DEGRADATION AND SCENARIO DEVELOPMENT IN THE 4TH DIMENSION

Helmut WENZEL[1], Saeed BABANAJAD[2], Moritz WENZEL[3]

ABSTRACT

Structural response depends on actual condition. Aging changes condition over time in a non-linear way. In order to allow prediction of performance in future, it becomes necessary to use a mathematical formulation of the aging process.
This process is influenced by a major number of parameters besides the basic ones which are: Structural configuration - materials - year of construction (quality), and the character of resilience.
A software solution for this complex problem will be presented. It comprises a basic aging model with additional parameters of performance. These are use-related - exposure-related or externally influenced. The quantification of these parameters is done based on information gained from satellite images – inspection reports – monitoring campaigns or non-destructive testing.
The tool allows the prediction of maintenance or intervention demands in order to keep the functionality on an acceptable level. These demands are linked to costs and time windows for implementation. A demonstration of the use at bridge structures will be given.

Keywords: Degradation; Aging Model; Structural Response; Condition Assessment; Lifetime Prediction

1. INTRODUCTION

The effective management of structures requires a good understanding of their life expectancies. Improved service life prediction is required to be developed in order to better understand structural deterioration and to find more effective maintenance and repair strategies.

1.1 Background of the Development

The developed models are integral components of the Long Term Bridge Performance Program (LTBP), a 20-year research effort initiated by the U.S. Federal Highway Administration (FHWA) to improve the understanding of bridge performance.

1.2 Probabilistic Framework

In this paper, the development of a life-expectancy model framework, as part of the research effort in this program, is presented. The framework is established based on a semi-probabilistic approach to adherently maintain the advantages of both deterministic and probabilistic techniques. The modeling follows a step-by-step process to incorporate added information and reduce uncertainties. The basic model is first trained by the network of bridge inventory and the uncertainties are being reflected by determining lower and upper margins. Then the model is improved through introduction and evaluation of new knowledge gained about the external attributes influencing the structure. Finally, the direct condition of bridge components is employed straightforward to refine the model for realistic assessment.

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[1]Managing Director, WENZEL Consult, Vienna, Austria, helmut.wenzel@wenzel-consult.com
[2]Senior Researcher, Center for Advanced Infrastructure and Transportation (CAIT), Rutgers University Piscataway, NJ, USA, Country, saeed.babanajad@gmail.com
[3]Junior Researcher, University of Trento, Trento, Italy, moritz_wenzel@hotmail.com

1.3 Application

The developed model is applicable to any other type of structure. The assumption that degradation (aging) is a similar process for all kind of structures applies. The parameters that determine the degradation curve are principally the same. Structural configurations considerably influence the resistance against environmental loads. A good example is the difference in performance under earthquakes between a chain of single-span beams compared to a continuous structure. The chosen materials influence lifetime by their specific deterioration behavior. The year of construction parameter brings in the fact that decisions how to build structures can vary considerably. In times where, low cost solutions are preferred, performance problems are most probable. Lifetime is reduced or heavy maintenance has to be introduced costly. Resilience also influences lifetime because the influence of exposure after damage is considerable over time.
In order to apply the methodology to different types of structures, it will be necessary to conduct studies on these parameters, using experience of the respective construction sector. The most advanced technologies are applied in bridge engineering. Therefore, bridges have been chosen as a starting point for detailed development. The application to other sectors – particularly building construction – is of highest priority for the next development steps. This complex work is characterized by the much higher variety in structural types – materials – and quality ranges are expected.

1.4 Asset management and maintenance scenarios

Proper modern asset management requires accurate prediction of performance over time. Asset management need information on the expected remaining lifetime and a point of warning when only a specific remaining period is left. Knowing that decision-making processes are followed by design and implementation of replacements. Very often ten years are considered an appropriate period for warning.

