PREDICTIVE ANALYTICS FOR HOLISTIC LIFECYCLE MODELING OF CONCRETE BRIDGE DECKS WITH CONSTRUCTION DEFECTS

by

Nichole Criner

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THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Julio Ramirez, Co-Chair

Lyles School of Civil Engineering

Dr. Shirley Dyke, Co-Chair

Lyles School of Civil Engineering

Dr. Randall Poston

Pivot Engineers

Approved by:

Dr. Dulcy Abraham

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GLOSSARY

Term	Definition
CR	Condition Rating
INDOT	Indiana Department of Transportation
FHWA	Federal Highway Administration
NBI	National Bridge Inventory
Baseline	The estimated current degradation pattern used by INDOT that does not include the effects of physical, chemical, or environmental parameters and is based solely on historical condition rating patterns
Construction Defect	A material or workmanship error during the construction of a concrete bridge deck
Covariate	The collection of all coding options of a specific external factor
Data Censoring	The process of assigning the title “censored” or “uncensored” to a historical condition rating assignment
Data Cleaning	The process of removing unreliable data from the data set
Data-Driven Degradation Model	Simulation of the state of the concrete deck over time using historical data gathered during inspections to account for relevant external usage factors
Degradation	The loss of condition rating value over time
Deterioration	The process of a concrete bridge deck losing effectiveness over time
Future Condition State	The future condition rating of a bridge deck based on the predictive degradation model calculations
Hazard Ratio	A value used to compare the effect on overall bridge deck degradation of an individual hazard group option
Intervention	Any action taken by INDOT that effects the condition rating of a bridge deck, can include but is not limited to; thin deck overlay, rigid deck overlay, crack sealing.
Native Degradation	Degradation with no interventions and/or maintenance actions performed on the deck during its lifespan
Non-Stationary Transition Probability Matrices	A set of stay-the-same transition probability matrices, one for every year into the future the condition rating of the bridge deck will be predicted
Physics-Based Deterioration Model	Simulation of the chemical and physical properties in concrete and the environmental factors that influence this behavior
Service Life	The total time a bridge deck is in service to the public. This time begins immediately after construction and ends when the bridge deck, superstructure, or whole bridge is replaced
Standard Construction	Indicates that the concrete bridge deck was constructed meeting all the material and workmanship criteria imposed by INDOT
Stay-The-Same Transition Probability	The probability of a bridge deck to stay in the condition rating it is currently in, in the next inspection cycle

Substandard Construction	One or more of the material and/or workmanship criteria imposed by INDOT was not fulfilled during construction
Time to Initiation	Time it takes for the chlorides to reach the rebar level of the deck
Time to Spalling	Time it takes for the deck to crack after the chlorides have reached the rebar level
Transition Probability	The probability of a bridge deck to transition from the current condition rating to the next lowest condition rating, in the next inspection cycle
Uncensored Data	Historical condition rating observation that is potentially shorter than it would have been if (1) the observation had not been interrupted by a maintenance action or (2) the timeframe of the dataset was not cutting off the beginning or end of the condition rating observation
Unreliable Data	Condition rating assignments that have been influenced by subjectivity in the inspection process or have been coded incorrectly

NOMENCLATURE

Symbol	Meaning
a_f	Fraction of corroded area
C	Chloride concentration
C_I	Cost of interventions
C_R	Cost of replacement
C_T	Total cost
c	Concrete cover
D	Diffusion coefficient of chlorides in uncracked concrete
D_{cr}	Diffusion coefficient of chlorides in cracked concrete
D_{FT}	Freeze-thaw cycle modified diffusion coefficient of chlorides in concrete
D_{H_2O}	Diffusion coefficient of water in concrete
d_b	Rebar diameter
d_N	Damage factor
E_n	n^{th} Estimated future condition rating
$E[\ x\ ]$	Expected cost of x
HR_k	k^{th} Hazard Ratio
$h(t)$	Hazard function
k_a	Ambient CO_2
k_c	Curing factor
k_e	Relative humidity factor
k_{NAC}	Carbonation rate
l_f	Fraction of corroded length
P_{kk}	k^{th} Stay-the-same transition probability (physics-based model)
P_{kk}^*	k^{th} Stay-the-same transition probability (data-driven model)
$P_{k(k-1)}^*$	Transition probability
P_n	n^{th} Transition probability matrix
R	Condition rating column vector
r	Discount rate (rate of inflation)
$S(t)$	Survival function
T_s	Survival Time
t	Instantaneous time
$W(t)$	Wetting events' factor
Z_n	n^{th} Condition state vector
β	Regression coefficient
ϕ_c	Critical rebar loss due to corrosion

ABSTRACT

During the construction of a bridge, more specifically a concrete bridge deck, there are sometimes defects in materials or workmanship, resulting in what is called a construction defect. These defects can have a large impact on the lifecycle performance of the bridge deck, potentially leading to more preventative and reactive maintenance actions over time and thus a larger monetary investment by the bridge owner. Bridge asset managers utilize prediction software to inform their annual budgetary needs, however this prediction software traditionally relies only on historical condition rating data for its predictions. When attempting to understand how deterioration of a bridge deck changes with the influence of construction defects, utilizing the current prediction software is not appropriate as there is not enough historical data available to ensure accuracy of the prediction. There are numerical modeling approaches available that capture the internal physical and chemical deterioration processes, and these models can account for the change in deterioration when construction defects are present. There are also numerical models available that capture the effect of external factors that may be affecting the deterioration patterns of the bridge deck, in parallel to the internal processes. The goal of this study is to combine a mechanistic model capturing the internal physical and chemical processes associated with deterioration of a concrete bridge deck, with a model that is built strictly from historical condition rating data, in order to predict the changes in condition rating prediction of a bridge deck for a standard construction case versus a substandard construction case. Being able to measure the change in prediction of deterioration when construction defects are present then allows for quantifying the additional cost that would be required to maintain the defective bridge deck which is also presented.

1. INTRODUCTION

In the U.S. there are over 617,000 bridges in service (ASCE, 2021). Immediately after construction of a new concrete bridge deck, the deck begins to deteriorate. This deterioration process can be influenced by various internal and external factors. Those internal factors are related to the physical and chemical processes happening within the concrete bridge deck and include but are not limited to; bonding of the steel rebar with the concrete, the amount of air voids in the concrete, the amount of freeze and thaw cycles experienced by the bridge deck, the corrosion of the steel rebar, and carbonation. Additionally, there are external factors that can be influencing the deterioration of the bridge deck in parallel, which include but are not limited to; the amount of traffic that drives over the bridge deck on a given day, the percentage of that daily traffic that is large trucks, the type of wearing surface that is present on the deck, and any physical dimension or parameter of the bridge deck design or construction.

When a bridge deck is constructed new, there are opportunities for things to go wrong during the construction phase, and such instances can be referred to as *construction defects*. Construction defects can be known from the time they happen and chosen to be accepted or fixed right away, or could be unknown until after completion of construction and only determined once unnatural deterioration patterns arise on the structure. In any scenario there will be additional cost incurred by some party to fix the problems that were an outcome of this defect. Often times if the defect does not affect the structural integrity and safety of the bridge deck then the defect may be accepted, because the cost incurred by the public during the additional time the structure is closed for construction, will be greater than the cost incurred by the bridge owner - the state Department of Transportation (DOT) - to have the defect fixed. However, in this case the bridge owner now has a defective bridge in service, that in the long run will lead to an additional monetary investment in preventative and reactive maintenance actions in order to keep it open to the public for the desired service life.

1.1 Existing Infrastructure for Concrete Bridge Deck Deterioration Modeling

The INDOT, like all other state DOT's, is required to visually inspect and assign a condition rating (CR) number to each of their bridge's components bi-annually. A bridge component refers to a structural element of the bridge and includes; the substructure, the superstructure, and the deck. The CR number assigned during this process is representative of the state of deterioration that the individual bridge components are experiencing at the time of inspection. Table 1.1 comes from the Federal Highway Administration (FHWA) *Recording and Coding Guide* (FHWA, 1995) and provides the CR scale and descriptions of what each CR represents for a bridge deck.

Along with the condition rating number assigned during visual inspection, there is also bridge specific data reported like location of the bridge, structure material identification, the number of lanes, the length of the bridge, the number of spans the bridge has, the average daily traffic load, the average daily truck traffic load, the type of wearing surface that is present on the bridge deck, the age of the bridge, etc. Records of these visual inspections in the state of Indiana date back to 1992, resulting in 30 years of historical data available. In order to perform a proper historical data analysis, a minimum of 20 years of data is necessary (Mauch & Madanat, 2001) thus it is appropriate to perform an analysis of data for the state of Indiana to determine what the typical deterioration pattern is for the state.

Table 1.1. Federal Highway Administration Condition Rating Scale

CR	Condition	Description
9	Excellent	
8	Very Good	No problems noted.
7	Good	Some minor problems.
6	Satisfactory	Structural elements show some minor deterioration.
5	Fair	All primary structural elements are sound but may have minor section loss, cracking, spalling, or scour.
4	Poor	Advanced section loss, deterioration, spalling, or scour.
3	Serious	Loss of section, deterioration, spalling or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.
2	Critical	Advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.
1	"Imminent" Failure	Major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put back in light service.
0	Failed	Out of service – beyond corrective action.

The INDOT has a method to which they currently perform an analysis of their historical data. The analysis yields a pattern of deterioration for the state and this pattern is input into their bridge management system (BMS) to determine how to properly allocate their annual budget. The BMS uses the condition rating history of any given bridge and the typical deterioration pattern (determined from analysis) to project the condition ratings of a given bridge, approximately 20 years into the future. This condition rating projection is used to determine the return on investment of different preventative or reactive maintenance and new construction actions for all bridges within the state, and ultimately produces a 5-year plan for maintenance and new construction, that adheres to the annual budget. The current analysis has determined a deterioration pattern in the state of Indiana to be on average; a bridge spends 4 years in CR9, followed by 8 years in CR8, and 12 years in each of the subsequent CRs 7-4. The FHWA labels a bridge as *structurally deficient* when at least one of the structural components (substructure, superstructure, or deck) has been assigned a CR of 4 or less (ASCE, 2021). Due to this, the INDOT aims to prevent their bridges from deteriorating below CR4, and if they can prevent it from even reaching a CR4 then they will aim to replace the bridge deck approximately halfway between the deterioration from CR5 to CR4. Thus, there is no pattern determined for CRs 3-1.

Srikanth & Arockiasamy (2020) provides an overview of the research advancements of deterioration models through the development of deterministic, stochastic, and mechanistic forms of modeling. Deterministic models assume that the rate of deterioration is set and based on a regression analysis of the data, often a linear regression analysis. Linear regression models have been found to lack in accuracy for long-term prediction by providing either an underestimate or overestimate of deterioration throughout the forecasted timeframe, however, they are easy to implement at a network level. Using a non-linear regression model can help to reduce the inaccuracy found in linear regression analysis, but is still not fully capable of solving the prediction accuracy problem.

Stochastic models consider the process of deterioration of a bridge component as a random variable allowing for the capture of uncertainty in the deterioration process. Stochastic models may fall into one of two categories; time based or state based. Time-based means the random variable is the duration spent in each CR and it is modeled by using a probability distribution, one example being Weibull. State-based means the modeling of the transition from one CR to the next lowest is done with a representative transition probability. Markov chains have been used extensively with state-based models.

Mechanistic models are simply physical models with the ability to relate the condition rating to physical parameters of the bridge like its material properties, its structural performance, and the distribution of stress within the component. Srikanth & Arockiasamy (2020) also compared many different mechanistic models that have been developed for use in deterioration modeling of concrete bridge components and helps to identify the advantages and disadvantages of this type of modeling. An advantage of mechanistic modeling is that it is able to be implemented on an individual project basis, as it can be made specific to each bridge. However, this means that it has the inherent inability to be applicable at a network level. Depending on the type of analysis desired by the user, this type of modeling may be beneficial or a hindrance.

Salmerón et al. (in review) and Criner & Salmerón et al. (2022) aimed to develop a mechanistic model that captures the internal physical and chemical processes of deterioration within a concrete bridge deck, when that bridge deck has one or a combination of two construction defect(s) present. The model requires physical inputs specific to the material properties, location, and severity of the defect, allowing for a case by case evaluation of the change in deterioration when a defect(s) is present. Even though this mechanistic modeling procedure allows for implementation in a case-by-case basis, it, like all other mechanistic models, lacks the ability to include the effects of external factors and how these external factors may separately affect the typical pattern of deterioration.

Cavalline et al. (2015) and Goyal et al. (2017) worked to develop a procedure for duration-based probabilistic deterioration modeling, based on regression analysis. The probabilistic deterioration model developed combines semi-parametric multivariable proportional hazards modeling (Cox, 1972) and semi-Markov theory (Jiang et al, 1988). This modeling approach is able to overcome the limitations of state-based Markovian models by first utilizing the Cox proportional hazards regression model to determine which external factors (covariates) are significant in their effect on deterioration rates. These significant factors are then run through a Cox proportional hazards model regression again to then calculate the corresponding hazard ratios which are applied to transition probability matrices determined from historical condition rating data. Finally, the model performs calculations to predict future condition ratings using semi-Markov theory. This modeling technique is very useful in its inclusion of external factors and their potential effect on the deterioration pattern of a bridge component throughout its service life. Even though this state-based Markovian model can capture the effect of external factors on typical deterioration patterns, it lacks the ability to include the physical modeling element that mechanistic models provide.

1.2 Development of Holistic Lifecycle Modeling of Concrete Bridge Decks

As explained in Section 1.1, there are numerical modeling methods available for separately representing the internal and external phenomena affecting deterioration of a concrete bridge deck during its service life. In addition, there are numerical models that capture the differences in deterioration of a bridge deck when construction defects are present within the deck, and there are cost models that have been developed to determine the optimal year in the future to perform intervention actions to a bridge for the best return on investment. However, there is a gap in the research in regards to the combination of the benefits of these separate individual models.

Thus, the motivation for this study is the need for a holistic numerical model that illustrates the differences in lifecycle deterioration and maintenance efforts of a bridge deck in the case of standard construction (built without construction defects) versus the case of substandard construction (built with construction defects) based on existing literature. To address the research need, the objectives of this study are three-fold; i) combine the effects on deterioration of a concrete bridge deck of both internal and external factors through numerical modeling, ii) introduce the effects of construction defects to this combined numerical model and predict the overall effect the defect(s) will have on lifecycle performance of the bridge, and iii) evaluate the additional lifecycle cost that a department of transportation would incur once an in service bridge deck has been identified as having a construction defect. A simple procedure of the study is illustrated in Figure 1.1.

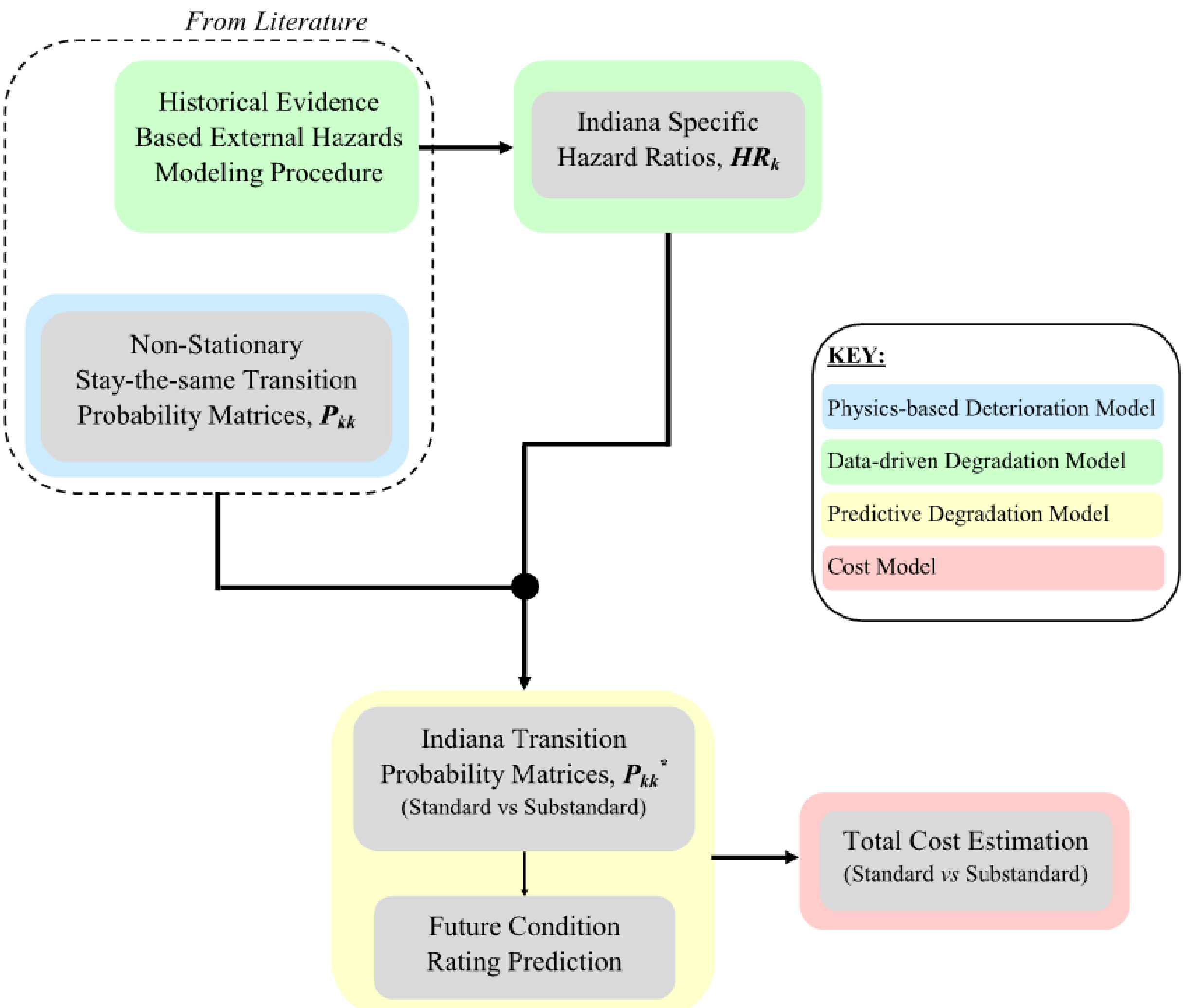

Figure 1.1. Simple graphical procedure of holistic lifecycle model development

2. LITERATURE REVIEW

The holistic numerical model developed and presented herein, combines the benefits of mechanistic modeling of a concrete bridge deck, the changes in the deterioration of the bridge deck when construction defects are present, as well as the benefits of using semi-parametric multivariable proportional hazards modeling to include the effects of significant external factors on deterioration patterns. The developed model is implemented based on data for the state of Indiana's roughly 17,000 bridges and 30 years of condition rating history, and is applied to a set of case study bridges to illustrate the results. The changes in deterioration of a bridge with construction defect(s) present are compared to the same bridge case as if it had no defect(s) present, and thus allows for the determination of an estimated loss of life of the bridge deck due to the construction defect. This framework then continues on to include a cost analysis of the defective bridge deck case versus the standard construction case, and allows for the estimate of additional cost over the lifespan of the deck when including the efforts of preventative and reactive maintenance. This section will provide a more detailed explanation of the already established modeling procedures that were combined to develop the holistic model introduced herein.

2.1 Physical and Chemical Modeling of Concrete Bridge Deck Deterioration

A study performed by Purdue University in partnership with the Indiana Department of Transportation, Salmerón et al. (in review) and Criner & Salmerón et al. (2022) were introduced in Section 1.1. This study created a model that captures the internal physical and chemical processes of deterioration within a concrete bridge deck, when that bridge deck has one or a combination of two construction defect(s) present. A more comprehensive review of the model can be found in Salmerón et al. (in review) and Criner & Salmerón et al. (2022). The mechanistic model developed incorporates deterioration occurring from corrosion, carbonation, cracking, and freeze-thaw cycles and evaluates the effect of the following construction defects on its deterioration; i) improper curing of the concrete deck, ii) improper mixing of the concrete, iii) insufficient concrete cover, and iv) damage to the epoxy coating layer on the rebar within the deck. A brief explanation of the equations used to capture these individual internal effects and how they are combined into one numerical model is included in this section.

