

Numerous studies, such as those conducted by Hong et al. (2006), Srikanth and Arockiasamy (2020), and Melhem and Cheng (2003), have investigated bridge deterioration through various modeling techniques. However, a critical concern persists: the overlooked influence of geographical location, climate nuances, material diversity, design intricacies, superstructure variations, age, traffic volume, span lengths, and highway classifications on bridge degradation. Despite their unique impacts on deterioration, crafting specific degradation rates for similar bridges remains a complex challenge inadequately addressed by current models. Additionally, most models rely on data ranging from 1992 to around 2010 from the National Bridge Inventory (NBI). As ongoing NBI data continues to accrue until 2023, incorporating this recent information becomes imperative to update and enhance different deterioration models. Particularly, recent data may offer valuable insights into how the evolving climate due to global warming affects bridge deterioration rates

Table 1 National Bridge Inventory Condition Rating (Item 57)

Condition Rating Value	Description
9	Excellent condition
8	Very good condition –No problem noted
7	Good condition – some minor problems
6	Satisfactory condition – Structural element show minor deterioration
5	Fair condition- all primary structural elements are sound but may have minor section loss, cracking, spalling or scour
4	Poor condition- advanced section loss, deterioration, spalling or scour
3	Serious Condition - loss of section, deterioration, spalling or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear
2	Critical Condition - advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support.
1	“IMMINENT" FAILURE CONDITION - major deterioration or section loss present in critical structural components or obvious vertical/horizontal movement affecting structure stability.
0	Failed Condition - out of service - beyond corrective action.

This research utilizes a deterministic approach by employing linear regression polynomial functions to derive deterioration rates. Despite the popularity of Markov chain models in stochastic techniques and their role in many bridge management system software, a deterministic method was chosen. A key reason for this decision was the simplicity and easy implementation of linear regressions, which can still achieve high accuracy depending on the application. Additionally, polynomial empirical equations from deterministic regressions serve as valuable inputs for developing Markov chains and applying probabilistic service life prediction models. Therefore, while stochastic techniques account for uncertainties, the calibrated deterministic approach employed in this study balances predictive performance with practical usability for infrastructure deterioration modeling.

1.2 Objective and Scope of Research

The study centered on Florida's highway state system, using the NBI database, selected due to its moderate climate similar to that of most cities in Ethiopia. It focused on bridges featuring concrete superstructures (slab, T-beam, and Box-beams) spanning between 6m to 40m across various ADTT ranges. The deterioration models developed in this study are exclusively applicable to Florida's bridges due to variations in construction standards, traffic, environment and inspection practices between locations. While the approach may provide a general reference for areas with comparable climates, the models should not be extrapolated or interpreted as globally representative. Regional characterization remains critical using local bridge inventory data.

The present study addressed its scope and problem statement through the following actions:

- Developed a polynomial regression model using condition rating data across various categories of bridges, categorized by material type, operational characteristics, climate, Average Daily

Track Traffic, Superstructure design type (slab bridge, T-girder, or Box-girder), Span, and Functional classification of Highway.
- Established a condition rate threshold for bridge decommissioning, indicating that the bridge can no longer provide the intended service.
- Using the developed polynomial regression models, estimate the remaining service life of bridges within each category and formulated a deterioration curve accordingly.

2. Literature Review

2.1 Factor affecting Bridge Deterioration

Placing reinforced concrete bridge structures in different environments exposes them to diverse deterioration processes, impacting their in-service durability. This can result in functional loss, unforeseen maintenance, remediation, or replacement needs, and in severe scenarios, compromises structural integrity, posing safety risks. Reinforced concrete deterioration broadly falls into two categories: (a) concrete degradation and (b) steel reinforcement corrosion (Chess & Green, 2020). Table 2 indicates the main causes of reinforced concrete structure deterioration.

Table 1 Causes of Degradation of Reinforced Concrete Structures

Degradation of concrete	
Mechanical	Abrasion , Erosion, Cavitation, Impact
Physical	Freeze-thaw , Fire
Structural	Overloading, settlement, Fatigue, shear, Tension, Torsion, Flexure, creep, shrinkage
Chemical	Alkali, aggregate reaction (AAR), Sulphate attack, Acid attack, Leaching and efflorescence, Slat solution, Alkaline solutions
Biological	Bacteria , Fungi, Algae
Corrosion of steel reinforcement	
Carbonation, Chlorides, Leaching and Stray current	

Concrete degradation primarily arises from exposure to environmental conditions, encompassing climatic impacts, chemical assaults, abrasion, and the effects of freeze-thaw cycles. The alteration of concrete, whether chemical, physical, or mechanical, impacting its long-term durability, is attributed to both external and internal factors. External factors pertain to the construction environment, while internal factors are associated with the material's structure and its components (Chemrouk, 2015).