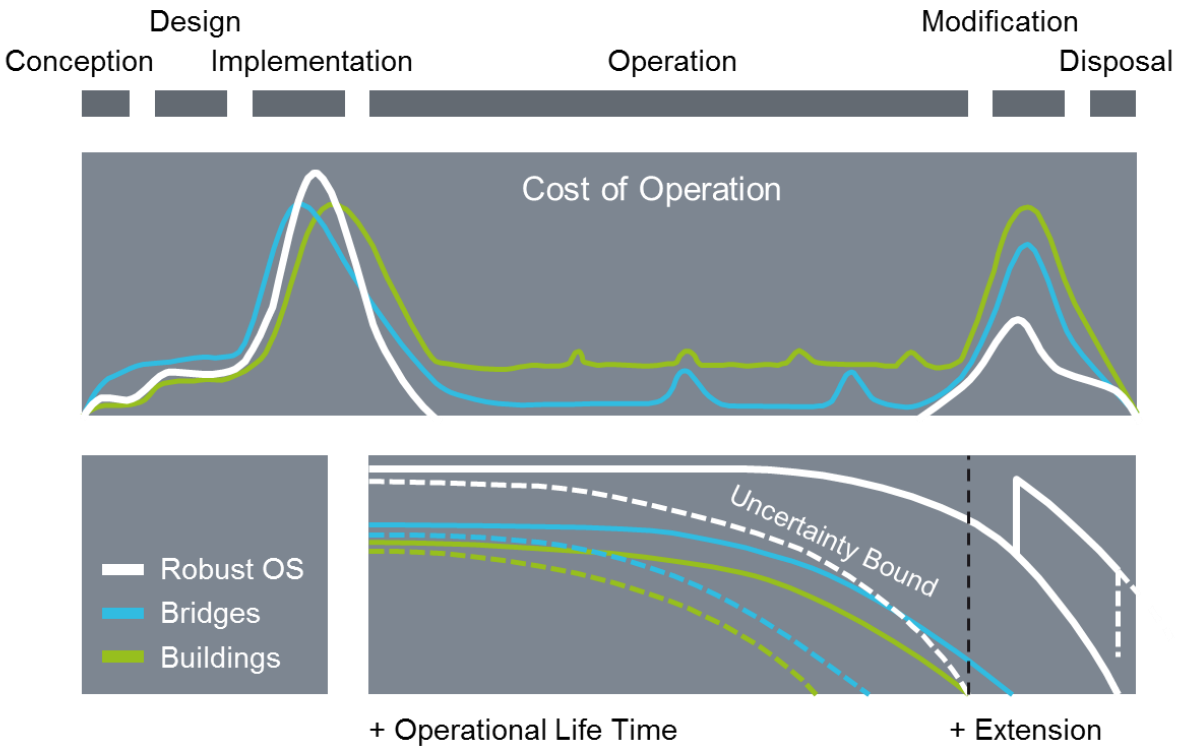


Figure 1. General concept of asset management of structures.