2.1.1 Numerical Modeling of Concrete Deck Internal Processes

Corrosion

Chloride-induced corrosion is the primary cause of corrosion of rebar in reinforced concrete; particularly in states like Indiana that apply de-icing salts (chlorides) to their roadways during the winter. When placing a new concrete deck there is a passivation layer made up of Iron oxides that develops naturally when the rebar interacts with the concrete that is placed. This protective layer can only withstand a certain amount of chlorides before breaking and allowing for the start of corrosion of the rebar. The time from construction of the concrete deck to the surpassing of the chloride threshold is termed *time to initiation*. This infiltration process can be expedited if cracks have formed along the surface of the concrete deck as well, making it easier for the chlorides to penetrate the concrete. Once the protective layer has broken, rust will begin to accumulate along the surface of the rebar and eventually lead to cracking of the concrete, followed by spalling of the concrete (once the corrosion of the rebar has worsened). The time from initiation of rusting to the time when corrosion related spalling has started is termed *time to spalling*. Fick's second law of diffusion (Equation 2.1) is used for modeling the flux of water and chlorides within the concrete deck, since water is the catalyst needed for chlorides to move to the rebar (Martín-Pérez at al., 2000). $\boldsymbol{C}$ is a function of chloride concentration at time $\boldsymbol{t}$, and at depth $\boldsymbol{x}$, and $\boldsymbol{D}$ is the diffusion coefficient of concrete. A series of simulations are run with various input parameters, ultimately to find the time to initiation of each input case.

$$\frac{\partial C}{\partial t} = \frac{\partial}{\partial x}\left(D\frac{\partial C}{\partial x}\right) \tag{2.1}$$

Once time to initiation is determined, the modeling continues in order to determine the time to spalling which is associated with the deck reaching critical corrosion loss, $\boldsymbol{\phi_c}$ in mil in Equation 2.2 (O'Reilly et al., 2011). $\boldsymbol{l_f}$ and $\boldsymbol{a_f}$ are non-dimensional fractions of the epoxy-coating damage length and area respectively, $\boldsymbol{d_b}$ is the diameter of the rebar in inches, and $\boldsymbol{c}$ is the concrete cover in inches.

$$\phi_c = 45\left[\frac{c^{2-a_f}}{d_b^{0.38} l_f^{0.1} a_f^{0.6}} + 0.6\right] \times 3^{a_f - 1} \tag{2.2}$$

Carbonation

Carbonation is an electrochemical process where earth's atmospheric carbon dioxide and moisture react with the calcium hydroxides in the concrete. Carbonation begins as soon as the surface of the concrete deck comes into contact with the atmosphere (when the formwork is removed) and the primary consequence is the loss of the concrete surface through the carbonation front or depth. In the case of insufficient concrete cover, there is a shorter path for the chlorides to reach the rebar and thus a reduced time to initiation of corrosion. The carbonation front at any given timestep, $\boldsymbol{t}$ can be computed using Equation 2.3 (Zambon et al, 2019). $\boldsymbol{k_{NAC}}$ is the carbonation rate, $\boldsymbol{k_e}$ is representative of relative humidity, $\boldsymbol{k_c}$ is the typical time it takes to cure the concrete deck in days, $\boldsymbol{k_a}$ represents the effect of CO_2 concentration in the air, and $\boldsymbol{W}(\boldsymbol{t_n})$ represents events in which the concrete deck would become wet.

$$x_c(t) = k_{NAC} \cdot \sqrt{k_e \cdot k_c \cdot k_a} \cdot \sqrt{t} \cdot W(t) \tag{2.3}$$

Freeze-thaw Cycles

As previously mentioned, concrete decks collect water and moisture throughout their life, and during the winter season the moisture within the deck will freeze then thaw depending on the external temperature. In the state of Indiana this freezing and thawing happens in a cyclic pattern due to inconsistent temperatures during the winter. Unfortunately, after several cycles of freezing and thawing the concrete will begin seeing damage which leads to it inability to contain the changes in water. This phenomenon can be included through a modification of the chloride diffusion coefficient originally introduced in Equation 2.1. This modification factor, $\boldsymbol{D_{FT}}$ can be calculated using Equation 2.4 where $\boldsymbol{d_N}(\boldsymbol{t})$ represents the damage experienced by the concrete deck at any given time $\boldsymbol{t}$, and is determined by the maximum number of freeze-thaw cycles a concrete deck is expected to undergo in any given year (Chen at al., 2020).

$$D_{FT}(t) = D + 26.25 \times 10^{-9} \left[1 - \frac{1}{1 + (2.5 d_N(t))^5}\right] \tag{2.4}$$

Cracking

Regardless of whether a concrete bridge deck meets all specifications, it will eventually begin to deteriorate and experience cracking. This is due to the environmental effects of the area in which the bridge is located, and also relies on its usage by the public. As mentioned previously, when cracking occurs on a concrete deck, that allows for water to infiltrate and thus chlorides. The cracking pattern used in Salmerón et al. (in review) and Criner & Salmerón et al. (2022) is represented by a simplified linear cracking pattern. By using this linear cracking pattern, the diffusion coefficient can be calculated at different stages of the aging of a given bridge deck using Equation 2.6, since it is a factor of the crack depth determined from the cracking pattern.

$$D_{cr}(t) = \begin{cases} D_{FT} & \omega < 1.18\,mil \\ 28.3 - 35.6e^{-0.00835\omega} & 1.18\,mil \leq \omega \leq 3.94\,mil \\ D_{H_2O} & \omega > 3.94\,mil \end{cases} \tag{2.5}$$

Integration of Individual Effects

The ability to model these internal processes individually is an important step; however, the purpose of the physical model development in this study was to capture how these processes interact with each other throughout the service life of a given concrete bridge deck. Salmerón et al. (in review) and Criner & Salmerón et al. (2022) accomplished this goal by executing the combination of these individual models in the following step-by-step process:

1. The chloride diffusion coefficient is adjusted to account for the cracking due to freeze-thaw cycles outlined in Equation 2.4.
2. The chloride concentration at each depth of $\boldsymbol{x}$, is calculated using Equation 2.1.
3. The carbonation front at each time $\boldsymbol{t}$, is calculated using Equation 2.3.

During step 3, the time to initiation is determined to be the time at which the chloride threshold (Equation 2.2) at the rebar level is surpassed. Also note that for each step; $\boldsymbol{D_{FT}}$ is dependent on the $\boldsymbol{D}$ calculated in the previous step and $\boldsymbol{D_{cr}}$ includes both freeze-thaw cycles and cracking effects thus resulting in $\boldsymbol{D = D_{FT}}$ in Equation 2.6.

Introduction of Construction Defects to the Numerical Model

In order to understand the effect of defects occurring during the construction phase of a given concrete bridge deck, the individual parameters in Equations 2.1-2.6 were adjusted to reflect defective values and the simulations were run again.

Table 2.1 outlines the construction defect accounted for, the parameter that was adjusted in its given equation, and how the parameter was adjusted (increased or decreased) to account for the construction defect. The numerical model is then run for different intensities of the individual defects and combinations of two defects. The variation of intensity is to account for the inherent uncertainty present when a defect occurs during construction.

Table 2.1. Parameters adjusted to account for construction defects

Construction Defect	Adjusted Parameter	Adjustment to the Parameter	Related Equation
Improper Curing	Initial Crack Width: $\boldsymbol{\omega_0}$	Increased	2.5
Improper Mixing	Diffusion Coefficient: $\boldsymbol{D}$	Increased	2.4
Insufficient Concrete Cover	Concrete Cover: $\boldsymbol{c}$	Decreased	2.2
Damage to Epoxy Coated Rebar	Corroded Rebar Length & Area: $\boldsymbol{l_f}$ **&** $\boldsymbol{a_f}$	Increased	2.2

2.1.2 Development of a Physics-Based Model

The next step included transforming the original deterministic model into a stochastic once to produce transition probability matrices to which this process herein will be referred to as the *Physics-based model.* This process required the following steps:

1. Determination of chloride concentration, crack width, and rebar section loss to which each transition from one CR to the next lowest is associated.
2. Estimation of probability distributions from the data found in step 1.
3. Development of transition probability matrices based on simulations run with data from probability distributions from step 2.

Step 1 of the Physics-based model requires defining threshold values for chloride concentration, crack width, and rebar section loss that would determine transition from one CR to the next lowest. These threshold values were selected based on criteria for CR assignment from the FHWA and the average time spent in each CR based on current INDOT observations.

Step 2 involved running 200 Monte Carlo simulations where the distribution of each defect parameter was sampled from a range representing each defect, and the time spent in each CR was determined for each individual simulation run. The Monte Carlo simulations were representative of a lognormal probability distribution (Equation 2.6) for each defective parameter.

$$T_k \sim \text{Lognormal}(\mu_k, \sigma_k), k = 1, \ldots, 6 \tag{2.6}$$

Step 3 utilized the probability distributions from step 2 to compute stay-the-same transition probability matrices representative of the probability of a bridge deck to stay in the CR it is currently experiencing. These matrices are considered non-stationary meaning there is a different matrix calculated for each year of deterioration.

2.2 Historical Evidence Based Modeling of Concrete Bridge Deck CR Deterioration

A study performed by the University of North Carolina at Charlotte in partnership with the North Carolina Department of Transportation (Cavalline et al, 2015) was introduced in Section 1.1. This study, along with a dissertation done in parallel to this study (Goyal, 2015) utilized the historical data collected and reported to the FHWA in the state of North Carolina to develop a basic procedure for probabilistic deterioration modeling. Their definition of probabilistic deterioration modeling consists of a combination of semi-parametric multi-variable proportional hazards modeling (Cox, 1972) and semi-Markov theory (Jiang et al, 1988). The probabilistic deterioration first performs a survival analysis utilizing the Cox multivariable proportional hazards model. The external factors that are evaluated in this study include the type of road system the bridge is located within, the reconstruction status of the bridge, the geographical region the bridge is located in, the type of wearing surface present, average daily traffic counts, average daily truck traffic counts, the length of the maximum span, the number of total spans, and the age of the bridge. This yields a North Carolina specific analysis of the chosen external factors and their individual effect on overall deterioration patterns within the state. The analysis results are then transformed into a probabilistic deterioration model using the well-established Markov-chain approach. Or in other words, the results of the survival analysis are used to create a process for predicting future condition rating values based on i) historical data patterns for the state of North Carolina, and ii) the influence of the evaluated external factors specific to any given bridge. The dataset of this study included approximately 17,000 bridges in North Carolina over a time period of 35 years. A brief explanation of the modeling procedures and equations used to capture the effect of external factors on typical deterioration patterns in the state of North Carolina is included in this section.

2.2.1 Survival Function

Survival analysis is a statistical procedure for which the desired outcome is an estimate of the "time until an event occurs" (Kleinbaum, 2012). Let the term *event* be defined as the occurrence of a bridge deck transitioning from its current CR to next lowest CR, as that is what's applicable to this study. The term *survival time* refers to the time the deck spends in a given CR. Thus, the *survival function* of a bridge deck is defined as the probability that the bridge deck will be in a lower CR than the current CR it experiences (Equation 2.7). Let T_s be the random variable representing the bridge deck survival time in a given CR. Then *t* denotes a specific value of the time of survival of the random variable, T_s.

The survival function is a cumulative measure over time and one could say that it focuses only on the bridge deck not failing. *h(t)* is the hazard function that gives an instantaneous potential for the desired deck to transition to the next CR, given that the bridge deck has survived in the current CR up until the current time, *t*. The hazard function contains a conditional probability in the numerator, but because the denominator is a time interval, it makes *h(t)* a conditional *failure rate* rather than a probability. One could say that the hazard function focuses on the bridge failing (the opposite of the survival function). The two functions can be derived from each other, and the formal relationship can be described as follows: If $\boldsymbol{h(t) = \gamma}$ then $\boldsymbol{S(t) = e^{-\gamma t}}$.

For a bridge deck, rather than considering just a single event of interest and thus one survival time/function, a series of events must be considered since the event being defined occurs multiple times over the lifespan of the bridge as it degrades. Each reduction in CR of the deck is thus a separate event, and therefore has a corresponding survival time. Additionally, the external usage factors that may influence this survival time are termed *explanatory factors*, and are also sometimes referred to as *covariates* or *hazards*.

Let T_s be the random variable representing the bridge deck survival time in a given CR. Then *t* denotes a specific value of the time of survival of the random variable, T_s. For example, if it was of interest to know whether a certain bridge deck has lasted in CR 9 for 4 years, then *t*=4 and whether T_s>4 would be evaluated. *S(t)* is defined as the survival function and represents the probability that the bridge deck will be in a given CR longer than the specified value, *t*.

$$S(t) = P(T_s > t) \tag{2.7}$$

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T_s < t + \Delta t | T_s \geq t)}{\Delta t} \tag{2.8}$$

There are three primary steps comprising the survival analysis process: i) estimating and interpreting survival functions; ii) comparing survival functions; and, iii) assessing the effect of explanatory factors (covariates) on the survival time. The third step is typically paired with a mathematical model that can correctly address a multivariable problem, such as a regression model (Kleinbaum, 2012). In this study, like in Goyal (2015), the regression model used to assess the effect of the chosen hazards is a Cox proportional hazards regression model (Cox, 1972). A model like Kaplan-Meier can achieve the same comparison however it is limited to only evaluating the effect of one external factor per individual model; whereas the Cox model allows for the evaluation of multiple external factors within the same model.

2.2.2 Cox Proportional Hazards Regression

When using a mathematical model to assess the effect of an explanatory factor on the survival time of a deck, a linear or logistic regression model is often used. The inputs of a linear regression model are data that include one or more explanatory factors (covariates), and the outcome is a continuous variable, called a *regression coefficient* that describes the impact of those explanatory factors (covariates). The Cox proportional hazards model analysis is analogous to that of a linear regression model, without the need to specify a particular form for the model (Kleinbaum, 2012). In addition, the Cox model is also able to evaluate the effect of multiple explanatory factors simultaneously, which is the reason this approach was adopted from Goyal (2015).

The Cox proportional hazards model (Cox, 1972) incorporates a non-parametric baseline hazard rate, $h_0(t)$ that varies with time, and a multiplier, $\vec{\beta}$, that is time-independent and uses an exponential function to model the effects of the evaluated explanatory factors in this study. The hazard rate function is given by Equation 2.9, where $\vec{z}$ is a row vector comprised of the explanatory factors and $\vec{\beta}$ is a column vector of the regression coefficients that correspond with the explanatory factors in $\vec{z}$ and describe the effect of those explanatory factors on the overall hazard rate.

$$h(t, \vec{z}) = h_0(t) e^{\vec{z}\vec{\beta}} = h_0(t) e^{(z_1\beta_1 + z_2\beta_2 + \cdots z_n\beta_n)} \tag{2.9}$$

The output of a regression model, the regression coefficients, $\vec{\beta}$, can be used to calculate a *hazard ratio* which can be expressed as $\boldsymbol{e^{\beta}}$. A hazard ratio value of 1 means there is no relationship between the explanatory factor and the survival time of a bridge deck, a hazard ratio greater than one (>1), means that the explanatory factor negatively affects (lowers) the survival time of a bridge deck, and a hazard ratio less than one (<1) means that explanatory factor positively affects (increases) the survival time of a bridge deck. Individual hazard ratios can then be combined to accurately describe the overall effect on a specific bridge's deterioration pattern. This hazard ratio is the form of application needed to incorporate the effect of the explanatory factors on the overall model used in Goyal (2015).

In Goyal (2015), the calculation of a stationary stay-the-same transition probability matrix is also performed. Such a matrix describes the probability of a bridge deck to stay in the condition rating it is currently in, as well as the probability of the bridge deck to transition to the next lowest CR. With the calculation of this matrix, Goyal proves that the calculated hazard ratios can be simply applied to the diagonal value of the stay-the-same transition probability matrix in order to capture the effect of those explanatory factors seen by a given bridge. Since a bridge will typically be subjected to multiple explanatory factors, the final hazard ratio value to apply to the stay-the-same transition probability matrix is determined by taking the product of the applicable individual hazard ratios.

A bridge that is currently in CR k, has the probability of staying in CR k in the next year represented by P_{kk}. The final applicable hazard ratio determined for a given bridge, in CR k can be represented by HR_k. Therefore, the application of the final applicable hazard ratio to the stay-the-same transition probability is illustrated in Equation 2.10 where P_{kk}^{*} represents the new stay-the-same transition probability with the final hazard ratio application. Equation 2.11 can then be used to compute the probability that the bridge deck will transition from CR *k* to CR *(k-1)* by subtracting the stay-the-same transition probability found in Equation 2.10, from a value of 1.00. This is because there is an assumption that a bridge deck can only transition one CR per inspection cycle, therefore the probability on the diagonal is the stay-the-same transition probability and the probability on the off diagonal (directly to the right of the diagonal) is the probability of transiting to the next lowest CR.

$$P_{kk}^{*} = P_{kk}^{HR_k} \tag{2.10}$$

$$P^*_{k(k-1)} = 1 - P_{kk}^{HR_k} \quad (2.11)$$

2.2.3 Future Condition Rating Prediction

Prediction of future CRs originates from the Markov chain approach (Goyal, 2015) and will be outlined herein. Let the current CR of a bridge component be represented as a row vector, Z_0, with nine elements. Each element in the vector corresponds to the probability that the bridge component is in the associated CR (in reverse numerical order). Thus, the vector consists of zeros with a single entry equal to a value of 1.00, placed in the position associated with its current CR. Assume that when the bridge deck is constructed with no defects, it receives a CR 9 after the first inspection. Thus, the initial condition state vector of a given bridge is $Z_0 = [1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]$, essentially encoding the assumption that at the initial time (i.e., the first inspection) there is a 100% chance the bridge deck is at CR 9 and a 0% chance the bridge deck is at any other CR.

Let P_1 be the non-stationary stay-the-same transition probability matrix for the first year. Here the hazard ratios determined in the Cox proportional hazards regression have been applied to the transition probability matrix, as illustrated in Section 2.2.2. To determine the predicted condition state vector, Z_n after 1 year of life one would multiply the matrix, P_1 by the initial condition state vector, Z_0 (Equation 2.12). The form of the predicted condition state vector, Z_n is similar to that of the initial condition state vector, Z_0 in that each element of Z_n represents the probability that the bridge deck will be in the corresponding CR n years in the future. Let R be a column vector, which contains all possible CRs, and is expressed as $R = [9\ 8\ 7\ 6\ 5\ 4\ 3\ 2\ 1]^T$. The predicted future condition state (CR) of the bridge deck is expressed as E_n and is found by multiplying the Z_n [1x9] row vector by the column vector, R [9x1] (Equation 2.13).

$$Z_n = Z_{n-1} * P_n \quad (2.12)$$

$$E_n = Z_n * R \quad (2.13)$$

To estimate the CR at a time several years in the future, one would apply Equations 2.12 and 2.13 until the target number of years in the future is reached. The final calculation of future CR prediction, E_n yields a decimal value. While decimal values are inaccurate for CR assignment, they are acceptable for the purpose of creating a smooth degradation curve.

2.3 Cost Prediction Modeling of Concrete Bridge Deck Management

The ability to associate a predicted condition state with an incurred cost at that state is vital for evaluating the overall effect that performing a preventative or reactive maintenance action, can have on the lifecycle cost of a bridge. Kleiner (2001) introduced an approach that allows one to compute the expected cost of failure of an asset, the cost of inspections and interventions of the asset, and the total expected cost over the future life of the asset. Kleiner creates a stay-the-same transition probability matrix to represent the pattern of deterioration of the asset and performs prediction calculations in order to obtain a vector of probabilities of the asset being in any given condition rating. This vector or probabilities is then multiplied by a vector of inspection and intervention costs and failure costs. The purpose of this model is to graph these expected costs over time to determine the optimal time to perform an intervention; the optimal time being the time that is representing the best overall return on investment.

The present-day time is represented by t_0 and the future time is represented by t. Kleiner uses values of intervention and replacement in present-day dollars and is sure to include the effect of inflation on the future costs, represented through the variable r. The expected cost of failure, $\mathbb{E}[C^F]$ can be calculated by Equation 2.14a where a_n^t represents the probability that the asset is in state n at time t.

$$\mathbb{E}[C^F(t)] = C^F a_n^t \tag{2.14a}$$

The expected cost of planned interventions, $\mathbb{E}[C^R]$ can be calculated by Equation 2.15a, where c_n^r is the cost of a planned intervention of an asset in state i. This assumes that the cost of intervention of an asset is typically different in state i versus state j when $i \neq j$.

$$\mathbb{E}[C^R(t)] = \{c_1^r, c_2^r, \dots, c_{n-1}^r\} * \{a_1^t, a_2^t, \dots, a_{n-1}^t\}^T \tag{2.15a}$$

Finally, the total discounted expected cost, $\mathbb{E}[C^{tot}]$ can be calculated by Equation 2.16a, where C^I is the cost of inspection of an asset and assumed to be time-independent.

$$C^{tot}(t) = (\mathbb{E}[C^F(t)] + C^I + \mathbb{E}[C^R(t)]) * e^{-rt} \tag{2.16a}$$

3. METHODOLOGY

Henceforth, the term *degradation* will be used to describe the loss of grading, or CR, of a concrete bridge deck over time. The modeling of such a loss will be referred to as a *degradation curve*. The term deterioration will continue to describe the physical worsening of the state of a bridge deck. The term *physics-based model* will be used to describe the model presented in Section 2.1, that numerically models the internal physical and chemical processes of the concrete bridge deck in both the standard construction and substandard construction cases. Finally, the term *data-driven model* will be used to describe a model that is developed solely based on historical evidence.

The degradation model developed for the state of North Carolina, as described in Section 2.2, can be easily applied to the state of Indiana as the same type of data is required to be collected by all 50 states. To develop the data-driven model used in this study, the Matlab code from Goyal (2015) was modified to reflect the differences in the data collected by the North Carolina Department of Transportation and those of INDOT.

3.1 Cleaning and Censoring of Indiana Data

As mentioned previously, condition ratings are assigned biannually based on a visual inspection performed by a trained bridge inspector. Even though these inspections are performed by a trained professional, the nature in which visual bridge inspections are performed, do still result in the inclusion of subjectivity in the results, the assigned CR. This inherent subjectivity can make it difficult to utilize historical data in the form of CR in prediction software without getting skewed data, thus it is protocol to first clean and censor the data in an attempt to remove the majority of the “noise” due to subjectivity or clerical errors.