Al-Rashed, et al., (2023) Undertook a comprehensive exploration into the factors dictating the degradation of bridges within the Gulf Cooperation Council. Their study adopted a qualitative approach, leveraging in-depth interviews with industry experts to glean nuanced insights. The findings of their investigation brought to the forefront several pivotal contributors to bridge deterioration within the GCC. Notably, factors such as reinforcement protection levels, design loads, chloride attack, and the age of bridges emerged as significant Determinants profoundly impacting the degradation Rates experienced by these vital infrastructures.

In a related study by (Fujiu, et al., 2022) an aligned investigation delved into the complex factors affecting the degradation of distinct bridge elements—the superstructure and the deck slab. Their comprehensive analysis encompassed a wide spectrum of considerations, spanning from material compositions to environmental influences. Their findings highlighted the paramount significance of various factors in steering degradation rates. Notably, their research pinpointed material type and proximity to the coastline as pivotal influencers for the superstructure, underlining their substantial role in the degradation process. Conversely, when examining the deck slab, the primary determinants identified were years in service and daily traffic volume, signifying their predominant impact on degradation rates within this specific bridge component.

2.2 Bridge Component Deterioration Models

The ability to forecast the future condition of bridge elements stands as a crucial factor in determining when maintenance actions will be necessary. Prior to the 1980s, the absence of substantial National Bridge Inventory (NBI) inspection data limited predictive methods to expert opinions from bridge or structural engineers. However, the accumulation of years of NBI data facilitated the development of specific mathematical models for predicting bridge element deterioration. This advancement became pivotal in enabling accurate deterioration modeling, a cornerstone for effective Bridge Life Cycle Costing Analysis (BLCCA).

BLCCA plays a pivotal role in bridge maintenance programming by offering insights into whether repairs should occur in the latter stages of a bridge's expected service life and by assessing the cost-effectiveness of various maintenance strategies. As highlighted by HURT & SCHROCK, (2016), the principal advantage of BLCCA lies in its capacity to inform decision-making regarding bridge repairs, allowing for comparisons between different maintenance approaches and enhancing overall economic efficiency. As introduced earlier, three primary methods are employed in modeling deterioration: deterministic approach, stochastic approach, and Artificial Intelligence (AI) modeling.

The subsequent sections will delve into discussions. Regarding the deterministic and stochastic approaches, elucidating their respective methodologies and applications in the context of modeling deterioration.

2.2.1 Deterministic Analysis

Deterministic models assume that tendency of bridge deterioration process is certain and are based on regression analysis of condition data. These model attempts to establish connections between the dependent variable (in this case, the condition rating ranging from 0 to 9) and independent variables such as age, Average Daily Truck Traffic (ADTT), Span, and others. This established relationship allows for the prediction of a structure's future performance based on these factors (HURT & SCHROCK, 2016). Deterministic approaches offer advantages due to their simplicity in predicting the future condition of bridges. Additionally, they prove practical at the network level.

Srikanth & Arockiasamy, (2020) Emphasize the significant advantage of deterministic approaches in predicting future bridge conditions, especially within network analysis, owing to their simplicity. However, despite their effectiveness in evaluating extensive networks, deterministic models neglect the inherent unpredictability in infrastructure deterioration and disregard the influence of unobserved variables. Additionally, they offer an average condition projection for a group of facilities, overlooking the distinctive current and historical conditions of individual structures, as highlighted by (G. Morcous, et al., 2002).

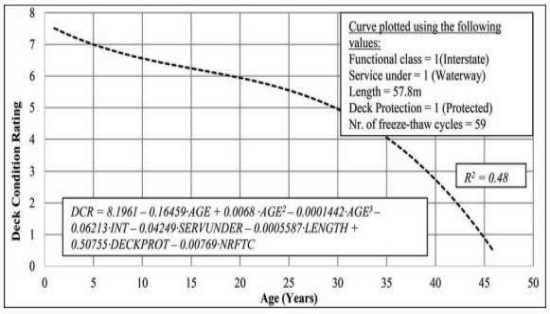


Figure 1 Cast-in-Place Concrete Slab Superstructure Deterioration Model—Northern Districts, NHS ((Moomen, et al., 2016)

A comprehensive deterioration model was previously developed by Moomen et al. (2016) for the Indiana bridge management system as shown in Figure 2, indicating an appropriate fit to the data. Similarly, Hong et al. (2006) developed deterioration models for 30 state DOTs in the US using polynomial functions. Their results showed that in 95%

confidence intervals, the condition ratings at which bridges were typically decommissioned ranged from 1-3 according to state DOT criteria, and 4 based on FHWA guidelines. In a manner consistent with these prior studies, the current research also employs polynomial functions fitted through linear regression analysis. Their average service life equaled 60.4 to 74.80 years for DOT_CRD and 54.95 to 63.19 years for FHWA structurally deficient failure condition.