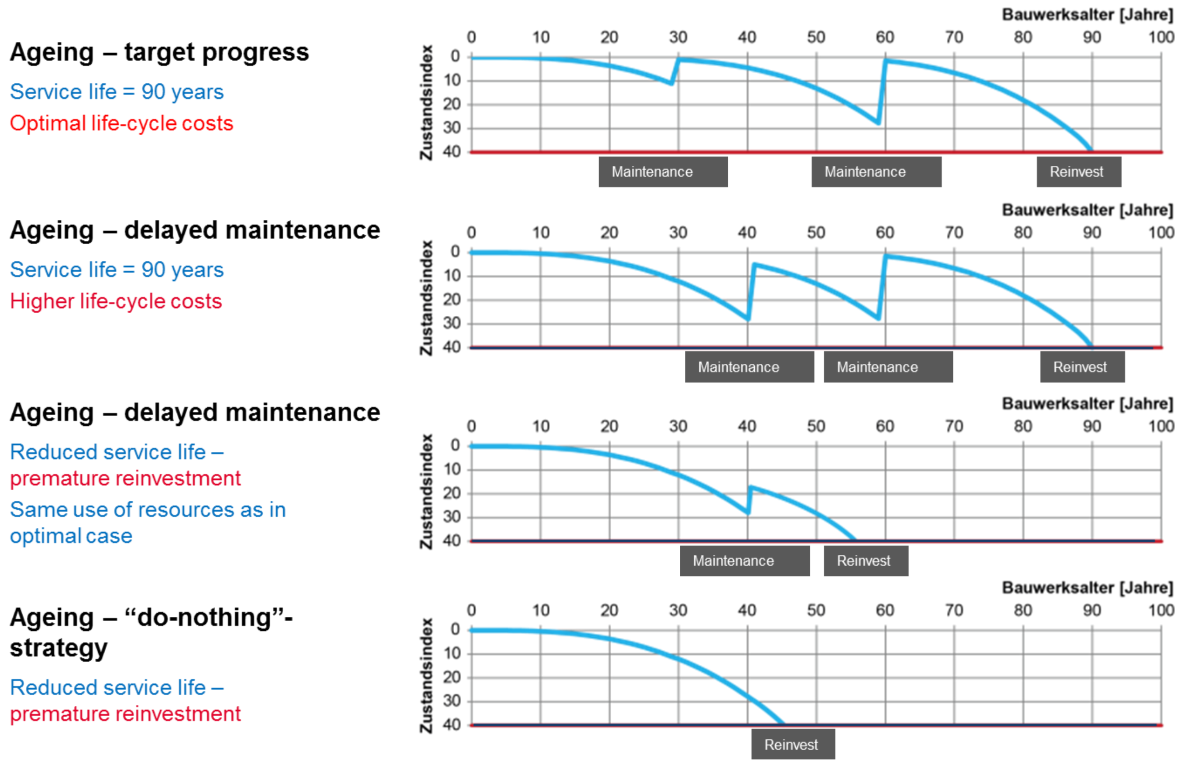


Figure 2. Asset management strategies, remaining life time, consequential costs.

2. THE MODEL DEVELOPED FOR THE LONG TERM BRIDGE PERFORMANCE PROJECT

2.1 Introduction to the LTBP

There are over 614,000 aging bridges in the United States with an average life of 38 years. Due to the economic hardship facing the federal and local agencies, it is inevitably critical to extend the lifespan of the nation bridges. Accurately predicting future conditions is a key input to effective maintenance and rehabilitation decision making for bridge owners. Indeed, the precise forecasting of bridge behavior creates a twofold benefit for the infrastructure owners: to efficiently manage the available budget for rehabilitation or reconstruction, and to properly monitor the bridge's functionality in both short- and long-term horizons. One way to predict future conditions of bridges is to utilize infrastructure deterioration models. Deterioration is a stochastic and complex process that varies widely depending on various factors, many of which are generally not captured by available data (Mishalani, R. G.,2002). Three different approaches have been routinely taken by the researchers to simulate the bridge deterioration, including deterministic, probabilistic, and artificial intelligence (AI). Review of technical literature reveals that each technique has its own pros and cons that eventually lead to failure in practical responses for deterioration modeling purposes. Deterministic models technically correlate age or a limited number of other parameters with the component's condition using a simple mathematical formulation, such as the mean, standard deviation and regression (Liu, H. T.,2013). Despite the ease of model development and interpretation, deterministic models neither account for the stochastic characteristics of bridge deterioration process nor consider the effects of unobserved explanatory variables (Jiang, Y., et. al.). By contract with deterministic models, probabilistic deterioration models view bridge deterioration as a stochastic process being affected by various parameters. The probabilistic models are basically relied on transition probabilities to capture the nature of the evolution of condition states from one discrete time point to the next. Despite the obvious advantages for being able to capture the uncertainties, these models suffer from underlying limitations. Several issues including the difficulties in transition probabilities estimation, incomplete capture of various explanatory variables, complex computation, lack of historical condition data for training, and data censorship are restraining the applicability of such models. Alternatively, AI models have also been proposed utilizing modern computer techniques to automate intelligent data "learning" process of bridge deterioration behaviors, such as artificial neural networks (ANN) and machine learning (ML). These techniques are mostly inspired by natural rules and express the solution by training from experience and developing various discriminators. In spite of their novelties, there are major setbacks disabling those types to create sufficient knowledge and transparency. As a result, those models act as black boxes and could not explicitly provide a transparent function correlating the output to the given inputs. The computations must be conducted in a priori format requiring significant trial-error operations. In essence, the consequences of the limitations associated with the various methods discussed above will directly lead to poor predictions of future infrastructure condition, thus compromising maintenance and rehabilitation decision making.