While it is impossible to know exactly how long a bridge deck remains in a specific CR (because a deck could degrade from one CR to another at any point during the two-year inspection interval), the maximum amount of time it is recorded in that CR is taken as the duration. For example, if a given bridge deck had a CR of 7 in 2006, and a CR of 6 in 2008, 2010, 2012, 2014, 2016, followed by a CR of 5 in 2018, the duration the bridge remained in CR 6 would be calculated by subtracting 2008 from 2018, yielding 10 years.

Data may also be classified as censored or uncensored. *Uncensored* data are defined as observations of a certain CR that are fully observed. In other words, the full durations are known and the data are considered reliable. An illustration of an uncensored observation is shown in Figure 3.1.

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
CR	7	6	6	6	6	6	6	6	6	6	5

Figure 3.1. Observation of CR 6, illustrating an observation that is considered uncensored

Censored data are interrupted in some way. There are different forms of censored data, the most common being left-censored or right-censored (Kleinbaum, 2012). In this study, the only form of censored data seen is right-censored. A *right-censored* CR observation is one in which the full duration of time that the bridge spent in that CR is not known exactly, due to some outside factor; therefore it could have been longer than the current observation length. A right-censored observation can occur for a number of reasons. Some examples of this type of an observation are as follows:

- The CR recorded for the bridge deck right before a maintenance action is performed, that alters the CR in some way.
- The first CR recorded in the analysis period, because the start of that CR observation is unknown as the analysis period is limited.
- The last CR recorded in the analysis period, because the end of that degradation period is unknown as the analysis period is limited.

An illustration of a right-censored observation that occurred due to some maintenance action being performed that increased the CR is shown in Figure 3.2.

Year	2001	2002	2003	2004	2005	2006	2007	2008
CR	6	5	5	5	5	5	5	8

Figure 3.2. Observation of CR 6, illustrating an observation that is considered right-censored

Due to the inherent subjectivity of the inspection process, the dataset needs to be cleaned and censored, as described above. However, there is also a need for additional criteria are applied to the dataset to remove unreliable data, even before they are determined to be censored or uncensored. One new criterion used herein to remove unreliable data is: if the observation of a certain CR is less than or equal to 8 years, and if the observation has a CR the year before the observation starts that is equal to the CR the year after the observation ends, then the observation is considered unreliable and removed from the analysis completely. This additional criterion is adopted because sometimes subjectivity causes individual CRs to fluctuate between two values for some time before finally degrading to an even lower CR. This additional criterion will help create a dataset that is "clean" and consists of only reliable data. An illustration of a CR observation that would be removed from the analysis dataset can be found in Figure 3.3.

Year	1998	1999	2000	2001	2002	2003	2004
CR	7	6	6	6	6	6	7

Figure 3.3. Observation of CR 6, illustrating data considered unreliable

Another benefit of using the Cox proportional hazards model is that it can incorporate both uncensored data and right-censored data. This option allows for more of the original dataset to be used in the analysis, which is likely to result in a more accurate final degradation model. Table 3.1 outlines how much information is available compared to how much is actually used in this study, after performing the cleaning and censoring process. Clearly the number of bridges with observations of CRs 1-3 are extremely low in comparison to the other CRs. Additionally, the total number of reliable observations of CRs 1-3 is extremely low. With a dataset this large, and the small amount of data with a CR 1-3, it is not reasonable to formulate a reliable degradation model with these data. Based on the previous discussion and the fact that very few bridges are allowed to degrade to CR 4, it was determined that performing the analysis for CRs between 4 and 9 only was the most appropriate approach.

Table 3.1. Basic dataset evaluation information

CR	Total No. Observations	No. Reliable Observations	No. Uncensored Observations	% Utilization Reliable Data	% Utilization Uncensored Data
9	3065	2361	1196	77	39
8	9640	8514	3441	88	36
7	14280	13398	3243	94	23
6	11922	11105	2370	93	20
5	7270	6552	1276	90	18
4	2688	2301	466	86	17
3	553	452	89	82	16
2	95	69	9	73	9
1	22	18	3	82	14

3.2 Data-driven Model Dataset Validation

INDOT currently only uses uncensored historical data in their model development. When separating the reliable historical data from the unreliable historical data, and the right-censored historical data from the uncensored historical data, as described in Section 3.1, the amount of historical data that is left as uncensored per CR is on average 21% (Table 3.1). This value is consistent with the percentage of total data that INDOT currently uses in their historical data analysis, meaning the data-driven model developed in this study is extracting a similar amount of historical data, compared to what INDOT views as reliable and usable in their current prediction methods. However, the Cox proportional hazards model does incorporate the available historical right-censored data as well as the historical uncensored data, so the data driven model developed in this study uses on average 88% of the total amount of historical data available for bridges, per CR, for CRs 4 through 9.

To validate the data-driven model developed in this study, the dataset that is used as an input to the Cox proportional hazards model will be validated. This validation is done by comparing the calculated average time spent in each CR to that of what INDOT currently observes (introduced previously in Section 1.2). The expected values based on INDOT observations and the computed average values from the dataset used in this study are compared in Table 3.2. The average time spent in each CR determined in this study are similar to what INDOT expects, and any difference could be explained by minor differences in general censoring protocol used in the two different dataset cleaning and censoring procedures.

Table 3.2. Comparison of average time in each CR

CR	INDOT Expectation of Avg Time in Each CR	Study Values of Avg Time in Each CR
9	4	4
8	8	8
7	12	10
6	12	8
5	12	8
4	12	8

3.3 Indiana External Factor Analysis

After executing the cleaning and censoring protocol on the historical data collected and used in this study, the covariates and corresponding design variables need to be determined in order to run the Cox proportional hazards model and calculate the applicable hazard ratios for Indiana.

3.3.1 Determination of Indiana Covariates

The explanatory factors of interest for the data-driven model in this study were selected based on those covariates evaluated in Cavalline et al. (2015) and slightly adjusted to reflect changes in data collection for the state of Indiana. For reference purpose, a covariate is an independent variable that can influence the outcome of a given statistical trial, but which is not of direct interest. The covariates selected for evaluation in this study include:

- Functional Classification
- Wearing Surface Presence/Type
- Average Daily Truck Traffic
- Maximum Span Length
- Number of Spans

- Age of Bridge

Of these selected covariates, there are additional opportunities for further subdivision. The subdivision of covariates is based on the coded value for each covariate in the FHWA *Recording and Coding Guide* (FHWA, 1995) and the subcategories are referred to as *design variables.* For example, the covariate *functional classification* is divided into two design variables; whether the bridge is located on a non-interstate versus interstate road. So, functional classifications coded as 1 or 11 are indicative of an interstate roadway, thus make up the *road system 1* design variable and all other coding values for functional classification are indicative of a non-interstate roadway, thus make up the *road system 2* design variable. However, for *wearing surface presence/type* there are a total of 10 wearing surface types, so a bridge deck could be 1 of 10 design variables. For covariates like age of the bridge and average daily truck traffic, there is a large range of possible data inputs. Due to the wide range of coded values available for these covariates, it is nearly impossible to include every input as its own design variable. Thus in an effort to reduce the number of design variables the degradation model has to work with (more design variables increases the complexity and computation time), the full range of data inputs are evaluated and divided equally into 3 or 4 categories containing a range of values. The division of the covariates and corresponding design variables selected for evaluation in this study can be found in Table 3.3 where the italicized design variable is representative of the baseline design variable of the applicable covariate.

Table 3.3. List of covariates and their corresponding design variables

Covariate	Design Variable	Design Variable Value Range (FHWA Recording and Coding Guide)
Functional Classification	Road System 1*	*2, 6, 7, 8, 9, 12, 14, 16, 17, 19*
	Road System 2	1, 11
Wearing Surface Presence/Type	None*	*0*
	Monolithic Concrete	1
	Integral Concrete	2
	Latex Concrete	3
	Low Slump Concrete	4
	Epoxy Overlay	5
	Bituminous	6
	Timber	7
	Gravel	8
	Other	9
Average Daily Truck Traffic (vehicles)	ADTT 1*	*≤4*
	ADTT 2	5 – 24
	ADTT 3	25 – 329
	ADTT 4	≥330
Maximum Span Length (meters)	Maximum Span 1*	*≤7*
	Maximum Span 2	8 – 14
	Maximum Span 3	≥15
Number of Spans	Number Spans 1*	*1*
	Number Spans 2	≥2
Age of Bridge (years)	Age 1*	*≤16*
	Age 2	17 – 26
	Age 3	27 – 44
	Age 4	≥45

*Baseline design variable

3.3.2 Computation of Indiana Hazard Ratios

For every covariate and its corresponding set of design variables, there is always a baseline option that the remaining variables are used to compare to in the calculation of the hazard ratios. Each of the baseline design variables are assumed to have a hazard ratio value of 1.00, so if a bridge happens to have the same design variables applicable to it, as the baseline design variables, then the degradation behavior of that bridge would be the same as if the calculation had no hazard ratios applied to it. The baseline variable is always taken as the first numerical coding option (example would be 0=none for wearing surface presence/type) or the first option in the list (for example, ADTT1). The Cox model is run initially with every covariate and its corresponding design variables, to determine which of the design variables are found to be statistically significant. The statistical significance of a design variable is determined by its *p*-value. In Goyal et al. (2015), the approach taken to evaluate a design variables significance is; only those design variables with a Wald statistic p-value less than or equal to 0.2 are considered significant. The same approach is adopted in this study. The p-value is a common parameter calculated in all programs and functions associated with regression modeling, and is automatically calculated within the *coxphfit.m* function within Matlab.

Once initial significance is determined for each explanatory factor, the Cox model is run again with every possible combination of only those design variables deemed significant in the previous step. An algorithm is used to determine the best combination of the design variables determined significant from the second run of the Cox model. The algorithm selected for use in Goyal (2015) and adopted for use in this study is the Akaike Information Criterion (AIC) and is calculated using Equation 3.1.

$$AIC_n = L_n(\widehat{\beta}) - 2n \tag{3.1}$$

In Equation 3.1, n represents the number of design variables included in the Cox model, $L_n(\widehat{\beta})$ is the log partial likelihood of the model, where $\widehat{\beta}$ is the maximum partial likelihood estimate of the regression coefficients (β) of the model. The log partial likelihood can only be used to compare models with the same number of design variables so the second part of Equation 3.1 is used to balance out the gain from the increase in the number of design variables in the model, by adding a penalty for increasing the number of design variables. This balance allows for the model to be optimally lean but does not hinder the capability of the model to perform just as well with less design variables. The goal is to maximize the AIC, thus the combination of design variables with the largest AIC is the set of design variables that will continue to have their hazard ratios calculated. The final set of hazard ratios computed for each CR between 4 and 9 is shown in Table 3.4.

Table 3.4. Final hazard ratios for the state of Indiana

	CR9	CR8	CR7	CR6	CR5	CR4
Road System 2	1.0000	1.0000	1.0000	1.0000	0.8107	1.0000
Monolithic Concrete	1.0000	0.6769	0.7047	1.0000	1.0000	1.0000
Integral Concrete	1.0000	1.0000	1.0000	0.7710	1.0000	1.0000
ADTT 3	1.0000	1.3132	1.4780	1.1154	1.0000	1.0000
ADTT 4	1.2299	1.3329	1.4551	1.2707	1.1575	1.0000
Max Span 3	1.0000	1.2133	1.0000	0.8592	1.0000	1.0000
Number Spans 2	1.0000	1.0000	1.0000	1.0000	1.0797	1.0000
Age 2	1.0000	1.0000	1.4020	0.8213	0.6372	1.0000
Age 3	1.0000	1.7698	1.8603	1.3555	1.8019	1.9597
Age 4	1.5087	2.0577	1.9389	1.4341	2.0402	1.7088

3.4 Introduction to Case Study Bridges

In order to determine the outcome of the holistic lifecycle model developed in this study, a set of case study bridges was selected to be used for analysis of results and model validation. This set of case study bridges was determined in major part by feedback from INDOT personnel. The bridges selected are similar in a few common characteristics to which this study defined as the *nominal case*. The nominal case characteristics include the following

- The main span superstructure is mostly “Tee beam” or “Stringer/Multi-beam or Girder”
- All of the decks fall under the category “Concrete Cast-in-Place”
- Most of them have a “Monolithic Concrete” wearing surface
- None of them have a membrane
- All of the decks have “Epoxy coated reinforcing” as protection against corrosion

Table 3.5 includes generic information about each of the case study bridges selected for use in this study.

Table 3.5. List of bridges in the catalog of case studies

Bridge Designation	Approximate Deck Area (sq. ft.)	Regional Location within State	Primary Construction Type	Functional Classification (Interstate vs Non-Interstate)	Noted Defect(s)
A	4,412	North	Prestressed	Non-Interstate	none
B	7,919	North	Steel	Non-Interstate	curing
C	12,236	North	Concrete	Non-Interstate	curing
D	57,838	North	Steel	Non-Interstate	w/c ratio & curing
E	8,714	Center	Concrete	Interstate	rebar
F	9,715	Center	Prestressed	Non-Interstate	none
G	33,263	Center	Steel	Interstate	w/c ratio & curing
H	5,486	South	Concrete	Non-Interstate	curing
J	5,541	South	Prestressed	Interstate	w/c ratio
K	14,889	South	Steel	Non-Interstate	curing

3.4.1 Hazard Ratio Determination for Case Study Bridges

The determination of which design variables were evaluated in this study was introduced in Section 3.3.1 and the final hazard ratios calculated for the state of Indiana were presented in Section 3.3.2. The hazard ratios that are applicable to a given bridge correspond to the specific design variables that are reported to be affecting the bridge throughout history. To calculate the hazard ratios for an individual bridge, one must first identify which Indiana bridge design variables are applicable to the bridge under consideration. This process requires evaluating the coded values for the design variables for each year of the bridge's history, from the data available on the FHWA website.

To accurately represent the bridge over its history, the values used for the design variable assignment can be determined as follows:

- For covariates with pre-determined design variables (ex: wearing surface), the <u>mode</u> (the value that occurs most in the dataset) may be taken of all values recorded in the historic record of that particular bridge, as this would identify the value that is most representative of that bridge's history.
- For covariates defined with a varying numerical input (ex: average daily truck traffic), the <u>average</u> may be taken of all values recorded in the bridge's historic record.

Once individual design variable assignment has been performed for the given bridge, the final hazard ratios for that bridge may be determined by calculating the product of the hazard ratios for the applicable design variables. Table 3.6 contains the design variable assignment for the case study bridge K. Table 3.7 contains the final hazard ratio determination and the product calculation for the case study bridge K to illustrate the process described above.

Table 3.6. Design variable assignment for case study bridge K

Covariate	Coding Value	Design Variable
Functional Classification	14	Road System 1
Wearing Surface	3	Latex Concrete
Average Daily Truck Traffic	547	ADTT 4
Maximum Span Length	29	Max Span 3
Number of Spans	3	Number Spans 2
Age	48	Age 4

Table 3.7. Final hazard ratio determination for case study bridge K

	CR9	CR8	CR7	CR6	CR5	CR4
Road System 1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Latex Concrete	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ADTT 4	1.2299	1.3329	1.4551	1.2707	1.1575	1.0000
Max Span 3	1.0000	1.2133	1.0000	0.8592	1.0000	1.0000
Number Spans 2	1.0000	1.0000	1.0000	1.0000	1.0797	1.0000
Age 4	1.5087	2.0577	1.9389	1.4341	2.0402	1.7088
$\prod$	1.8555	3.3279	2.8213	1.5657	2.5497	1.7088

Finally, Table 3.8 contains the applicable design variables to each of the case study bridges and Table 3.9 contains the final calculated hazard ratios for each case study bridge for CRs 9 through 4. Recall that a hazard ratio value of 1 means there is no relationship between the explanatory factor (covariate) and the survival time of a bridge deck, a hazard ratio greater than one (>1), means that the explanatory factor negatively affects (lowers) the survival time of a bridge deck, and a hazard ratio less than one (<1) means that explanatory factor positively affects (increases) the survival time of a bridge deck.

Table 3.8. Applicable design variables for case study bridges

Bridge Designation	Road System	Wearing Surface	ADTT	Max Span	Number Spans	Age
A	1	1	4	2	2	1
B	1	1	4	3	2	1
C	1	0	4	3	2	1
D	1	1	4	3	2	1
E	2	3	4	2	2	4
F	1	1	3	3	2	1
G	2	1	4	3	2	1
H	1	1	3	3	2	1
J	2	3	4	3	2	4
K	1	3	4	3	2	4

Table 3.9. Final hazard ratios for case study bridges

Bridge Designation	CR 9	CR 8	CR 7	CR 6	CR 5	CR 4
A	1.2299	0.9023	1.0255	1.2707	1.2497	1.0000
B	1.2299	1.0947	1.0255	1.0918	1.2497	1.0000
C	1.2299	1.6173	1.4551	1.0918	1.2497	1.0000
D	1.2299	1.0947	1.0255	1.0918	1.2497	1.0000
E	1.8555	2.7428	2.8213	1.8223	2.0670	1.7088
F	1.0000	1.0785	1.0416	0.9584	1.0797	1.0000
G	1.2299	1.0947	1.0255	1.0918	1.0131	1.0000
H	1.0000	1.0785	1.0416	0.9584	1.0797	1.0000
J	1.8555	3.3279	2.8213	1.5657	2.0670	1.7088
K	1.8555	3.3279	2.8213	1.5657	2.5497	1.7088

4. APPLICATION AND RESULTS

A physics-based model can be utilized to predict the degradation of a bridge deck over time. However, the physics-based model used in this study, adopted from Salmerón et al. (in review) and Criner & Salmerón et al. (2022) alone has its limitations. Although, the physics-based model is necessary because it provides the ability to change the physical parameters of the bridge deck with a scientific basis, and allows for reflecting construction defects in a degradation curve. Furthermore, observations in the form of CRs from inspections are used to make decisions regarding intervention actions or replacement. Thus, in this study the physics-based model (which incorporates standard and substandard construction cases) is linked to the data-driven model that reflects historical CRs by trained inspectors. This linkage empowers the predictive degradation model developed in this study, to capture the influence of construction defects on the typical degradation pattern for a given bridge in the state of Indiana. The combination of the physics-based model and data-driven model adopted for use in this study, resulting in the development of the predictive degradation model, will be outlined in this section. The application of the cost model to the predictive degradation model will also be outlined, and the results of the application of these models to the case study bridges will also be outlined.

4.1 Formulation of an Indiana Specific Predictive Degradation Model

As outlined in Section 2.2.2 the application of the hazard ratios determined from the survival analysis performed in the data-driven model itself, is simple. The diagonal values of a stay-the-same transition probability can be raised to the power of the hazard ratio product for a given bridge. In Section 3.3.2 the process of calculating a set of Indiana specific transition probabilities was introduced. Therefore, the method of combining the benefits of a model that encapsulates the physical and chemical processes happening internally within a concrete deck in Indiana, with the model that represents historical patterns of degradation within Indiana, is by using the Indiana specific transition probabilities determined from the physics-based model and the Indiana specific hazard ratios determined from the data-driven model in Equations 2.11 and 2.12. The application of Equations 2.11 and 2.12 can be illustrated in Figure 4.1 which is an adaptation of Figure 1.1 with the predictive degradation model section shown in more detail.