2.2.2 Stochastic Analysis

The stochastic approach considers the degradation in condition as influenced by one or more random variables. This method enables the incorporation of uncertainty and randomness within the deterioration process. Typically, two extensively employed methods within this approach are Markov chain models and the utilization of Weibull distribution. These techniques are commonly utilized to account for the unpredictability inherent in the deterioration of structures (Srikanth & Arockiasamy, 2020).

a. Markov Chain Model

The Markov chain technique employed to forecast bridge lifespans involves defining condition states based on ratings and establishing transition probabilities between states in a transition probability matrix. Given a bridge's current state, its future condition and time to transition between ratings can be predicted by multiplying the initial state vector by a transition matrix. However, deterioration rates are expected to vary as bridges age, whereas Markov chains assume time-independent transition rates between states. To address this, bridge ages were grouped into 6-year intervals where rates are assumed homogeneous within each group. Additionally, it was posited that a bridge's rating would decrease by at most 1 in a single year. As a result, the transition matrix was structured to allow for either maintaining the current rating or transitioning to the next lower rating within a year. Grouping bridges into age cohorts and limiting annual rating changes to 1 helped account for non-stationary deterioration over time within the Markov chain framework (JIANG & C. SINHA, 1989).

$$\begin{vmatrix} p(1) & q(1) & 0 & 0 & 0 & 0 & 0 \\ 0 & p(2) & q(2) & 0 & 0 & 0 & 0 \\ 0 & 0 & p(3) & q(3) & 0 & 0 & 0 \\ 0 & 0 & 0 & p(4) & q(4) & 0 & 0 \\ 0 & 0 & 0 & 0 & p(5) & q(5) & 0 \\ 0 & 0 & 0 & 0 & 0 & p(6) & q(6) \\ 0 & 0 & 0 & 0 & 0 & & 1 \end{vmatrix}$$

where q(i)= 1-p(i) , p(i) corresponds to $p_{i,i}$ and q_i to $p_{i,i+1}$ Therefore, p(I) is the transition probability from Rating 9 (State 1) to Rating 9, and q(I), from Rating 9 to Rating 8, and so on.

Formulating the estimation of transition probabilities for each age group involved creating the following nonlinear programming objective function:

$$\min \sum_{i=1}^{N} |Y(t) - E(t,P)| \qquad \text{(Eqn. 1)}$$

Subject to

$0 \le p(i) \le 1 \quad i= 1, 2, ….,i$

Where

N=6, the number of years in one age group
I=6, the number of unknown probabilities
P= a vector length I equal to [p(1), p(2)……p(i)]
Y(t)= the average of condition ratings at time t, estimated regression function and
E(t,p)= estimated value of condition rating by Markov chain at time t.

Using the Markov chain, the state vector at any given time 't', represented as Q(t), is derived by multiplying the initial state vector Q(0) with the transition probability matrix P raised to the power of 't'.

$$Q(t) = Q(0) * P^t \qquad \text{(Eqn. 2)}$$

If R represents a vector of condition ratings [9 8 7 6 5 4 3], and R' denotes the transformation of R, then the estimated condition rating through the Markov chain method is obtained as follows:

$$E(t,p)= Q(t) * R' \qquad \text{(Eqn. 3)}$$

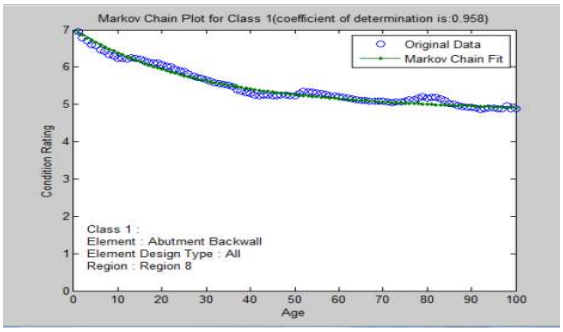


Figure 3 Markov Chain Plot Showing Comparisons Between Original and Fitted Data (Agrawal, A.K. & Kawaguchi, A, 2009)

(Agrawal, A.K. & Kawaguchi, A, 2009) created an extensive deterioration rate specifically for the New York State Department of Transportation (NYSDOT), illustrated in Figure 3, showcasing a highly accurate curve fit. One primary drawback of the Markov chain model is its sole reliance on current states to predict future bridge conditions, disregarding historical data. Additionally, the model assumes a consistent transition from one condition state to another over time, potentially leading to inaccuracies in the predictive model. (S-K NG & F.Moses, 1996).