In 2008, the U.S. Federal Highway Administration (FHWA) launched its largest bridge research effort, the Long-Term Bridge Performance (LTBP) Program. The LTBP Program is a 20-year research endeavor to collect scientific performance field data from a representative sample of bridges across the U.S (FHWA-PD-96-001,1995). This will assist the bridge community with better understanding of bridge deterioration and performance. The products from this program comprise a collection of data-driven decision-making tools, including predictive deterioration and life cycle analysis models that will assist bridge owners with their bridge management. In a collaboration with the individual campaign from WENZEL Consult under the course of Integrated European Industrial Risk Reduction System (IRIS) project, a novel life cycle assessment framework has been developed. The objective of the research described herein is to present the backbone skeleton of the proposed framework. The methodology is established on the basis of a semi-probabilistic approach to adherently maintain the advantages of both deterministic and probabilistic techniques. The model is organized in a step-by-step structure to incorporate the associated uncertainties. The basic model is first trained by the user specified network of bridge inventory and uncertainties are being reflected by determining lower and upper margins. In the second step, the model is improved through introduction and evaluation of new knowledge gained about the external attributes influencing the structure. Finally, the direct condition of bridge components is employed straightforward to refine the model for realistic assessment. The developed model is later automated into the LTBP Bridge Portal—as the main core of the bridge-performance data warehouse. The Bridge Portal was primarily developed by LTBP to act as an intelligent web platform containing data sets including the National Bridge Inventory (NBI), the American Association of State Highway and Transportation Officials (AASHTO) bridge elements, traffic, environmental parameters, bridge elevations, inspection reports, and maintenance data as well as data acquired through LTBP program field testing. The LTBP Bridge Portal is publicly accessible at www.fhwaapps.fhwa.dot.gov/ltbpp. In the following section, the core elements of the developed life cycle assessment model are introduced, followed by a case study for completeness.

2.2 Developed Methodology

The formulations described herein pertain to the long-term prediction of bridge's NBI condition rating. The model is established on a multi-level approach to incorporate multiple structural and external attributes. The general model is derived on the base of the general deterioration process of the bridge inventory and provides a rough estimation of the expected structural service life in general. In the second step, an adapted model considers certain structural and external (environmental and traffic) information to adjust the lifeline progression. Finally in the last step, the model is refined based on performance-specific information, including but not limited to Non-Destructive Testing (NDT), Structural Health Monitoring (SHM) and or advanced inspections.

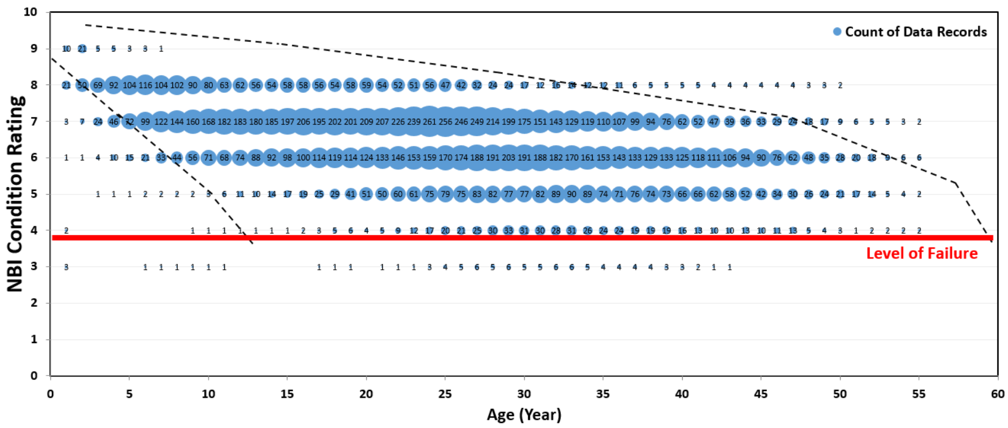
2.2.1Global Model

In general, the structural assessment has been done first and foremost by compulsory visual inspections. For critical cases, in-depth studies are initiated – mostly in terms of numerical simulations or structural health monitoring. To merge the results from all individual investigations and to obtain a more detailed picture of structural performance over the entire service life, Eqs. 1-2 have been utilized, as following

$$h_i^t = h_1 + a_n \left[(S_i - S)\right]^c \quad (1)$$
$$a_n = (h_f - h_1) / \left[(S_f - S_1)\right]^c \quad (2)$$

Where h_i^t=current condition; h_1=initial condition; h_f= final condition; S_i=current year of service life; S_1=initial year of service life condition; S_f=final year of service life; c= deterioration power exponent which is a constant empirical values derived from sensitivity analysis and is taken to be 3 for bridge components; and a_n=slope of deterioration.