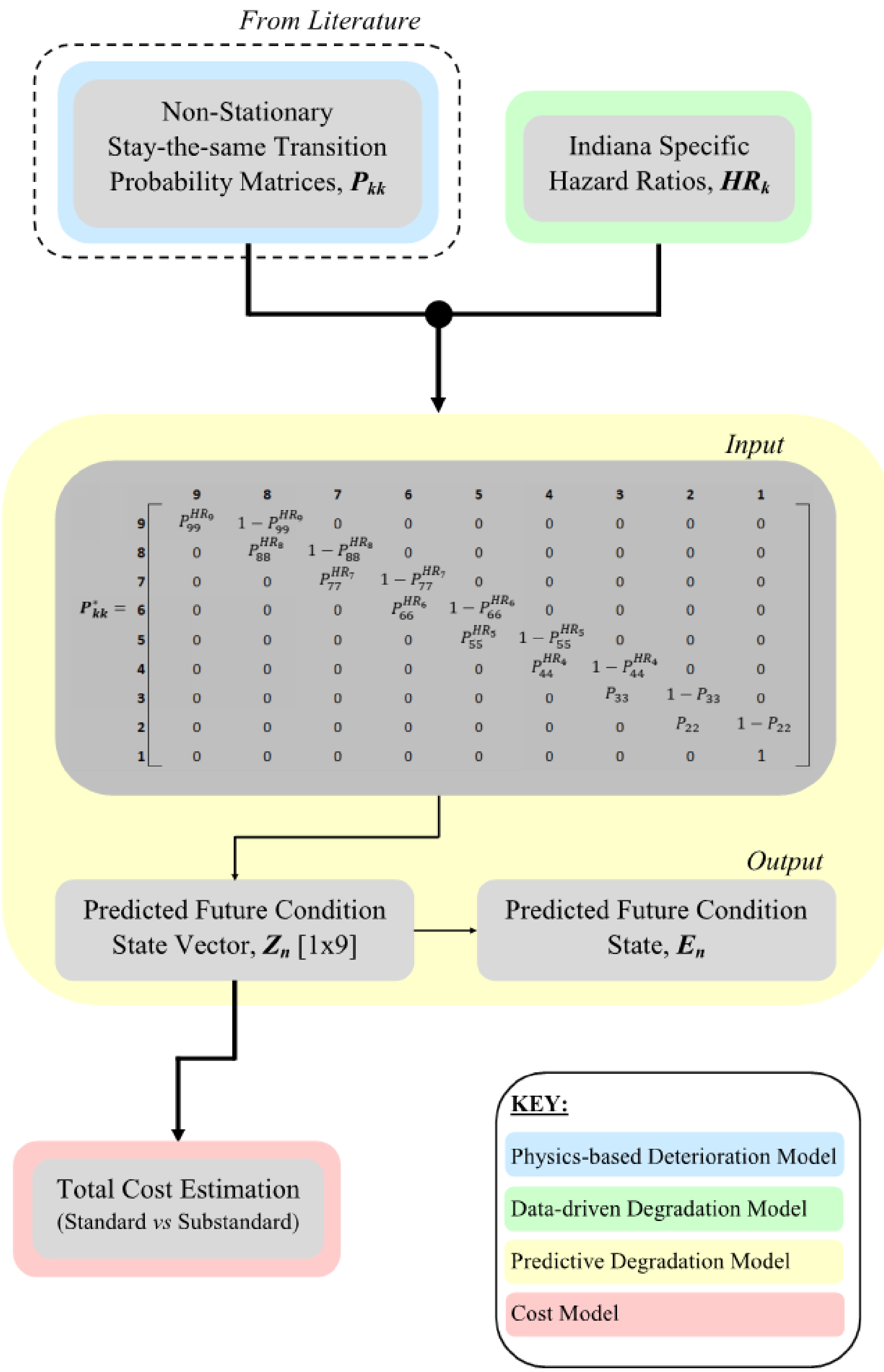

Figure 4.1. Detailed view of predictive degradation model logistics

4.1.1 Validation of the Predictive Degradation Model

To validate the predictive degradation model, the predicted service life of the bridge deck is compared to the service life that INDOT has historically observed. Here the term *native degradation* is introduced, which refers to only the act of degradation of the bridge deck, and it precludes any effects on CR that result from intervention actions.

In reality, intervention actions are performed on concrete bridge decks during their lifespan, some of which either improve the CR of the deck or extend the expected survival time of a particular CR of the deck. When the effects of intervention actions are included, the behavior is referred to as *non-native degradation*. Discussions with INDOT personnel pointed out that a bridge deck will usually be replaced when it is believed to be halfway between CR 5 and 4. According to INDOT this is expected to occur approximately 40 - 50 years after construction, assuming only native degradation is taking place. In this study, exclusively native degradation is considered. Thus, all values associated with service life expectancy and the subsequent cost analysis refers to those of concrete bridge decks experiencing native degradation. Since the INDOT does not currently use anything similar to the hazard ratios calculated in this study, the method of validation of the predictive degradation model is to use the stay-the-same transition probability matrices from the physics-based model in the future condition rating prediction calculations, and deem that set of predicted CRs as the *baseline* set. This baseline distinction refers to there being no hazard ratios applied to the stay-the-same transition probability matrices yet. The predictive degradation model is validated by determining when each of the case study bridges baseline CR predictions reach the halfway point between CR 5 and 4, and comparing that to the time window of 40 - 50 years currently observed by INDOT. Table 4.1 confirms that the future CR prediction method is reasonable as every bridge has an estimated time of rebuilding the deck between 40 and 50 years after construction.

Table 4.1. Estimated native degradation service life of case study bridges

	Estimated Baseline Native Service Life (years)
A	42
B	41
C	41
D	42
E	41
F	42
G	41
H	41
J	42
K	41

4.2 Formulation of an Indiana Specific Cost Model

Kleiner's (2001) equations introduced in Section 2.3 were adapted to fit the needs of this study and those adaptations are introduced herein. The following terms will so forth be exhibited by different variables for better application to this study. Cost of replacement (previously known as C^F) will be represented by C_R, the cost of interventions (previously known as C^R) will be represented by C_I, and the total cost (previously known as C^{tot}) will be represented by C_T. Firstly, the cost of interventions will only include additional intervention actions performed as opposed to including the cost of performing an inspection (previously known as C^I), since inspections are not done in conjunction with intervention actions in Indiana. Secondly, the additional intervention actions being evaluated in the cost of interventions is limited to a thin deck overlay and a rigid deck overlay as these are the only typical interventions actions built into the INDOT business rules at this time.

The determination of intervention and replacement costs will allow for the value assignment of variables C_R and C_I and then the final calculation of C_T. Since the CR scale includes CR starting 9 and continues through CR 1; in order to avoid any unnatural skew in the predictive degradation model output, the full range of potential CR values is used to represent the full lifecycle of the bridge deck. CR 1 is used to indicate the end of the life of the bridge deck, also known as the associated condition rating with replacement. This leaves CRs 9-2 to be associated with potential intervention actions. It is important to note that this method is consistent with the creation of the stay-the-same transition probability matrices, which include transition probabilities for the full scale of CRs 9 through 1 as well.

The method introduced in Section 2.2.3 for performing future condition rating prediction calculations plays an important role when using the Kleiner equations for estimated additional cost calculations. The future condition rating prediction calculations have a step in which the vector, Z_n is calculated. This represents the probability of the bridge deck being in each of the possible CRs (1-9) at year *n* which is directly beneficial in the Kleiner equations, as it will be replacing the a_n^t and $\{a_1^t, a_2^t, \ldots, a_{n-1}^t\}^T$ in Equations 2.15a and 2.16a respectively.

Since replacement has been determined to be associated with CR 1, another change is in Equation 2.15b, where $a_n = Z_{n(1)}$, which results in $\{a_1^t, a_2^t, \ldots, a_{n-1}^t\}^T = \left\{Z_{n(9)}, Z_{n(8)}, \ldots, Z_{n(2)}\right\}^T$.

This study aims to determine the additional cost in present day dollars when a construction defect is present thus the Kleiner equations have been adapted to work with present day dollars throughout the entire analysis. This adaptation comes from the removal of the exponential term in Equation 2.16a. The adapted Kleiner equations (2.14b-2.16b) are included below the respective original Kleiner equations (2.14a-2.16a) which are shown in this section with the original numbers as presented in Section 2.3.

The expected value of C_R, the cost of replacement is found using the adapted Equation 2.14b.

$$\mathbb{E}[C^F(t)] = C^F a_n^t \tag{2.14a}$$

$$\mathbb{E}[C_R(t)] = C_R Z_{n(1)}(t) \tag{2.14b}$$

The expected value of C_I, the cost of interventions is found using the adapted Equation 2.15b.

$$\mathbb{E}[C^R(t)] = \{c_1^r, c_2^r, \ldots, c_{n-1}^r\} * \{a_1^t, a_2^t, \ldots, a_{n-1}^t\}^T \tag{2.15a}$$

$$\mathbb{E}[C_I(t)] = \left\{C_{I(9)}(t), C_{I(8)}(t), \ldots, C_{I(2)}(t)\right\} * \left\{Z_{n(9)}(t), Z_{n(8)}(t), \ldots, Z_{n(2)}(t)\right\}^T \tag{2.15b}$$

The total expected cost, C_T at a time *t* years in the future is found using the adapted Equation 2.16b.

$$C^{tot}(\tau) = (\mathbb{E}[C^F(t_0 + \tau)] + C^I + \mathbb{E}[C^R(t_0 + \tau)]) * e^{-rt} \tag{2.16a}$$

$$\mathbb{E}[C_T(t)] = \mathbb{E}[C_R(t)] + \mathbb{E}[C_I(t)] \tag{2.16b}$$

4.2.1 Action Item Cost Determination for Case Study Bridges

It has been established that in order to correctly apply the Kleiner cost equations, the deck replacement action needs to be assigned to CR 1 leaving CRs 9-2 to be included in the cost of interventions vector. This cost of interventions vector is specific to a given bridge because it consists of the estimated costs of performing an intervention action on that specific bridge. The INDOT provided a table that has the initial cost estimate per square foot estimate for the three primary action items for a given bridge deck; thin deck overlay, rigid deck overlay, and deck replacement. These costs are based on whether the bridge is located along an interstate highway versus a non-interstate highway and the total area of the deck. Thus, once the user knows these two characteristics of the bridge (provided in Table 3.5), the user can then find a per square foot approximation for the cost of the three action items and thus the full cost approximation to perform each of those intervention actions. The approximate cost per square foot values are used for the determination of the C_R and C_I for each case study bridges and can be found in Table 4.2.

Table 4.2. Approximate cost per square foot for typical intervention actions

Intervention Action	Roadway Type	≤ 2,650 sq. ft.	2,651 – 4,590 sq. ft.	4,591 – 7,240 sq. ft.	7,241 – 11,524 sq. ft.	11,525 – 30,000 sq. ft.	≥ 30,001 sq. ft.
Thin Deck Overlay	Interstate	$115	$65	$40	$35	$20	$20
	Non-Interstate	$85	$40	$30	$25	$20	$15
Rigid Deck Overlay	Interstate	$475	$230	$190	$155	$105	$80
	Non-Interstate	$380	$185	$130	$105	$80	$65
Deck Replacement	Interstate	$765	$425	$285	$235	$170	$145
	Non-Interstate	$570	$390	$290	$220	$140	$130

The C_I vector must be determined based on the typical set of intervention actions performed over the service life of a concrete bridge deck. After discussions with multiple INDOT personnel, a baseline estimate was created for this. This baseline is reflected in the cost of interventions vector by following the typical pattern of performing a thin deck overlay while the bridge is experiencing a CR 8, another thin deck overlay some years later while the bridge is experiencing a CR 7, and finally performing a rigid deck overlay again some years later while the bridge is experiencing a CR 6. In order to implement this pattern in the C_I vector, one would multiply the price per square foot value of the respective intervention action (determined from Table 4.2) by the deck area. However, one cannot simply assign the cost of the maintenance action to the CR value in the vector.

At each CR association, the intervention cost must reflect the accumulated cost of all intervention actions applied to the bridge thus far, during its service life. The CRs unassigned with an intervention action will have an additional cost at that CR of $0, thus the accumulated cost over time will remain the same as the previous CR value.

The C_R value is approached in a similar manner. The estimated cost for deck replacement per square foot found in Table 4.2, is multiplied by the deck area, yielding the replacement cost, which is then added to the total intervention cost reflected in the CR 2 position in the cost of interventions vector. Previous intervention costs must be included because, before the bridge deck is replaced, multiple intervention actions have been performed over its lifetime. Including the price of those intervention actions in the replacement cost reflects this assumption.

Take case study bridge K as an example; one would determine the estimated cost of each action item by first determining the deck area and what type of roadway the bridge is located on. Table 3.5 indicates that case study bridge K has a deck area of 15,000 sq. ft. and is located on a Non-Interstate roadway. From there one would use Table 4.2 to determine the estimated cost per square foot of each of the action items. In the case of case study bridge K, that would be \$20 per sq. ft. for a thin deck overlay, \$105 per sq. ft. for a rigid deck overlay, and \$170 per sq. ft. for a deck replacement. This yields a roughly estimated cost of performing a thin deck overlay, rigid deck overlay, and deck replacement on case study bridge K as \$298,000, \$1,564,000, and \$2,531,000 respectively. Using the pattern of typical intervention actions introduced earlier in this section, one can calculate the cost of interventions vector, C_I and thus the cost of replacement C_R which for this. Referencing the calculation procedure outlined in Table 4.3, the cost of interventions vector, C_I for case study bridge K in dollars is

$$C_I = \{\$0 \quad \$298{,}000 \quad \$596{,}000 \quad \$2{,}160{,}000 \quad \$2{,}160{,}000 \quad \$2{,}160{,}000 \quad \$2{,}160{,}000 \quad \$2{,}160{,}000\}$$

Thus, the cost of replacement, C_R is \$4,691,000.

Table 4.3. Cost of interventions and cost of replacement calculations for case study bridge K

	Cost of Interventions							Cost of Replacement
	CR9	CR8	CR7	CR6	CR5	….	CR2	CR1
Associated Action	-	*Thin Deck Overlay*	*Thin Deck Overlay*	*Rigid Deck Overlay*	-	….	-	*Deck Replacement*
Associated Action Cost	-	$298,000	$298,000	$1,564,000	-	….	-	$2,531,000
Accumulated Cost	$0	$298,000	$596,000	$2,160,000	$2,160,000	….	$2,160,000	$4,691,000

4.3 Case Study Bridge Results

In the Section 4.2 the CR range of evaluation was defined. This definition is used to determine at what point in time the cost values will be calculated and compared. It is necessary to choose the same point in time for both the standard construction and substandard construction cases so that the evaluation timeframe is equal. The selected time is chosen as the time at which the standard construction case for a given bridge deck is predicted to need replaced (degradation point halfway between CR 5 and 4) based on INDOT standards.

4.3.1 Loss of Life

Assuming native degradation in all instances, a sample predictive degradation curve is provided for case study bridge K in Figure 4.2. Appendix A provides the predicted degradation curves for each case study bridge. In Figure 4.2, the dashed black line corresponds to the predicted bridge degradation assuming it is built with standard construction, the solid black line assumes standard construction but with the addition of the hazard ratios determined in this study, and the solid red line corresponds to the predicted degradation pattern of the bridge built with its specific construction defect(s) and includes the same applied hazard ratios. The hazard ratios are applied to the stay-the-same transition probability matrices determined from the physics-based model. When following the prediction process outlined in Section 2.2.3, the future CR prediction calculations start from the current CR of the bridge, which may be a value other than 9. However, to facilitate comparison in this study, the degradation depicted is the estimated degradation from the first year of the service life of a given bridge deck, assuming that it started in CR 9, even though the bridge may have already been in service for some time. This simplification is made so that the case study bridges can be easily compared with the same starting point of immediately after construction, rather than the current CR which may be years after the initial construction.

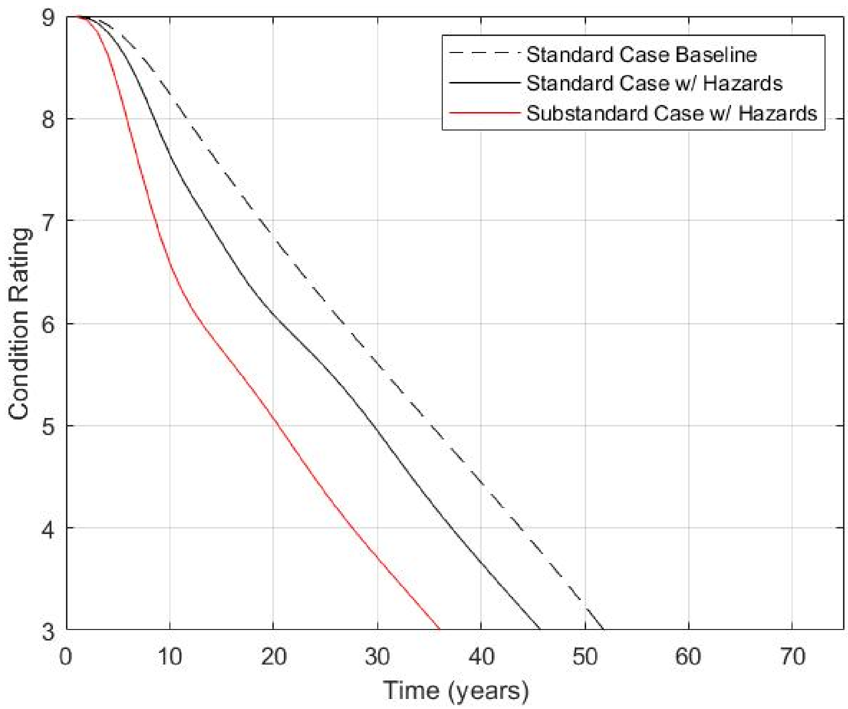

Figure 4.2. Degradation curve for case study bridge K

The protocol that a bridge deck is replaced in its degradation halfway between CR 5 and 4 is applied here and used to generate a prediction of the estimated time to replacement for each case study bridge. Table 4.4 contains the predicted year when a bridge deck reconstruction would take place based on the average between the year at which each case study bridge is predicted to cross from CR 6 to 5 and the year at which each case study bridge is predicted to cross from CR 5 to 4. The last column provides the difference between the estimated year of bridge deck reconstruction for the standard construction and the substandard construction cases resulting in the estimated loss of life of the bridge deck. Bridges that have a (-) in columns 2 and 3 do not contain defects, thus do not have a substandard construction case for comparison.

Table 4.4. Estimated reconstruction years and life lost for case study bridges

	Estimated Reconstruction year for Standard Construction	Estimated Reconstruction year for Substandard Construction	Estimated Loss of Life (years)
A	40	-	-
B	40	19	21
C	39	25	14
D	41	18	23
E	34	34	0
F	41	-	-
G	40	31	9
H	41	31	10
J	35	27	8
K	35	26	9

4.3.2 Estimated Additional Cost

The estimated total cost values for the standard construction and substandard construction cases can be found in Table 4.5, along with the estimated additional cost. All cost values are shown in present day dollars.

Table 4.5. Estimated additional cost for case study bridges (in present day dollars)

	C_T, Total Estimated Cost for Standard (STD) Construction Case	C_T, Total Estimated Cost for Substandard (SUB) Construction Case	Estimated Additional Cost (SUB – STD)
A	$1,180,200	$1,180,200	-
B	$1,259,900	$1,997,400	$737,500
C	$1,498,000	$1,732,000	$234,000
D	$5,455,500	$9,099,700	$3,644,200
E	$1,983,900	$1,984,000	$100
F	$1,538,500	$1,538,500	-
G	$4,057,700	$4,163,200	$105,500
H	$1,074,100	$1,133,300	$59,200
J	$1,523,800	$1,536,700	$12,900
K	$1,823,800	$1,845,900	$22,100

For a graphical representation of the application of the cost calculation, see Figure 4.3 where case study bridge K is used as an example. Here, solid lines represent the standard construction case, and dashed lines represent the substandard construction case. Two red lines are associated with the expected value of the intervention costs, C_I, and two blue lines are associated with the expected value of the replacement cost, C_R, and two pink lines correspond to the total cost, C_T. Lastly, the horizontal black lines are included for a visual illustration of the two total cost values used in the comparison. Please note that not all lines may be visible in a given bridge's cost curve graph because in some cases the calculated cost of replacement is near zero for a large portion of the timeline (the bridge does not reach CR1 until later). However, the year determined for INDOT practice replacement is being used, which is halfway between CR 5 and CR 4, causing the C_R curve to lie on the x-axis. In this case, the intervention cost and total cost are identical (and overlapping) for some time. Also take note of the possibility for the C_I curve to decrease after some time. This is because the probability of the bridge being in one of the CRs assigned to an intervention action decreases, and the probability of the bridge being in the CR assigned to the replacement action increases. The reduction in intervention cost reflects this logical progression.

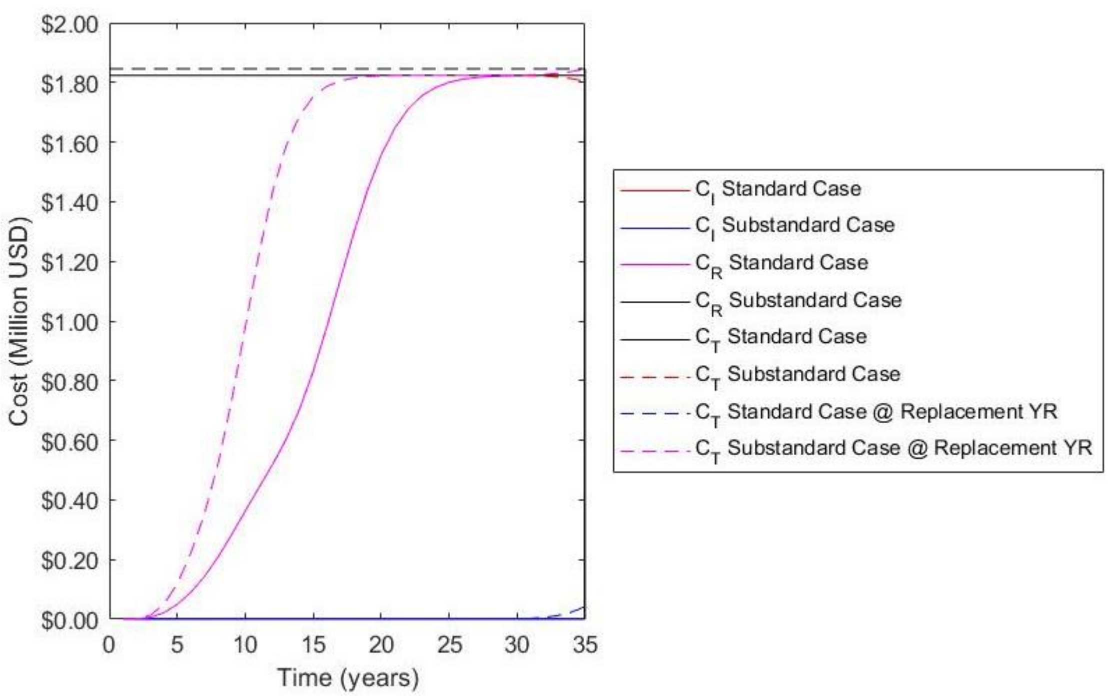

Figure 4.3. Present day cost curves for case study bridge K

5. CONCLUSIONS AND RECOMMENDATIONS

The purpose of this study was to address the need for a holistic numerical model that illustrates the differences in lifecycle deterioration and maintenance efforts of a bridge deck in the case of standard construction versus substandard construction. The holistic model developed consists of a physic-based model originating from Salmerón et al. (in review) and Criner & Salmerón et al. (2022), a data-driven model originating from Goyal (2015), and a cost model originating from Kleiner (2001). Each of these individual models came from literature and were adapted to fit the needs of this study, specifically to make them applicable to the state of Indiana and the available data. The development of a predictive degradation model that can estimate a loss of life of a bridge deck when the deck was built with a certain construction defect(s) was achieved in this study. In addition, a cost model was adapted to the needs of this study and applied resulting in the ability to estimate the additional cost that will be incurred in order to keep the bridge deck in service for the expected timeframe if it has not been built with a construction defect. The predictive degradation model and cost model were applied to 10 case study bridges to illustrate its use and the results.