a. Weibull Distribution-Based Models

Time-based models utilize probability distributions like Weibull or Gamma distributions to represent the deterioration process, considering the duration a bridge element spends in a specific condition state as a variable subject to chance. These models present clear advantages and limitations (Srikanth & Arockiasamy, 2020). Notably, Weibull models are seen as more realistic due to their incorporation of observed duration variability for a given condition rating, treating this duration as a random element. Furthermore, they have contributed to enhancing the traditional Markov model by establishing an age-dependent probability of failure. However, drawbacks exist: these models often overlook the interplay between different structural elements impacting structural integrity. Additionally, estimating distribution parameters, especially in lower condition states with limited data, poses complexities. Lastly, time-based models are deemed suitable only when more than 20 years of inspection data are available; otherwise, state-based models are preferred (S-K NG & F.Moses, 1996). Figure 4 illustrates deterioration model based on Weibull developed for NYSDOT.

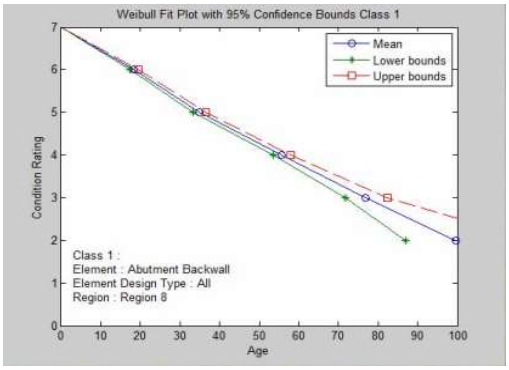


Figure 4 Weibull Based Deterioration Curves Fitted Data with 95% Confidence Level Bounds (Agrawal, A.K. & Kawaguchi, A, 2009)

3. Methodology

A linear polynomial regression model, as denoted in Equation 4, has been employed to explore the correlation between the condition rating of reinforced concrete bridge superstructures and chosen independent variables (such as Age, ADTT, span, etc.). The primary objective of this regression model is to demonstrate the statistical relationship between the dependent variable, which in this case is the Condition Rating value and selected independent variables.

Earlier studies investigating bridge deterioration models through deterministic approaches propose that the optimal representation for the degradation trends of bridge components involves fitting a polynomial function to the data, as indicated by (Agrawal, A.K. & Kawaguchi, A, 2009), (Bolukbas, et al., 2004), and (Jiang & Sinha, 1989).

$$Y = b + \sum_{i=i}^{n} \alpha \beta i x^{i} \quad \text{(Eqn. 4)}$$

3.1 Independent Variables

When establishing deterioration models for the different DOT's, the focus was placed solely on two crucial criteria: achieving a high R-squared value and ensuring significance levels exceeding 95%. Various researchers, such as (Moomen, et al., 2016) attempted to construct deterioration models integrating independent variables like average daily traffic (ADT) and average daily truck traffic (ADTT) while attempting to meet these criteria. However, these models often yielded lower R-squared values. On the contrary, studies such as ABED-AL-RAHIM & JOHNSTON (1995), Hong (2003), and Ramey & Wright (1997) concentrated solely on the age as an independent variable in their models, and as a result obtained a better correlation in their models with high R square values.

This study focuses on age as the independent variable and condition rating as the dependent variable when developing deterioration models for bridges. However, an attempt was made to indirectly incorporate the impacts of average daily truck traffic (ADTT) and span length, by categorizing them into separate groups and developing individual deterioration models for each category. The effect of ADTT is indirectly incorporated by dividing ADTT into two categories of less than 500 and greater than 500 trucks per day, developing separate deterioration models for each ADTT group, with the maximum observed ADTT in the dataset being 2000 trucks. The effect of span length is indirectly incorporated by developing separate deterioration models for span length groups of slab bridges from 6 to 12 meters, T-girder bridges from 12 to 25 meters, and box girder bridges from 25 to 40 meters. The linear regression methods used is given as follows.

$$Y = b + b_1X \quad (3.2)$$

$$Y = b + b_1X + b_2X^2 \quad (3.3)$$

$$Y = b + b_1X + b_2X^2 + b_3X^2 \quad (3.4)$$

Where Y= condition rating value, X= age of bridge and b, b1, b2, b3= coefficient estimate

Out of three polynomial functions considered, the linear cubic polynomial function demonstrated a strong accuracy in representing the dataset.

3.2 Data Collection

The primary data source for modeling bridge deterioration models was the National Bridge Inventory (NBI) database. Accessible to anyone, the NBI holds crucial bridge information, encompassing component condition ratings from 1992 to 2023. Renowned as one of the most comprehensive bridge databases globally, it offers extensive details about various bridges.

For this study, NBI data specific to the state of Florida was employed. Florida was chosen due to its moderate climate, which closely resembles the moderate climate of most cities in Ethiopia, in comparison to other states in the US. Moreover, the primary objective of this study is to enhance existing models by creating comprehensive deterioration models for reinforced concrete superstructure bridges in Florida. These improved deterioration rates could potentially serve as rough estimation tools for sub-Saharan countries like Ethiopia, which lack recorded historical databases of their bridges.

3.3 Data Preparation

To ensure the model included only necessary data, extensive filtering was performed on the complete NBI dataset of Florida from 1992 to 2023 with a total condition rating data set of 427,989. Table 3 shows total number of bridge in Florida by year and type.

Table 1 Total Number of Bridges by Year and Type

Year	Total bridge (no)	Concrete Bridges	Slab bridges	T-beam bridges	Box-beam /stringer bridges
1992	12624	4130	1725	211	336
2000	14214	4004	1611	279	113
2010	11912	4167	1693	232	19
2020	12592	4396	1715	196	26
2023	12881	4503	1719	180	35

A secondary filtering process was implemented, specifically excluding bridges that underwent reconstruction, which could have significantly improved their condition ratings compared to earlier values. This precautionary step was taken to mitigate potential errors stemming from enhanced condition ratings. By excluding these instances, the model aims to accurately depict authentic deterioration trends over time, rather than potential enhancements resulting from reconstruction efforts.

A third filtering stage was applied to the remaining dataset, excluding bridges constructed before 1940. This decision was motivated by the understanding that incorporating very old bridges in deterioration rate calculations could introduce significant bias into the results. For instance, elements of bridges built in the 1940s might have been replaced before inspections commenced in 1981. Without specific work history data, determining the age of rebuilt elements in these bridges would rely on calculating it based on the original construction year of the bridges. However, the condition ratings of these elements would reflect their rebuilt condition rather than their original state.

3.4 Further Data Filtering

a. Rating Subjectivity of Bridge Inspectors

Variations in element ratings can stem from the subjective nature of assessments by different bridge inspectors. Simple algorithms have been created to detect such occurrences and rectify the identified data anomalies. For instance, if inspection records spanning 15 years consistently show a rating of 5, except for occasional spikes to 6, these deviations are likely due to inspector subjectivity.

b. Drastic Condition Rating Drop

Bridge Element ratings typically decline gradually over time. Yet, if there's a sudden and significant decrease in ratings across two consecutive inspections, it might be due to uncommon incidents like collisions with ships, vehicles, or other accidents. These abrupt drops don't signify the usual wear and tear from regular use. Filters have been integrated to spot these specific elements, and their inspection data has been excluded from the database.

c. Improper Condition Rating for Newly Constructed Bridges

Upon reviewing the dataset, it was noted that some bridges marked as newly constructed (0 years old) had been assigned condition ratings below the expected value of 9. This divergence from the typical trend of gradual deterioration in bridges over time could be attributed to either issues with construction quality or unresolved minor problems arising during the construction phase. To address this inconsistent pattern in the data, the specific points corresponding to bridges rated below 9 when listed as newly constructed

were identified. An adjustment was made to properly align these outlier data points with the general expectation that bridges should have a rating of 9 when first built, because they have not yet undergone service and the research aims to capture deterioration due only Service stage vehicle loading and environmental impacts over time. This rectification helped ensure the dataset better represented the normal pattern of infrastructure deterioration unfolding over decades of service life under traffic and weathering forces.

Table 4 Deterioration Model Categories / Families

No	Material type	Superstructure Type	Span	Design load	ADTT
1	RC	Slab	6m-15m	H20, HS20,HS25 and HS,95	< 500
2	RC	Slab	6m-15m	H20, HS20,HS25 and HS,95	> 500
3	RC	T-Girder	12m-30m	H20, HS20,HS25 and HS,95	< 500
4	RC	T-Girder	12m-30m	H20, HS20,HS25 and HS,95	> 500
5	RC	Box-Girder, Multi beam, Girder	25m-40m	H20, HS20,HS25 and HS,95	0-2000

d. Age Limitations: Highest & Lowest Age

The NBI database holds instances where bridge components were replaced, yet their condition ratings weren't adjusted in the records. The calculation of bridge ages usually hinges on the original construction or reconstruction year. But without the work history, relying on the original build year results in inaccurate component condition ratings. For example, a 60-year-old bridge deck wouldn't typically warrant a pristine condition rating like 9, and conversely, a fairly new deck (say, 2 years old) wouldn't usually receive a low rating like 2 or 3.

Table 5 Minimum & Maximum Age Limitation for Superstructure Condition Rating (Moomen, et al., 2016)

Condition Rating	Minimum Age (Years)	Maximum Age (years)
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

To tackle this issue, the study by (Moomen, et al., 2016) is adopted as shown in Table 5, which establishes minimum and maximum age limits for specific condition ratings, was used for further data filtering.