The results from this holistic model can serve as an educational resource for training of bridge inspectors and asset managers, by showing how substandard construction practices impact the long-term cost of maintaining the bridge deck. This could motivate all parties involved to enforce construction stage specifications to ensure only standard construction is occurring. Please note that the physics-based model used in the creation of the holistic model developed in this study, utilized information in the current design and construction specifications. As these specifications continue to improve over time, the results of this model could then be conservative.

5.1 Sensitivity Analysis

Indiana bridges are subject to multiple external factors that could potentially speed up or slow down the degradation process over the bridge's life. In order to better understand which external factors were significant to the degradation pattern observed within the state, the Cox proportional hazards model was used. Each individual external factor was assigned the term covariate and the span of data values applicable to that group were divided into further subcategories, called design variables. The sensitivity of the final degradation curves to the presence of these design variables was evaluated; by applying one at a time and evaluating the effect of the individual design variable to the same base degradation pattern. The transition probabilities obtained from the physics-based model of one of the case study bridges that is considered non-defective (case study bridge F) was used. The resulting degradation curves for each covariate and its respective design variables are included in its own plot (see Figures 5.1-5.6), where each line represents a different design variable for that covariate. Any design variables in the covariate group that is not shown has been determined to have no impact on final degradation. Thus, that case had the same degradation curve as the baseline indicated with a (B) in the corresponding legend.

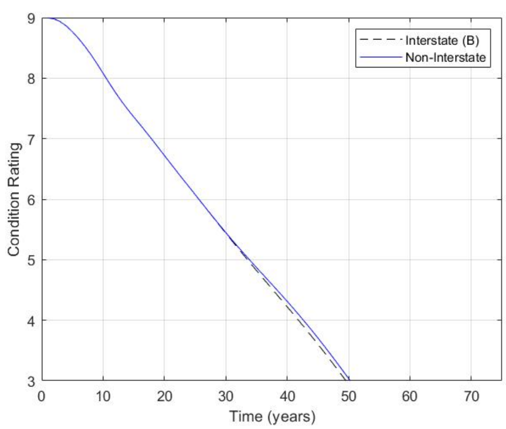

Figure 5.1. Degradation curve for functional classification comparison

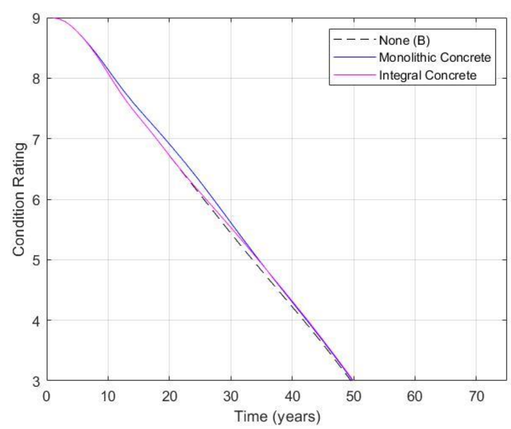

Figure 5.2. Degradation curve for wearing surface presence/type comparison

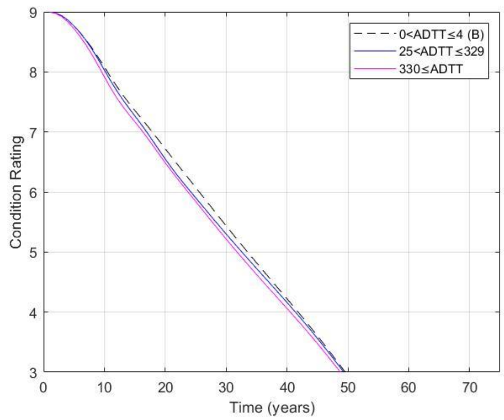

Figure 5.3. Degradation curve for functional classification comparison

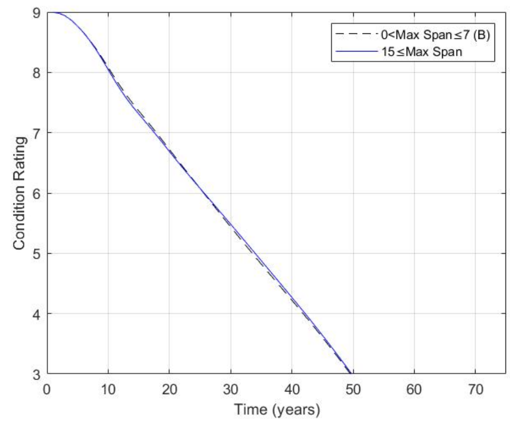

Figure 5.4. Degradation curve for wearing surface presence/type comparison

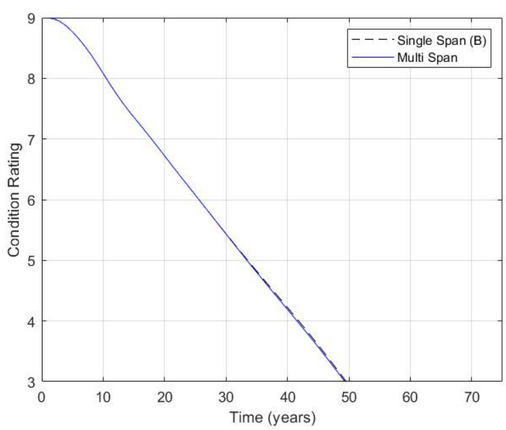

Figure 5.5. Degradation curve for number of spans comparison

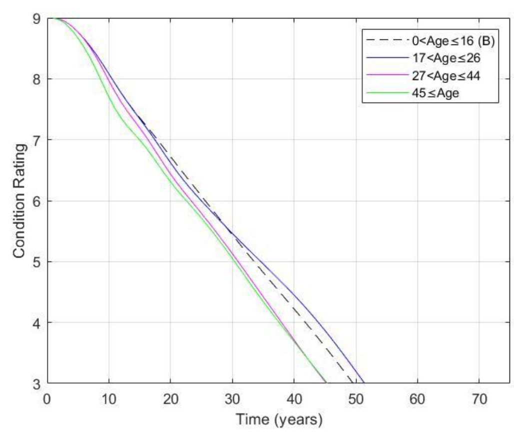

Figure 5.6. Degradation curve for age comparison

When comparing the individual design variables (i.e. Interstate versus Non-Interstate), often one single design variable does not exhibit much variation in expected life lost/gained. The observed maximum variation is approximately 2 years in this study. That is, of course, for all covariates other than age. The covariate age results in a variation of approximately 6 years among its respective design variables. Another difference to note is when the hazard ratios are combined for individual bridges (as most bridges are subject to multiple covariates at the same time), the effect of the design variables greatly increases. See Figure A3.17 for an illustration of the difference in loss/gain of life that can happen from different levels of variable combination. The curve representing "Negligible Hazards" has the design variables for 'Monolithic Concrete' and

‘15 ≤ Max Span’ applied. The curve representing “Moderate Hazards” has the design variables for ‘Monolithic Concrete’ and ‘27 < Age ≤ 44’ applied. The curve representing “Severe Hazards” has the design variables for ‘330 ≤ ADTT’, ‘Multi-Span’, and ’45 ≤ Age’ applied.

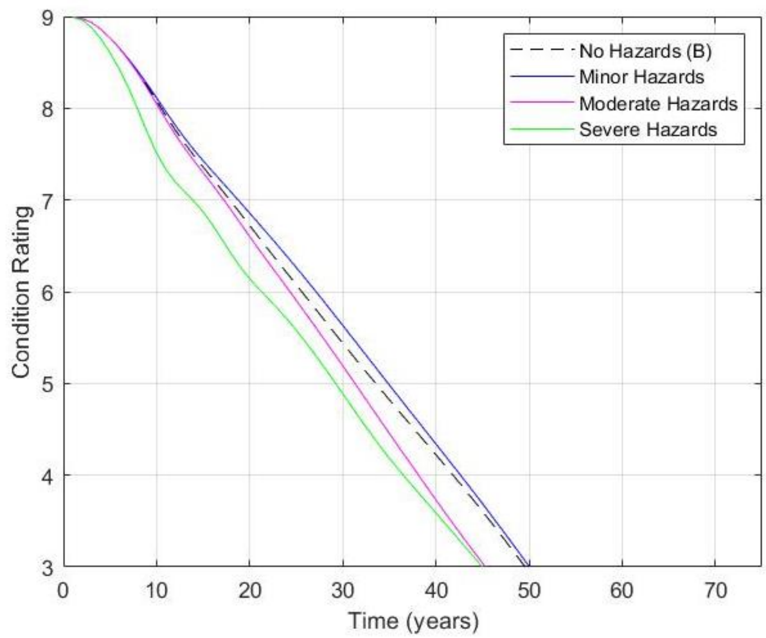

Figure 5.7. Sensitivity analysis for different hazard ratio combinations

5.2 Recommendations for Improved Development of Future Models

During the refinement of the data-driven model, there were some instances of missing data that would have improved the accuracy of the process. In this section, a summary of the outcomes from the model analyses is presented. Some suggestions about data that could be collected to improve the modeling of the related phenomena are given and, when available, possible methods to gather such data. Section 5.2.2 provides a compilation of recommendations from the INDOT personnel that were interacted with over the course of this study. These recommendations represent the first-hand experience from experienced INDOT personnel and add great value to the findings and recommendations from the research team.

5.2.1 Recommendations for Data Relevant to the Data-Driven Model

One of the main obstacles of a data-driven model is unreliable data. Data can be unreliable for a number of reasons including the standards for collection, the rates of collection, and the quality and quantity of the data collected. The current method of data collection used by INDOT is based on the 1-9 CR scale. This approach is not precise and leads to subjective decision-making in the final assigned CR. There is also limited guidance for the type, quality, or quantity of data collected during these routine inspections, further leading to the subjective nature of the results. Changes to the inspection process would aid to improve results from inspections, and in the long run lead to more effective asset management and more refined data-driven models. However, to improve the data-driven models for future use at least 20 years, based on the research conducted in this study, of data are required. Thus, it is recommended to implement changes to the bridge inspection process as follows.

- The current routine bridge inspection procedure requires only 2 photos of the bridge be taken and documented per inspection. These photos seldom provide tangible information to document the condition of the bridge or instances of deterioration. Hence, we recommend INDOT consider, for the purposes of improving the deck modeling, covering the entire surface using high-definition digital images to allow zooming on critical areas. We also recommend INDOT consider providing a simple sketch of the bridge to mark in what order the photos were taken and in what location in relation to the bridge, to ensure an accurate documentation of deterioration progression over time and ensure the correct assignment of CRs.
- For data-driven models to be beneficial, the data used in the creation of the model must be as accurate as is practically feasible. It may be the case that some data item values reported based on the requirements of the FHWA's *Recording and Coding Guide* may not be accurately updated with each submission. This oversight can influence model development and application if the values of data items like average daily traffic and average daily truck traffic, for example, are not accurately updated in each submission. We recommend ensuring all data values are up to date in the submission of at least every routine bridge inspection.
- Training of the bridge inspectors of course benefits data collection procedures as it prepares all bridge inspectors to perform high quality inspections. However, during the interviews

with INDOT personnel, it was also emphasized the importance of providing the inspectors with adequate tools and training on the use of the tools in the inspection.

- Stay-in-place metal forms present an obstacle to the routine bridge inspection process because they obstruct line-of-sight to the underside of the concrete bridge deck. Being able to see and accurately assess the condition of the bridge deck from underneath the bridge is vital to the management of the bridge deck during its life. Therefore, we recommend the use of either (1) removable deck forms, or (2) clear stay-in-place forms when building a bridge deck.
- Develop and refine language to aid bridge inspectors in understanding both the differences and similarities between abrasion and wearing on a bridge deck, and how to evaluate the presence of each on a wearing surface versus a deck. This clarification will allow for better distinction between wearing surface and deck in the assigned CRs, as well as keeping bridge asset managers up to date on the abrasion and wearing patterns present on their bridges.

5.2.2 Recommendations Based on Input from INDOT

There were multiple instances to meet and engage with INDOT personnel from various departments to better understand the processes involved in the construction, inspection, and management of concrete bridge decks under INDOT ownership. During this knowledge gathering process, INDOT personnel shared their concerns and suggestions for improvement in relation to each of their respective job duties. Those concerns and suggestions for improvement are summarized below, in order of priority assigned by the interviewees.

- Include the respective INDOT district Bridge Asset Engineers/Managers in the final bridge inspection for determination of acceptance of a newly constructed bridge by INDOT.
- Adapt INDOT business rules to allow for changing preventative maintenance practices, without these business rules being the sole policy hindering the life expectancy of a bridge component. In other words, adapt the preventative maintenance business rules so that they are not the sole indicator of replacement of a component if the component’s condition does not point to the same decision.

- Consider expanding the material testing specification to include taking additional concrete samples from the beginning of the batch prior to concrete placement to test for minimum quality requirements before a significant portion of the concrete is poured.
- Incorporate the use of alternatives to deicing salt that mitigate corrosion.
- Determine a more appropriate way to adequately code data item categories from the FHWA *Recording and Coding Guide* when new data item options are present for INDOT. An example would be making silica fume overlays their own category, rather than placing them in the 'other' category or an improperly labeled category. This addition allows for proper data analysis on the performance of said data item in the future.
- Assign an inspector to perform inspections of the INDOT in-house maintenance department's work, ensuring all maintenance actions are following craftsmanship quality standards and material standards.
- Incorporate more specific and clearer epoxy-coated rebar handling instructions. An example of more clear storage instruction may include "Coated bars or bundles shall be stored above the ground on wooden or padded supports with timbers placed between bundles when stacking is necessary. Space the supports sufficiently to prevent sags in the bundles" (ASTM D3963). An example of more clear handling instructions may include "All systems for handling coated steel reinforcing bars shall have padded contact areas…. All bundles of coated steel reinforcing bars shall be lifted with a strong back, spreader bar, multiple supports, or a platform bridge to prevent bar-to-bar abrasion from sags in the bundles of coated steel reinforcing bars" (ASTM 775).

APPENDIX A. CASE STUDY BRIDGE CATALOG AND RESULTS

Bridge Designation: A **Estimated Loss of Life:** N/A

Region: North **Estimated Additional Cost:** N/A

Noted Defect(s): None

Defect Notes:

"(…) hairline short longitudinal cracks at both ends of deck (…) Good condition".

Hazard Ratios:

9	8	7	6	5	4
1.2299	0.9023	1.0255	1.2707	1.2497	1.0000

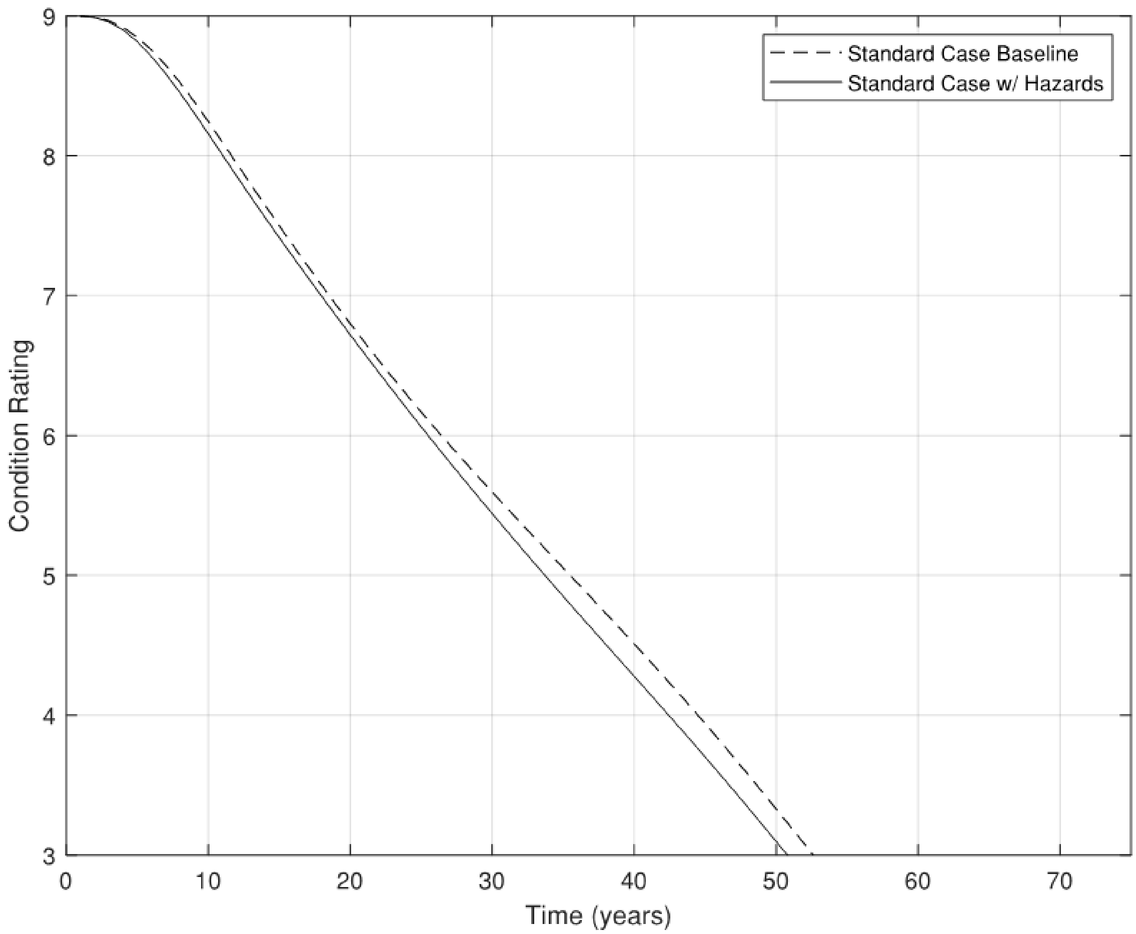

Figure A.1. Degradation curve for case study bridge A

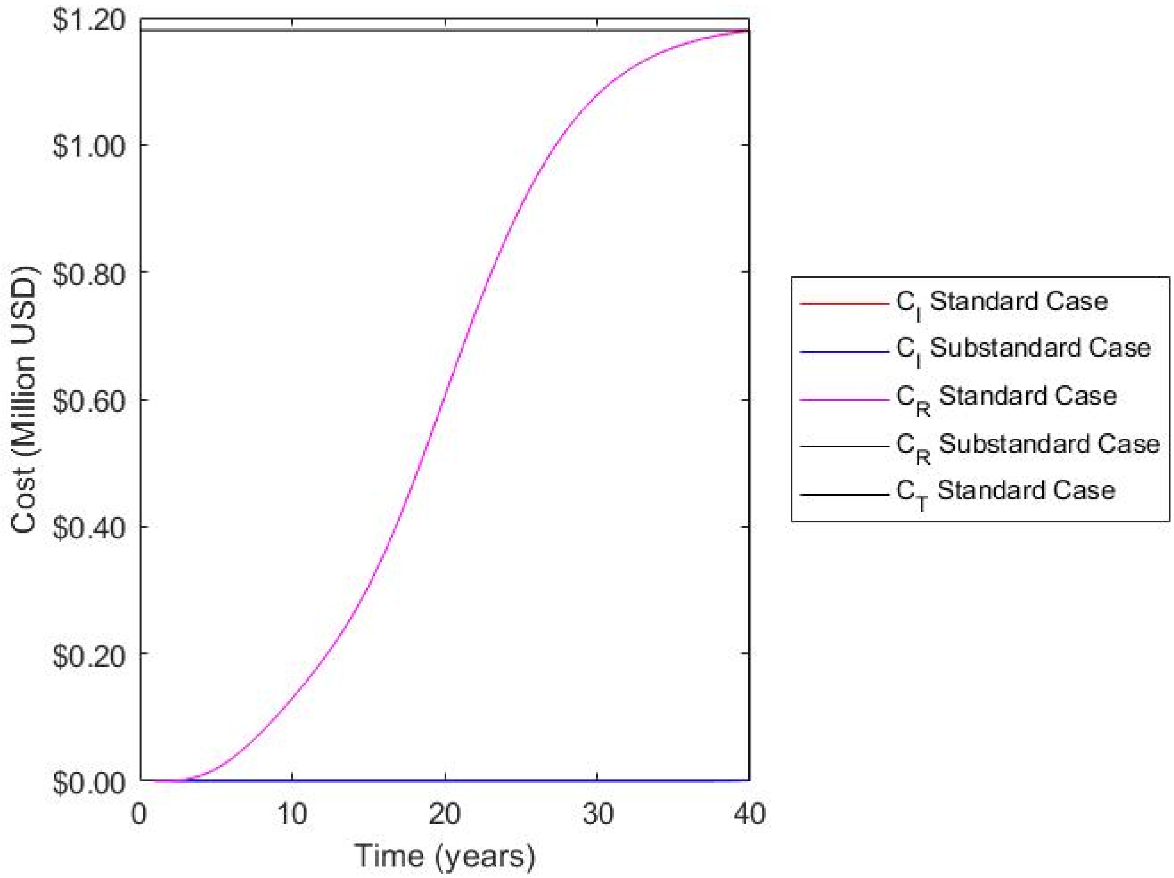

Figure A.2. Present day cost curve for case study bridge A

Bridge Designation: B **Estimated Loss of Life:** 21 years

Region: North **Estimated Additional Cost:** $737,500

Noted Defect(s): Improper curing

Defect Notes:

"(…) deck also heavily cracked throughout".