3.5 Model Calibration

The deterministic model was calibrated using the SPSS 27 statistical software package. Component condition ratings were regressed against various explanatory variables, with age being the only independent variable considered. Throughout the modeling process, the intercept was left unconstrained at 9.0 (i.e. the maximum condition rating associated with new built bridge). This value based on the data values. Consequently, it was observed that the initial point for most models often varied from 9.0. Further details can be found in Section 4.

3.6 Model Validation

The model validation process utilized the root mean square error (RMSE) method to assess the dispersion of data around a regression line. This involved squaring the residuals, summing them up, calculating the mean squared residuals, and computing the square root. Additionally, the software included a built-in model validation feature employing the R-square method. This method was

applied individually to each of the five deterioration models to evaluate their goodness of fit and assess how well they captured the relationship between variables. Specifically, it measured the proportion of the variance in the dependent variable (condition rating values) explained by the independent variable (age of the bridge).

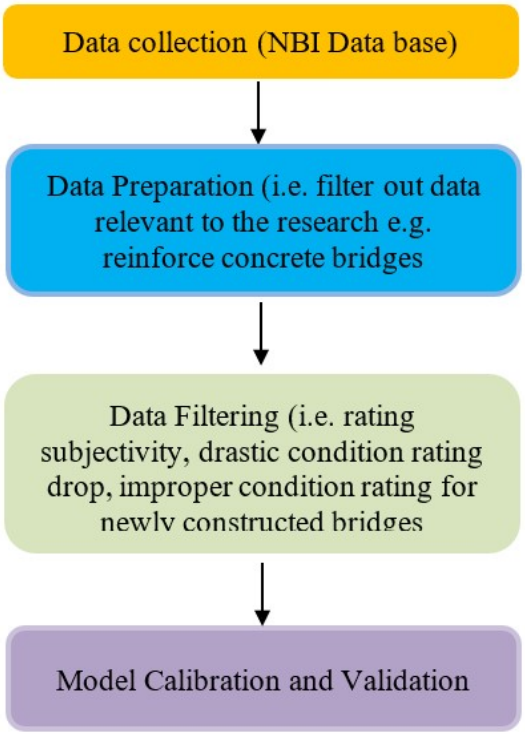


Figure 5 Methodology Flow Chart

4. Results and Discussions

4.1 Deterioration Curves for Slab Type Superstructures

Two distinct models were constructed specifically for slab-type RC superstructures. The first model caters to those with an Average Daily Truck Traffic (ADTT) of less than 500, while the second addresses those with an ADTT exceeding 500. Utilizing a cubic polynomial function, the model yielded R-square values of 0.725 for ADTT less than 500 and 0.64 for ADTT greater than 500, indicating the respective goodness of fit for each subset.

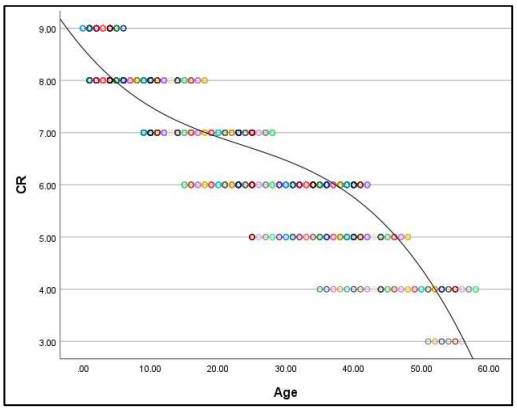


Figure *6* Deterioration Curve for Slab Type Bridge Superstructures with ADTT < 500

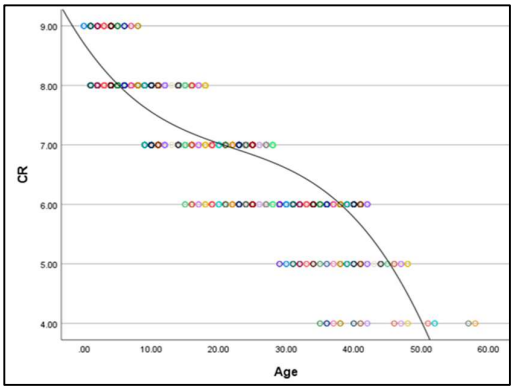


Figure 7 Deterioration Curve for Slab Type Bridge Superstructures with ADTT > 500

As shown in Figures 6 and 7, it's noticeable that slab-type superstructures with an ADTT < 500 exhibit slightly longer service life compared to those with an ADTT > 500, aligning with the expected trend.

4.2 Deterioration Curves for Slab T-Beam /Girder Superstructures

In a similar manner, Two distinct models were constructed specifically for T-girder RC superstructures. The first model caters to those with an Average Daily Truck Traffic (ADTT) of less than 500, while the second addresses those with an ADTT exceeding 500. Utilizing a cubic polynomial function, the model yielded R-square values of 0.883 for ADTT less than 500 and 0.848 for ADTT

greater than 500, indicating the respective goodness of fit for each subset.

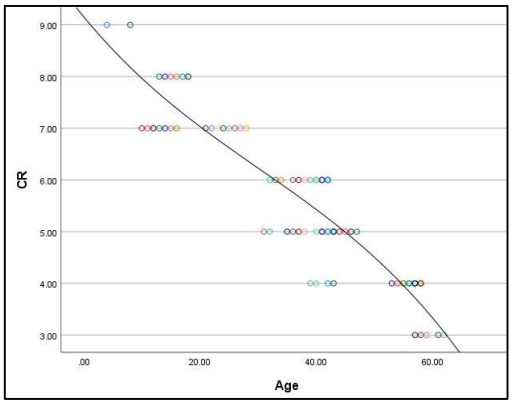


Figure 8 Deterioration Curve for T-Beam /Girder Bridge Superstructures with ADTT < 500

As depicted in Figures 8 and 9 , there's a discernible trend: T-girder superstructures with an ADTT < 500 showcase marginally longer service lives than those with an ADTT > 500. This observation supports the anticipated trend, suggesting that bridges experiencing higher ADTT tend to have slightly shorter service lives. The equation of regression model is summarized in Table 6.

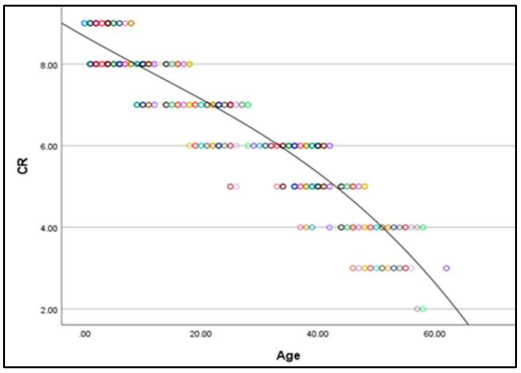


Figure *9* Deterioration Curve for T-Beam/Girder Bridge Superstructures with ADTT > 500

4.3 Deterioration Curves for Box-Girder and Other Bridge Superstructures

Due to a lack of sufficient data after filtering, it was not feasible to develop separate regression models for box-girder bridges and other superstructure types. As a result, a single cubic polynomial regression model was utilized to predict superstructure condition ratings, as depicted in Figure 10. By employing this unified approach, an R-squared value of 0.837 was achieved, demonstrating a strong overall fit to the mixed superstructure data. While distinct models for different bridge types may have provided better fits, the limited data post-filtering did not support such segregated modeling. Thus, the single cubic function proved useful for accurately representing the collective superstructure deterioration trends despite pooling various bridge design categories together.

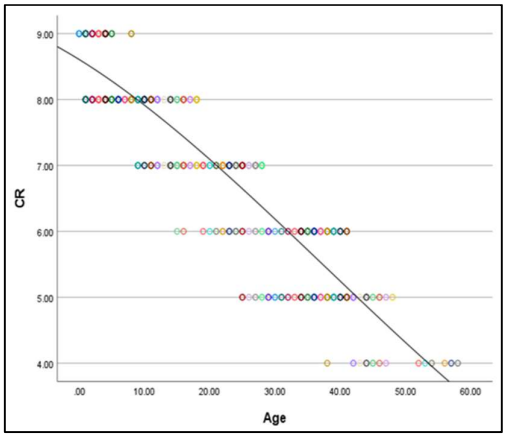


Figure *10* Deterioration Curve for Box-Beam /Girder Bridge Superstructures

4.4 Determination of the Service Life of RC Bridge Superstructures

Following the formulation of regression models for each category, the subsequent stage involves estimating the bridge's service life using these models. However, to proceed, it's crucial to ascertain the condition rating value that designates a structure as structurally deficient, particularly regarding its load capacity. It's important to note that the National Bridge Inventory (NBI) database provides a condition assessment of bridges based on visual inspection and non-destructive testing, which are indirectly indicative of the bridge's load-carrying capacity. The NBI condition rating ranges from 0 to 9, with criteria for each rating

detailed in Table 1. Therefore, to identify bridges qualifying as structurally deficient based on Hurt & Schrock, 2016 and AASHTO recommendations, we need to focus on NBI condition ratings that are known to be correlated with load capacity and that fall within the range of 4 or lower

For a more practical and realistic estimation of a bridge's service life, a condition rating of 3 or lower has been chosen. This rating serves as the threshold for considering decommissioning, categorizing the bridge as being in a state deemed "under serious condition" (FHWA-PD-96-001, 1995). This standard ensures that the estimation of a bridge's service life aligns with a critical assessment of its condition, allowing for proactive measures in managing infrastructure that falls below this specified threshold.