Hazard Ratios:

9	8	7	6	5	4
1.2299	1.0947	1.0255	1.0918	1.2497	1.0000

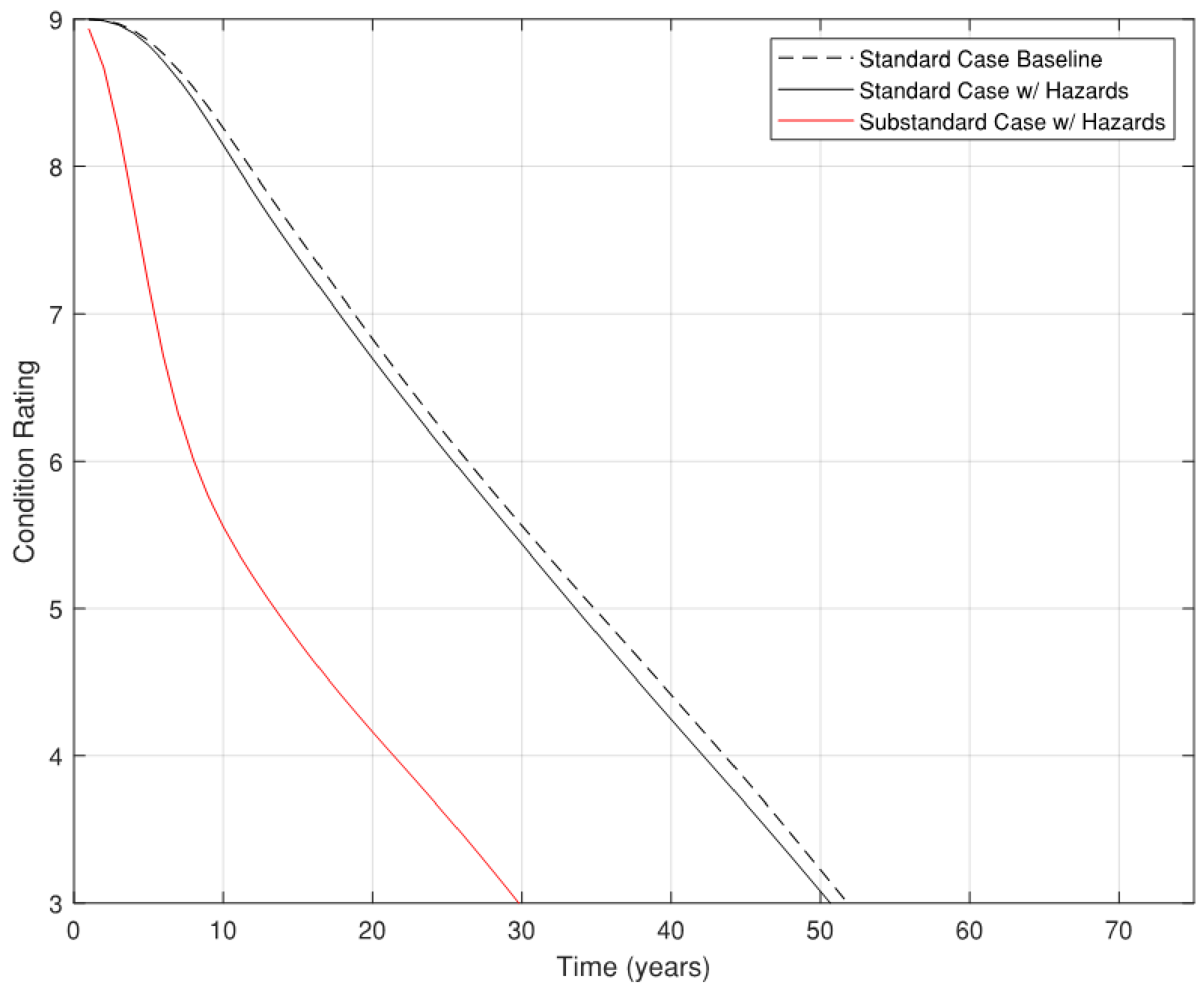

Figure A.3. Degradation curve for case study bridge B

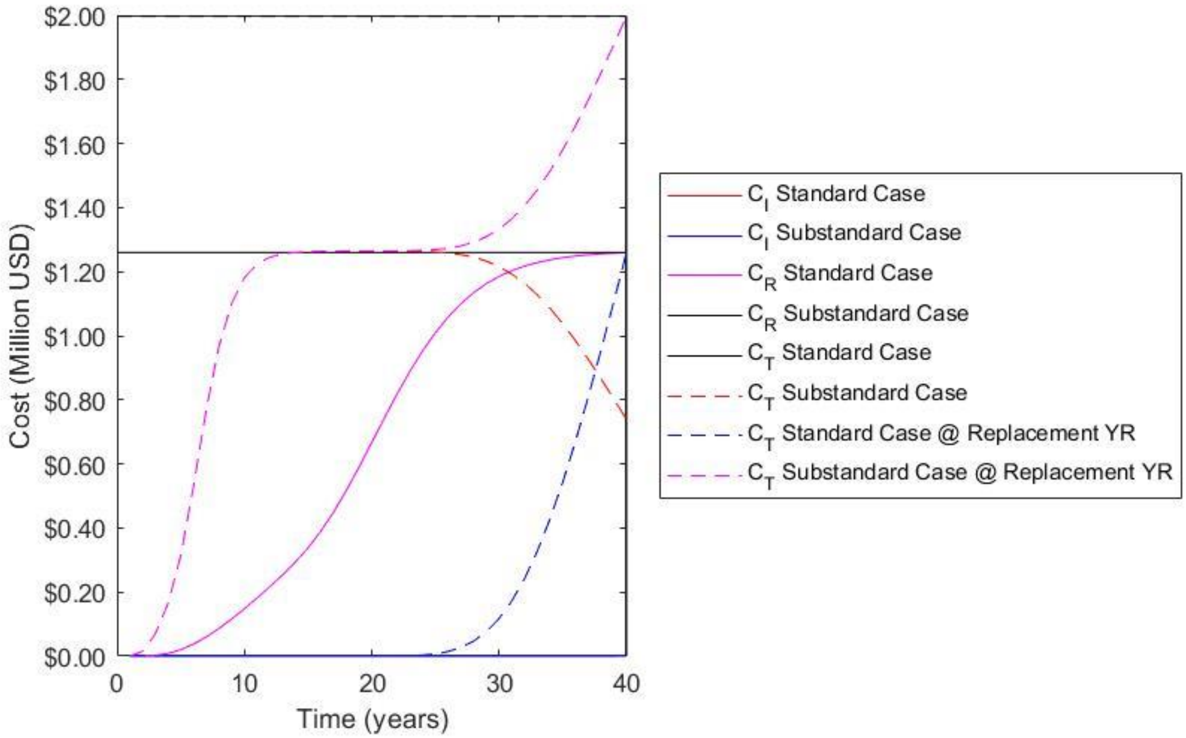

Figure A.4. Present day cost curve for case study bridge B

Bridge Designation: C | **Estimated Loss of Life:** 14 years

Region: North | **Estimated Additional Cost:** $234,000

Noted Defect(s): Improper curing

Defect Notes:

> "Moderate width cracking throughout the deck, signs of water leaking through the deck and staining the slope walls underneath. Efflorescence forming on the bottom of the deck".

Hazard Ratios:

9	8	7	6	5	4
1.2299	1.6173	1.4551	1.0918	1.2497	1.0000

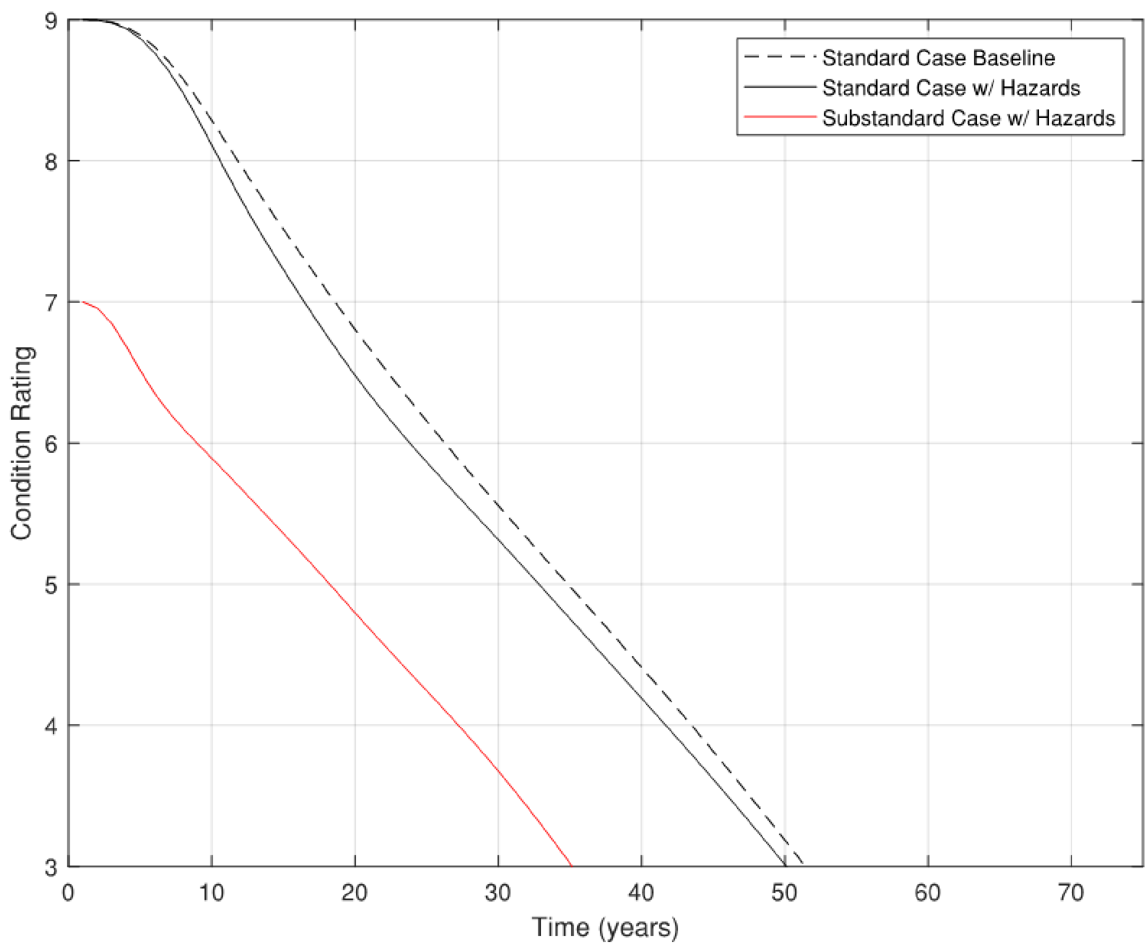

Figure A.5. Degradation curve for case study bridge C

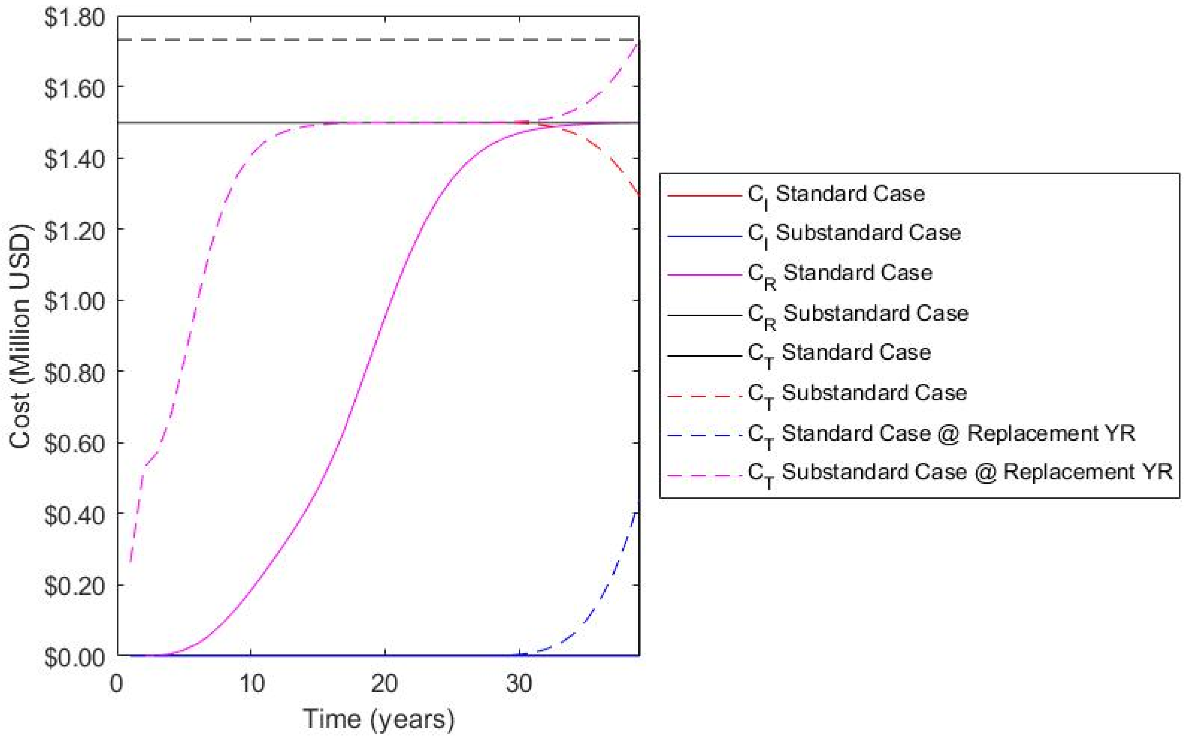

Figure A.6. Present day cost curve for case study bridge C

Bridge Designation: D **Estimated Loss of Life:** 23 years

Region: North **Estimated Additional Cost:** $3,644,200

Noted Defect(s): Non-standard w/c ratio & improper curing

Defect Notes:

> "(…) some efflorescence on closure angles (of SIPs) in SE corner and at Pier2 (NB) (…) Several transverse cracks visible under the deck at the center seam with efflorescent."

> "(…) incorrect concrete was used in deck".

Hazard Ratios:

9	8	7	6	5	4
1.2299	1.0947	1.0255	1.0918	1.2497	1.0000

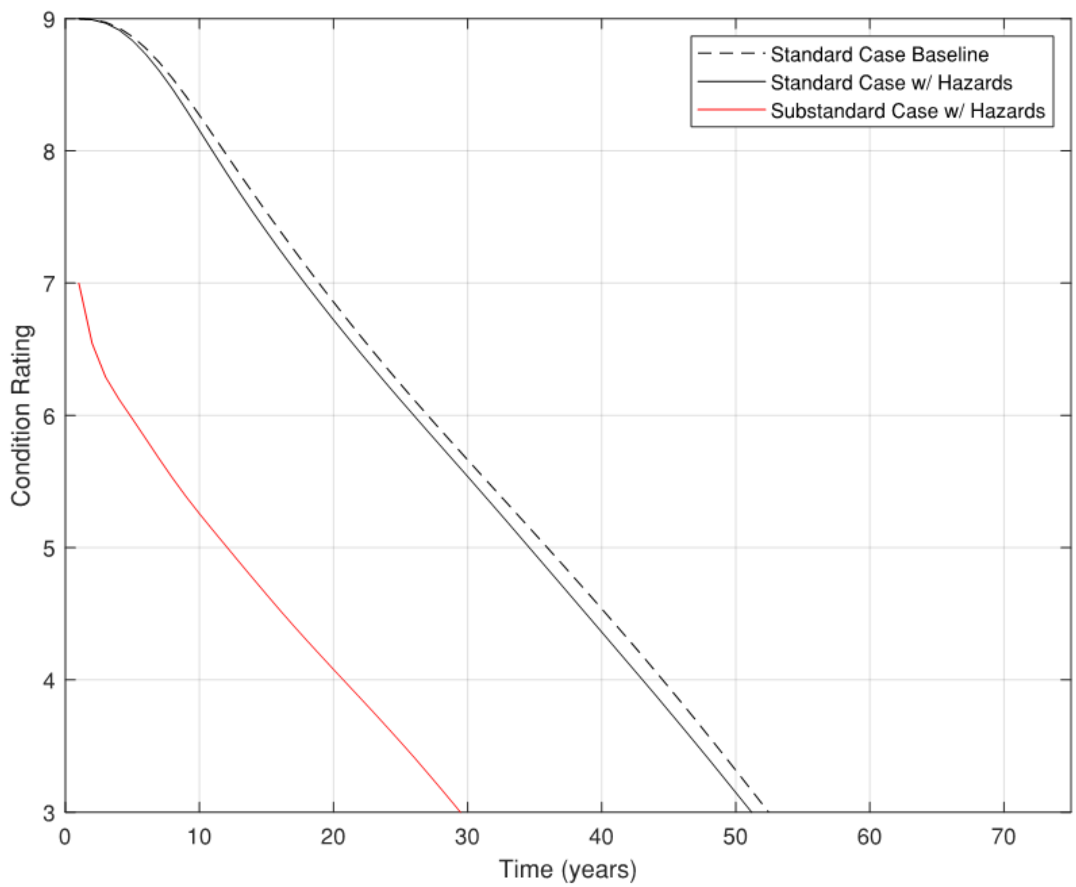

Figure A.7. Degradation curve for case study bridge D

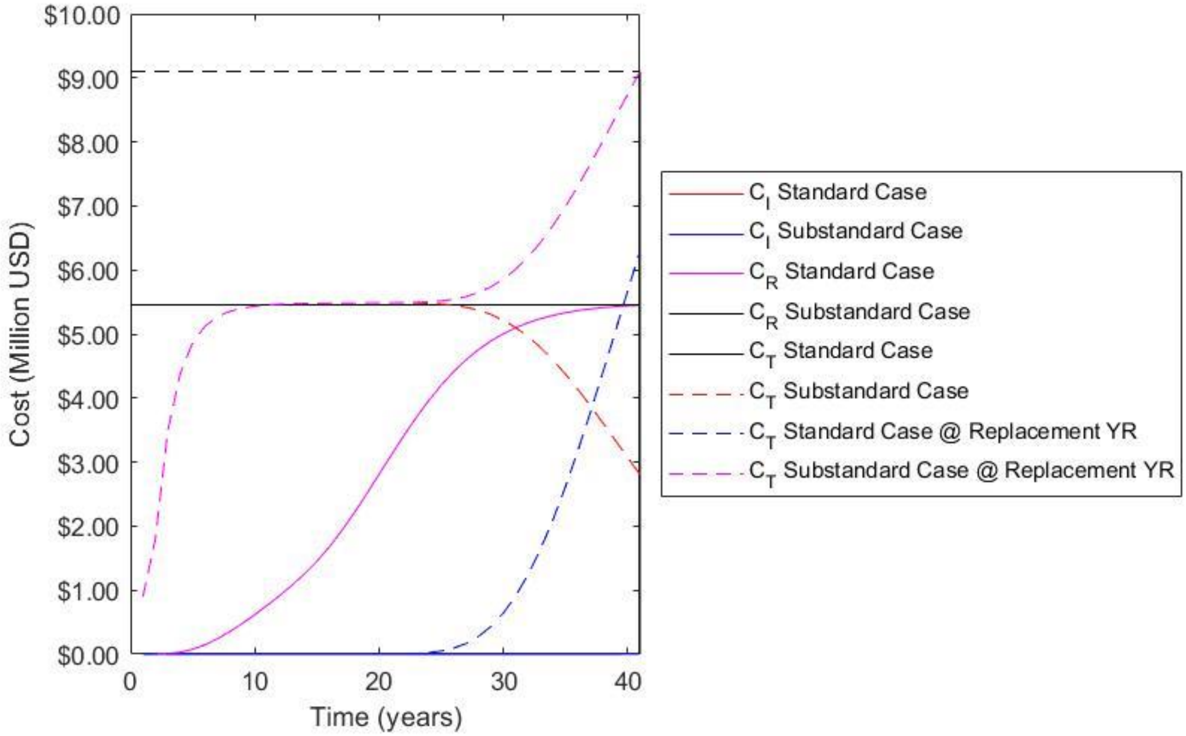

Figure A.8. Present day cost curve for case study bridge D

Bridge Designation: E **Estimated Loss of Life:** 0 years

Region: Center **Estimated Additional Cost:** $100

Noted Defect(s): Improper rebar handling

Defect Notes:

> "There were issues with the rebar cover and rideability after the superstructure pour (…)".

Hazard Ratios:

9	8	7	6	5	4
1.8555	2.7428	2.8213	1.8223	2.0670	1.7088

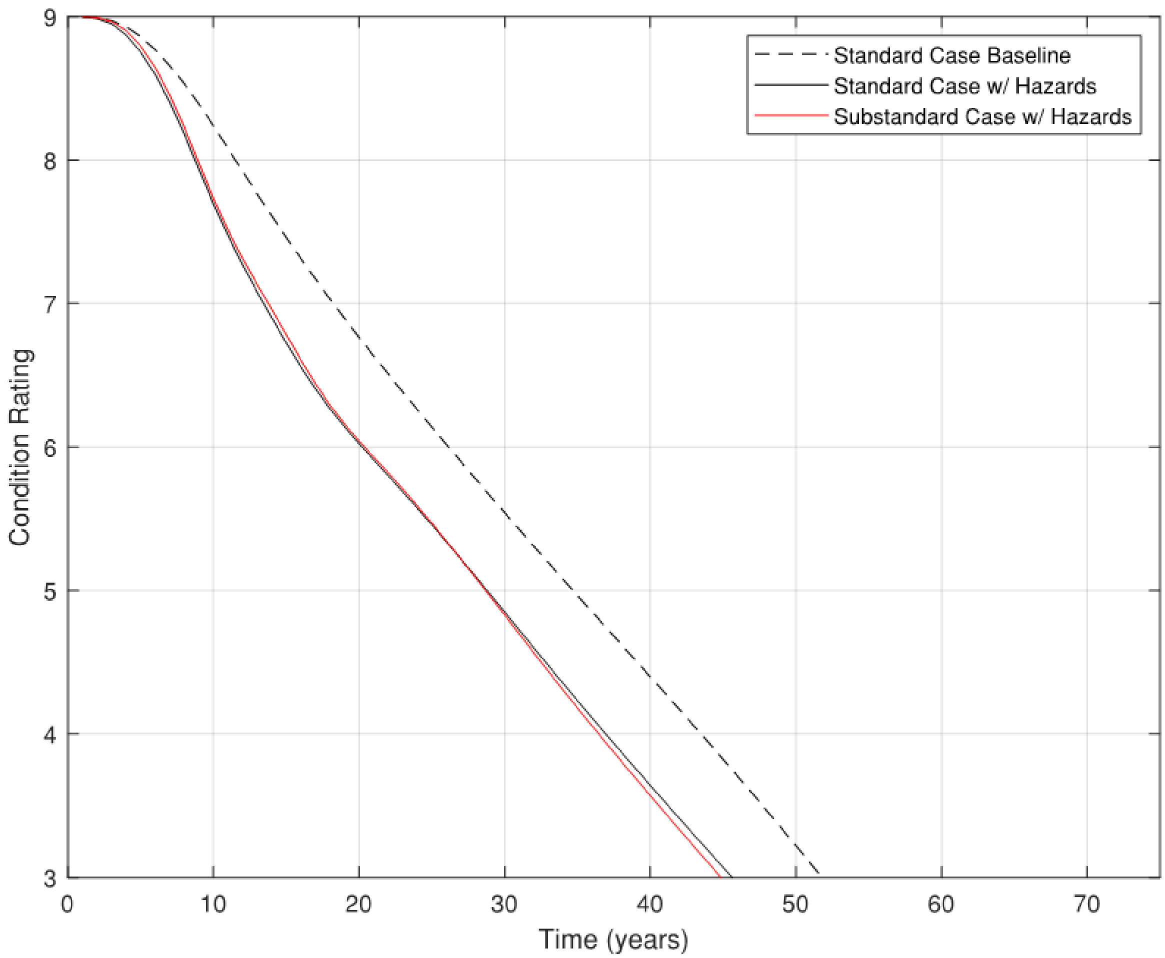

Figure A.9. Degradation curve for case study bridge E

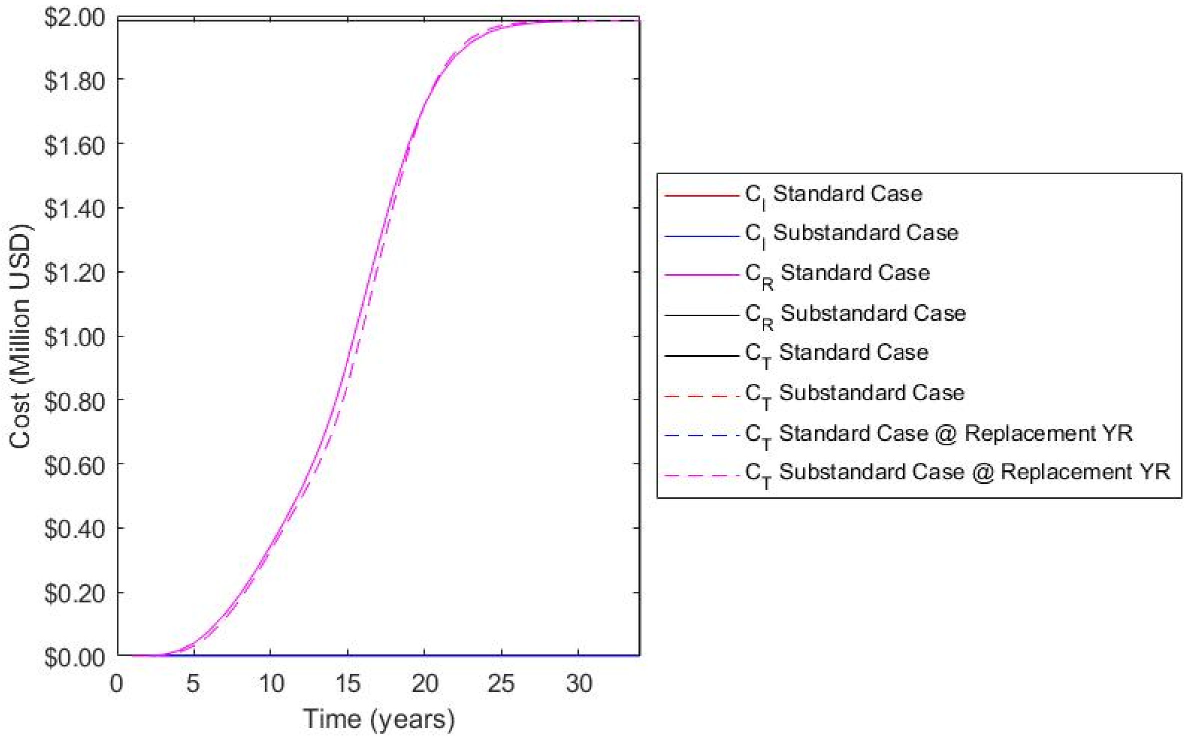

Figure A.10. Present day cost curve for case study bridge E

Bridge Designation: F **Estimated Loss of Life:** N/A

Region: Center **Estimated Additional Cost:** N/A

Noted Defect(s): None

Defect Notes:

"Deck (underside): no corrosion to metal forms".

Hazard Ratios:

9	8	7	6	5	4
1.0000	1.0785	1.0416	0.9584	1.0797	1.0000

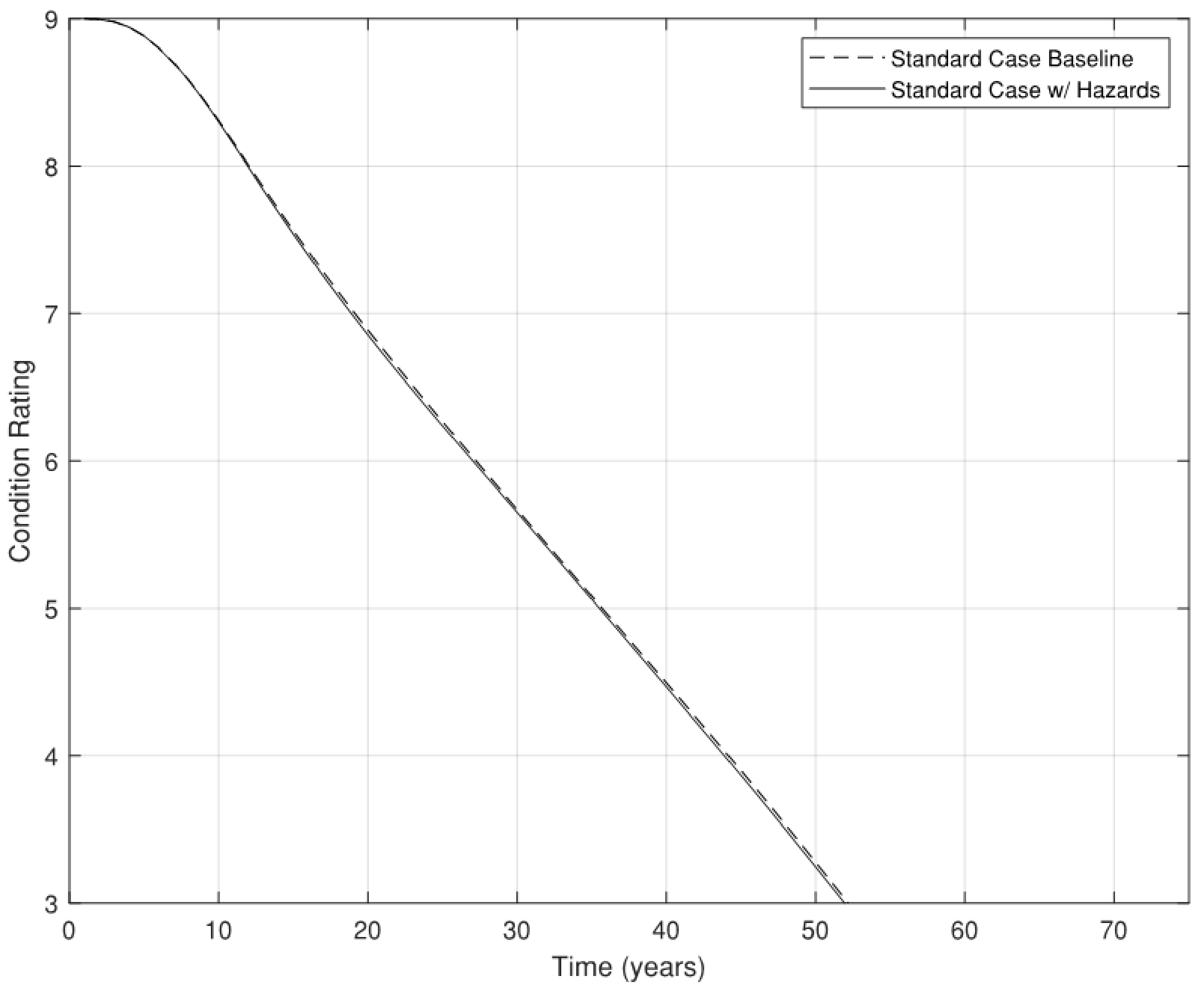

Figure A.11. Degradation curve for case study bridge F

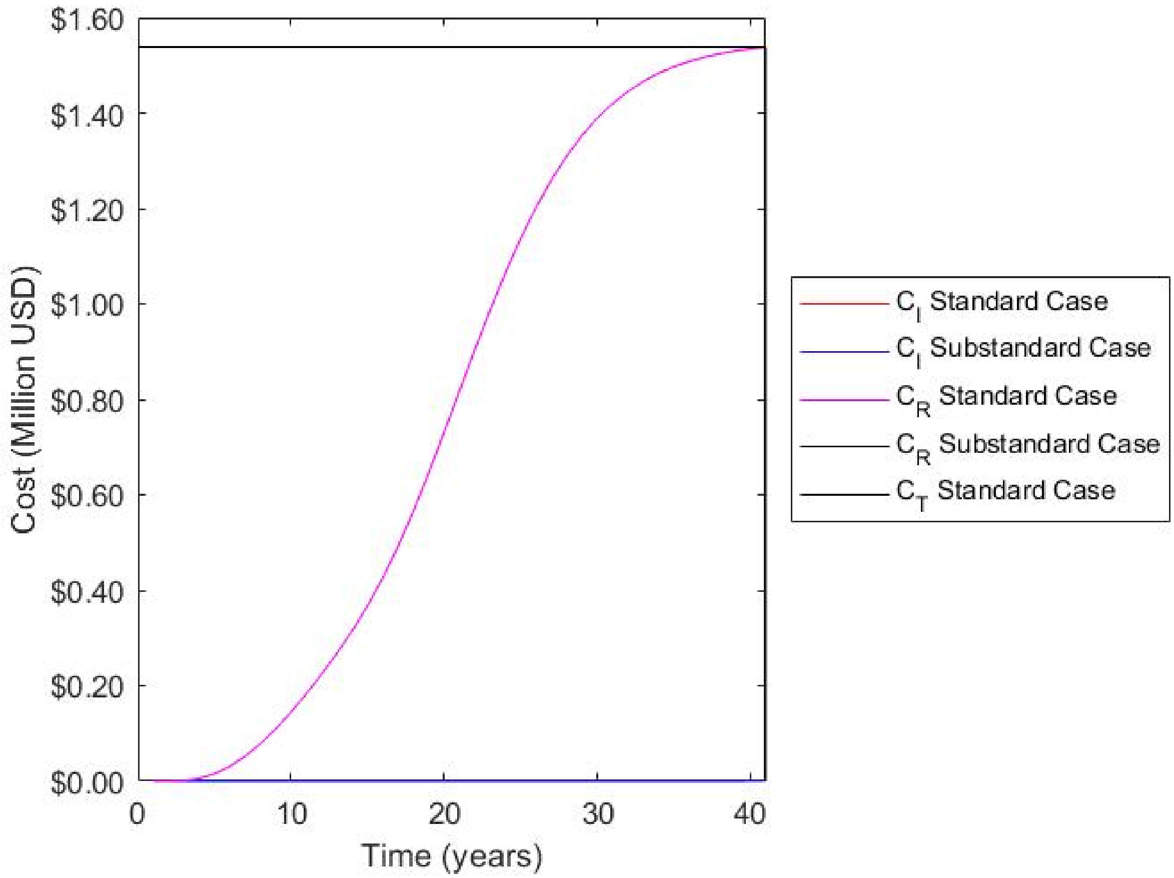

Figure A.12. Present day cost curve for case study bridge F

Bridge Designation: G **Estimated Loss of Life:** 9 years

Region: Center **Estimated Additional Cost:** $105,500

Noted Defect(s): Non-standard w/c ratio & improper curing

Defect Notes:

> "(…) the contractor was allowed to utilize a substitute concrete mix during the winter months provided they provide for special curing considerations (…) those considerations were not followed".

Hazard Ratios:

9	**8**	**7**	**6**	**5**	**4**
1.2299	1.0947	1.0255	1.0918	1.0131	1.0000

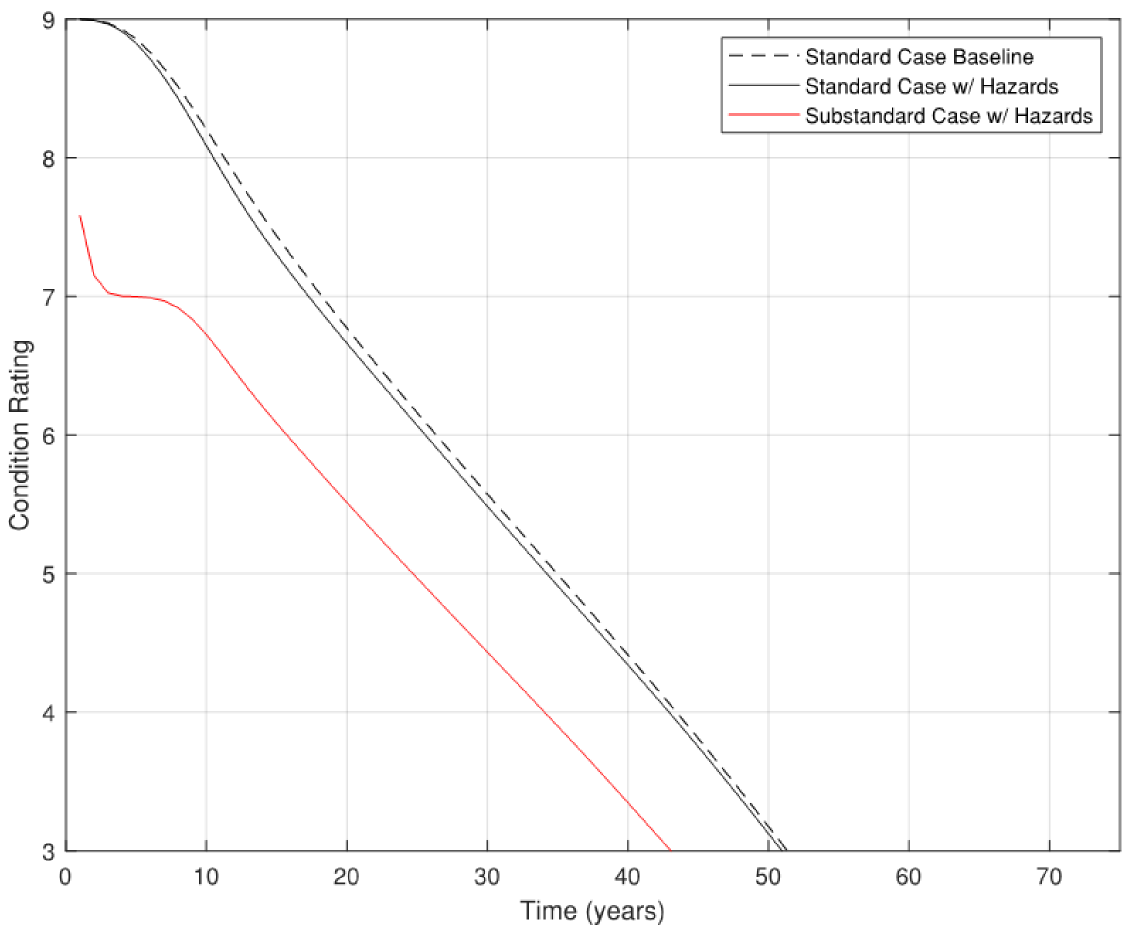

Figure A.13. Degradation curve for case study bridge G

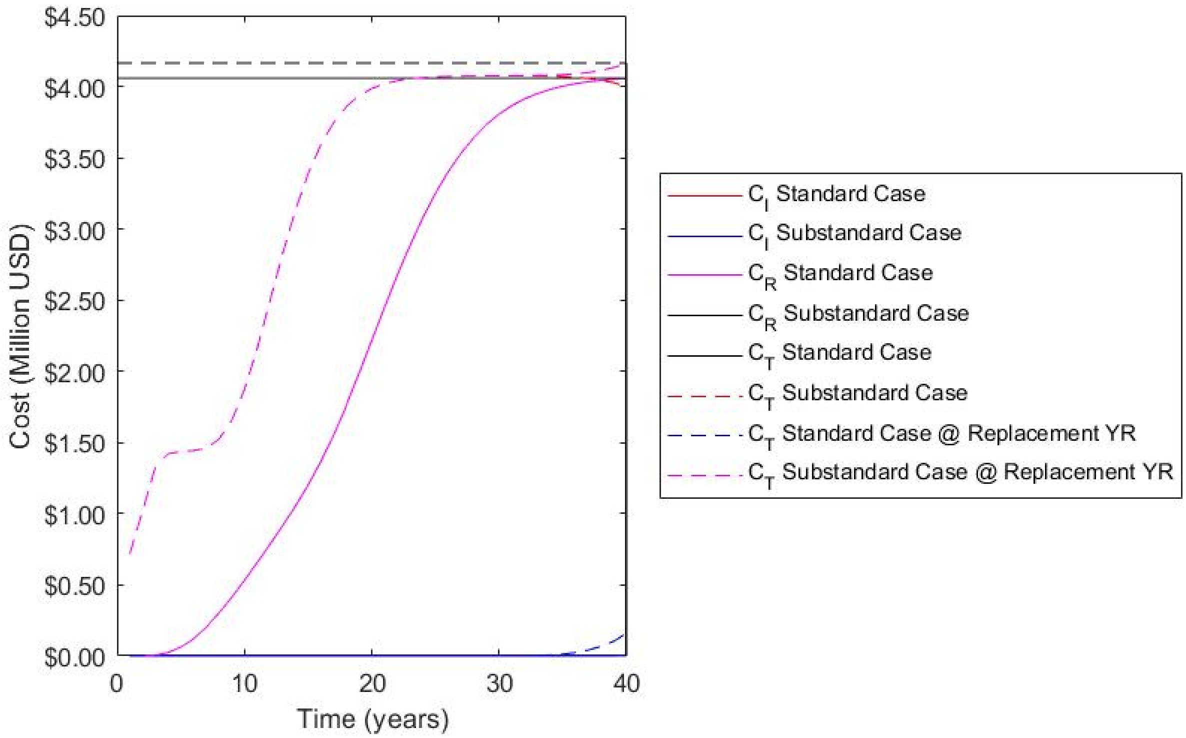

Figure A.14. Present day cost curve for case study bridge G

Bridge Designation: H **Estimated Loss of Life:** 10 years

Region: South **Estimated Additional Cost:** $59,200

Noted Defect(s): Improper curing

Defect Notes:

"(…) slightly diagonal cracks with efflorescence".