By establishing the decommissioning condition rating at 3, the age of each superstructure type is calculated using the equations outlined in Table 6. Consequently, the estimated service life for each superstructure type is clearly delineated within the same table. Upon computation, the average service life is determined to be approximately 60 years. This estimation aligns reasonably well with the typical design lifespan of bridges, generally expected to range between 50 to 100 years. This average figure of 60 years provides a practical and plausible estimate for the longevity of these structures.

Table 6 Summary of Linear Polynomial Model for RC Superstructure Deterioration

Model 1	Super Structure Type	ADTT	Polynomial Regression Equation	Average Service Life
1	Slab	< 500	$Y= 8.617 – 0.152X + 0.05X^2 - 0.00006644X^3$	60.5 years
2	Slab	> 500	$Y= 8.706 – 0.164X + 0.006X^2 - 0.00008577X^3$	56.89 years
3	T-beam	< 500	$Y = 9.15 - 0.136X + 0.002 - (0.00002110) X^3$	64.8 years
4	T-beam	> 500	$Y = 8.68 – 0.081X + 0.000452X^2 (0.00001302)X^3$	58.0 years
5	Box-Girder, Multi beam, Girder	-	$Y= 8.608 - 0.061X - 0.001X^2 + 0.00000779X^3$	60.31 years

5. Conclusion and Recommendation

5.1 Conclusion

In summary, this research found that linear and cubic polynomial regression models using age as the sole independent variable and condition rating as the dependent variable provide a reasonably good estimate of bridge deterioration trends over time. By utilizing the extensive National Bridge Inventory database updated through 2023, the models were able to accurately predict deterioration patterns. While models were initially developed without considering additional influential variables like Average Daily Truck Traffic (ADTT) or span length, the study demonstrated that calibrating separate regression equations for categories of ADTT classes and span ranges based on superstructure type yielded stronger correlations. This approach indirectly incorporated the effects of characteristics like traffic volumes and spans of structures. Overall, the research concluded that by leveraging the NBI's long-term records, basic regression techniques can offer a decent estimation of a bridge's remaining useful lifespan. More nuanced predictions result from segregating bridges into loading and dimensional groupings for independent model calibrations

Based on the results obtained from this research, the following conclusions can be drawn:

- Regression models that center solely on age as an independent variable, indirectly encapsulating the impacts of other crucial

factors such as ADTT and span, tend to exhibit stronger correlations for reinforced concrete superstructures. This approach often outperforms models incorporating multiple variables in terms of correlation strength.

- Typically, reinforced concrete (RC) superstructures with lower Average Daily Truck Traffic (ADTT) tend to showcase slightly longer service lives compared to RC bridge superstructures experiencing higher ADTT.
- Overall, the service life of various types of RC superstructures—slab, T-girder, and Box-girder—exhibits minimal variation. This suggests that the span of a bridge superstructure doesn't significantly impact the deterioration rate of a bridge.
- The average service life a bridge superstructure was computed to be around 60 years.

5.2 Recommendation

For countries like Ethiopia that do not have established bridge management systems with historical condition records, service histories, and other key data, the findings of this research can provide a useful starting point. Ethiopia has a tropical climate similar to Florida, without major issues related to frost and thaw cycles due to freezing temperatures. By examining deterioration rates and estimated service life from this Florida-based study, Ethiopia may begin to develop comprehensive bridge maintenance plans that incorporate lifecycle cost analysis.

However, the results should not be taken as precise predictions, as geographical location, traffic volumes, loading conditions, and construction quality can vary greatly between the two regions. While this outcome provides initial guidance, local factors would need further evaluation to refine deterioration projections and maintenance planning customized for Ethiopia's specific bridge infrastructure and environmental exposures. The overarching goal would be establishing an inventory and inspection program akin to databases in developed nations.

Furthermore, This study sets the stage for further research to advance the findings. As technologies progress, artificial intelligence techniques such as supervised and reinforcement learning using neural networks warrant exploration for predicting bridge remaining life. Neural networks may better model complex deterioration patterns compared to regression approaches. Potential focus areas include developing AI models with expanded feature sets incorporating attributes like materials, designs, inspection histories and maintenance records. Recurrent neural networks could utilize sequential condition data for forecasting. Reinforcement learning also shows potential for evaluating maintenance strategies. Leveraging artificial intelligence presents opportunities to enhance predictions & optimize preservation planning as data and computing power grow..

Additionally, comparative analyses between regression and AI-based techniques using the same NBI dataset could provide insight into their relative predictive capabilities. As bridge monitoring technologies evolve with new sensors, future studies may also integrate real-time structural health data streams to refine predictions. With further refinements, AI deterioration models show promise to more dynamically project whole-life cycles for optimized management of aging infrastructure assets.

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