Hazard Ratios:

9	8	7	6	5	4
1.0000	1.0785	1.0416	0.9584	1.0797	1.0000

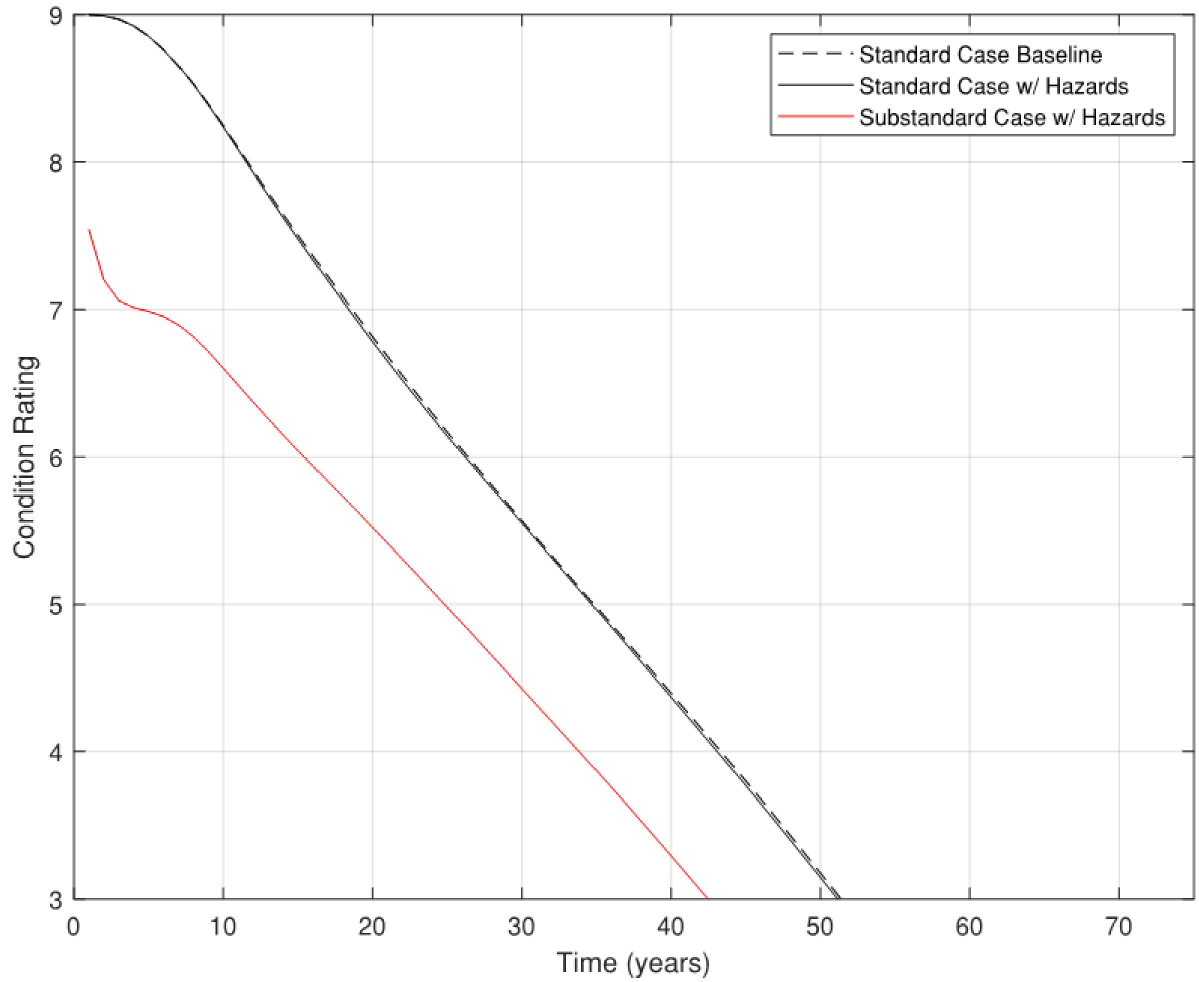

Figure A.15. Degradation curve for case study bridge H

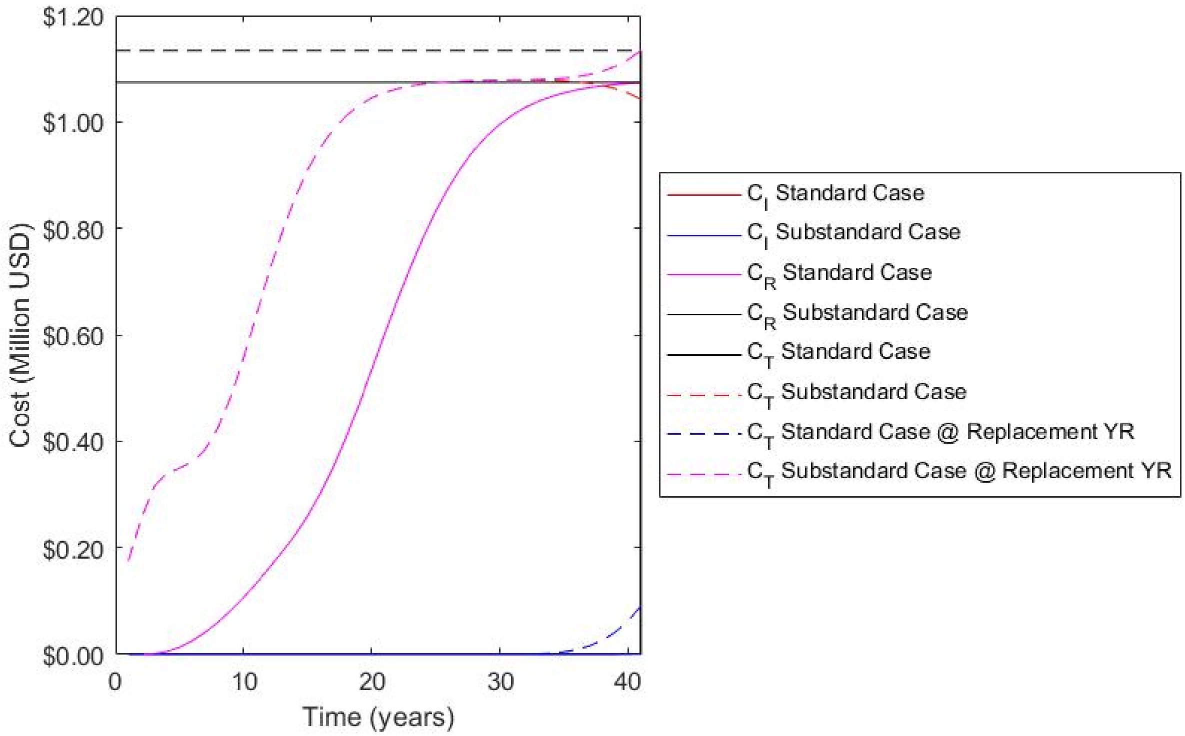

Figure A.16. Present day cost curve for case study bridge H

Bridge Designation: J **Estimated Loss of Life:** 8 years

Region: South **Estimated Additional Cost:** $12,900

Noted Defect(s): Non-standard w/c ratio

Defect Notes:

"Failed air test".

Hazard Ratios:

9	8	7	6	5	4
1.8555	3.3279	2.8213	1.5657	2.0670	1.7088

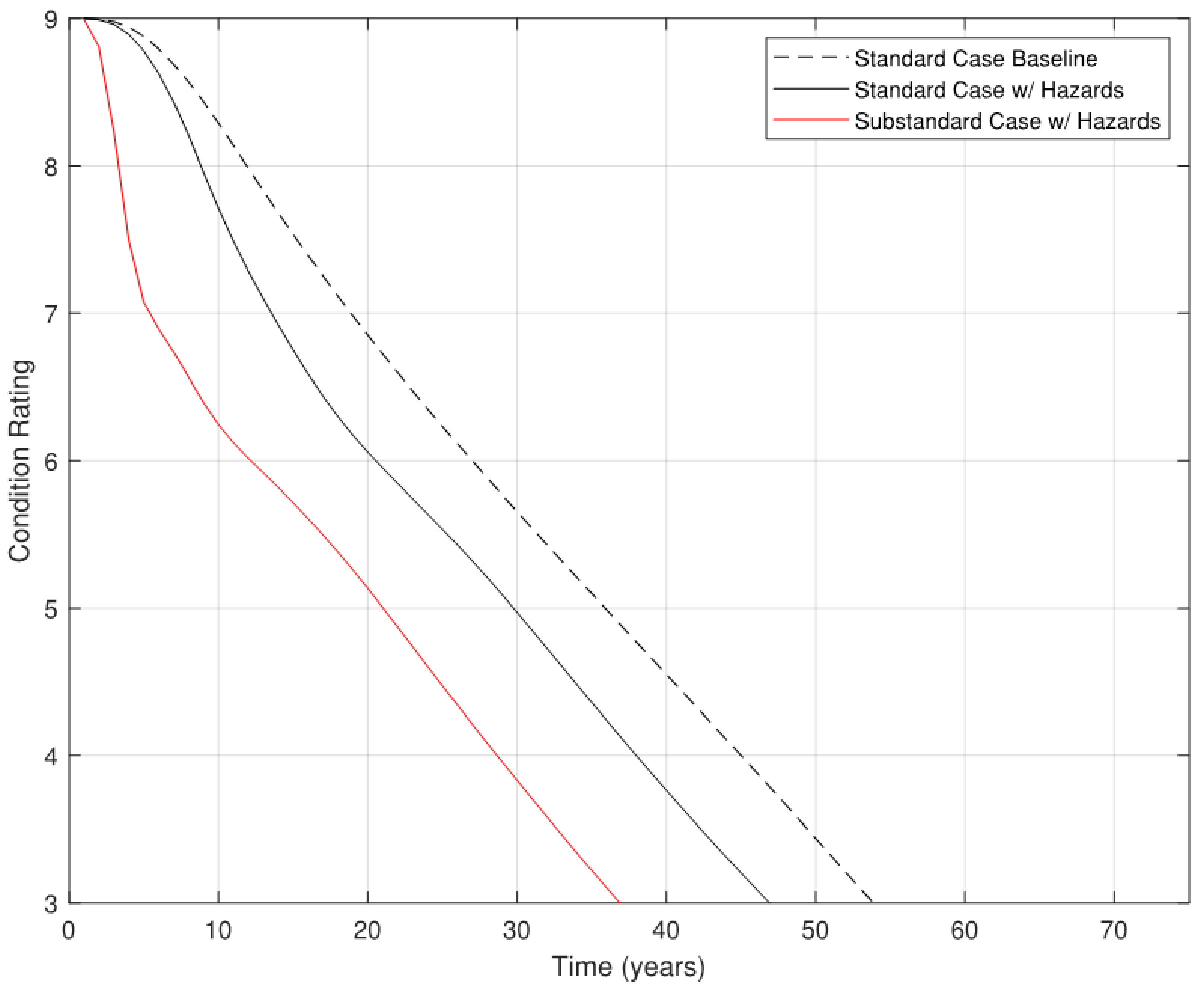

Figure A.17. Degradation curve for case study bridge J

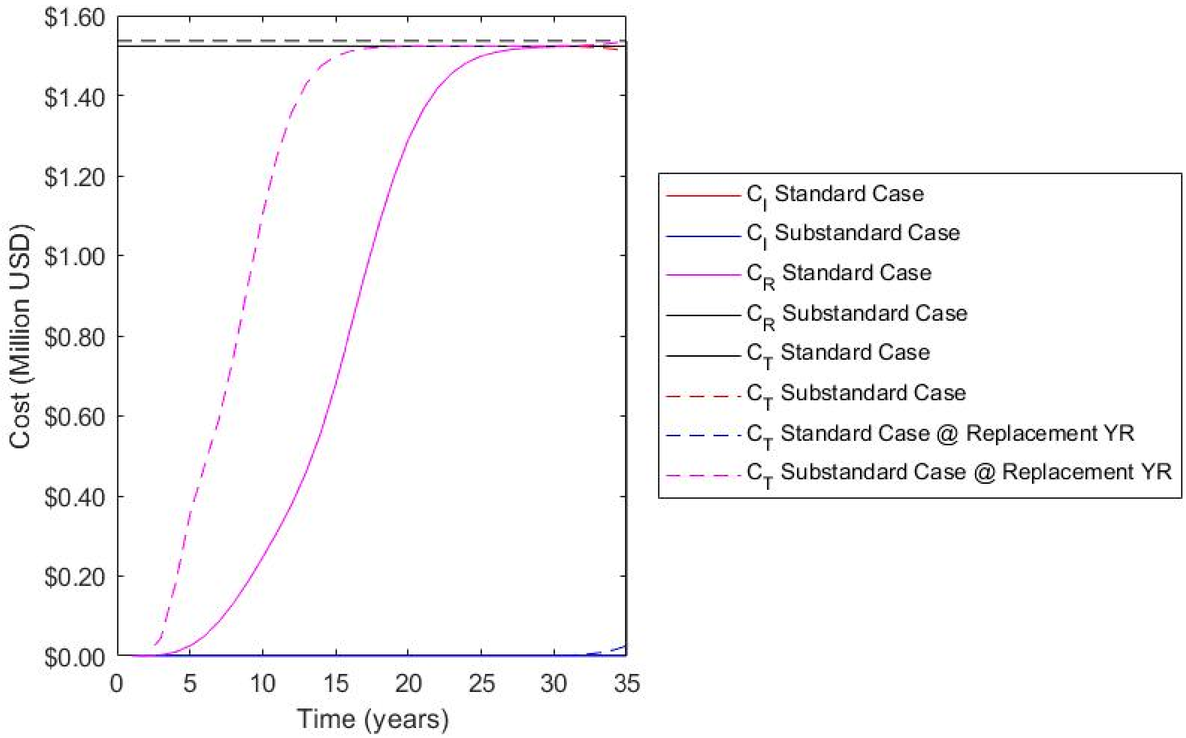

Figure A.18. Present day cost curve for case study bridge J

Bridge Designation: K **Estimated Loss of Life:** 9 years

Region: South **Estimated Additional Cost:** $22,100

Noted Defect(s): Improper curing

Defect Notes:

"(…) longitudinal and transverse map cracking up to approximately 0.020" nominal width visible throughout topside of deck".

Hazard Ratios:

9	8	7	6	5	4
1.8555	3.3279	2.8213	1.5657	2.5497	1.7088

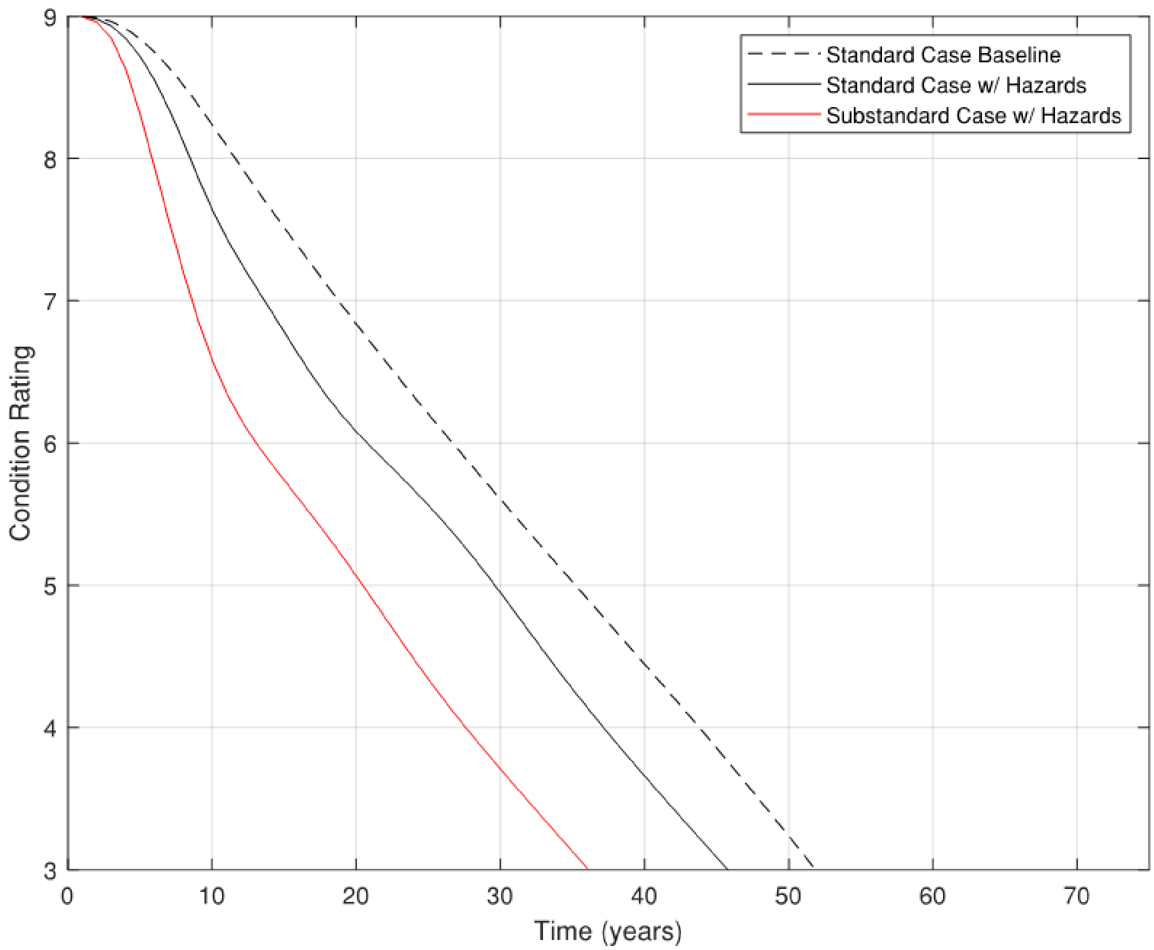

Figure A.19. Degradation curve for case study bridge K

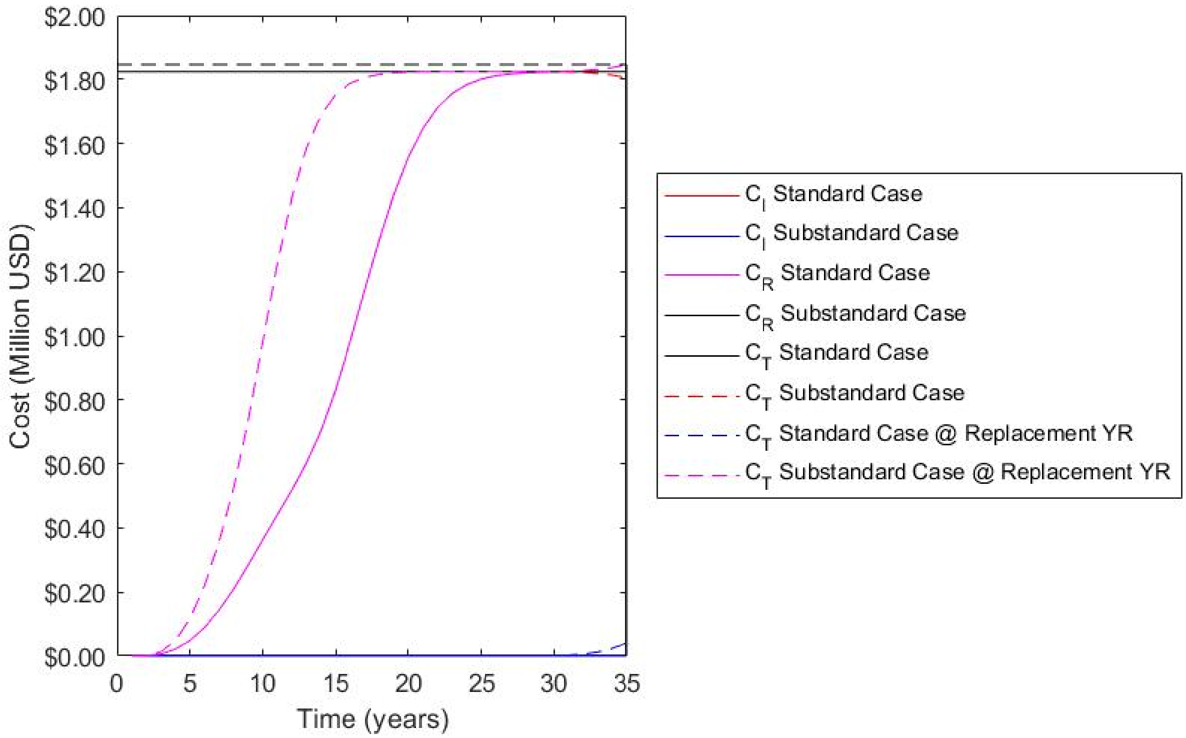

Figure A.20. Present day cost curve for case study bridge K

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