The model is primarily established by Miyamoto and Ishida (2008) and was later adapted by Wenzel et al. (Wenzel, H.,2013), schematically shown in Fig. 1. In principal it covers all the major sources of deterioration and describes the lifeline progression within a stated service life expectancy. The ranges for service life expectancy and the total deterioration capacity must be known in advance. To estimate the a_n and S_f, a large number of NBI condition rating from the selected bridge inventory have to be analyzed thoroughly. To do so, the historical NBI condition rating records are plotted versus the age of the corresponding bridge at the time of inspection. Next, the plot is accumulated for all of the condition ratings records collected from the entire bridge inventory. Fig. 1 also presents a sample of collected NBI condition rating records for pre-stressed concrete bridges located in the Mid-Atlantic cluster, including Pennsylvania, New Jersey, Maryland, Virginia, West Virginia, and Delaware. The magnitude of points in the plot indicates the frequency of NBI condition rating records.



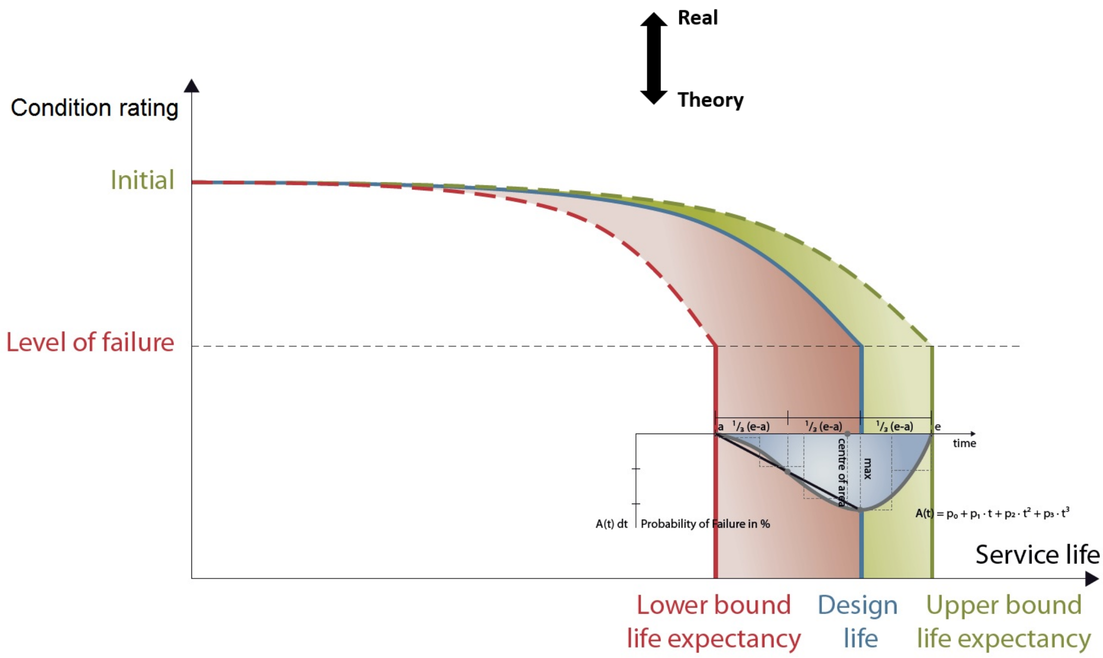


Figure 3. General concept of structural ageing.

It is obvious that different condition ratings follow tangible correlations in terms of bridge age. The input terms in Eqs. 1-2 are constants that embody the performance specifications of each specific bridge. In essence, the c and a_n parameters define the general shape and rate of deterioration curve in terms of bridge age and m $(= S_f - S_1)$ indicates the average life expectancy of the bridge. Accuracy of the model will be dependent on the accurate determination of the discussed inputs. Although these terms can be determined from finite element analysis or a priori from the known geometric, material, and performance properties of each individual bridge, a more realistic approach is to compute them during the calibration process applied on a large-scale database with sufficient numbers if bridge records. During the calibration process, the input parameters are determined by defining an error function (ψ), representing the differences between measured (historical NBI condition rating records) and theoretical condition ratings. ψ is minimized with respect to m for which the minimization function is given below:

$$\psi=\left\{\sum_{i=1}^{n} \left[h_i^r-h_i^e\right]^2\right\} \quad (3)$$

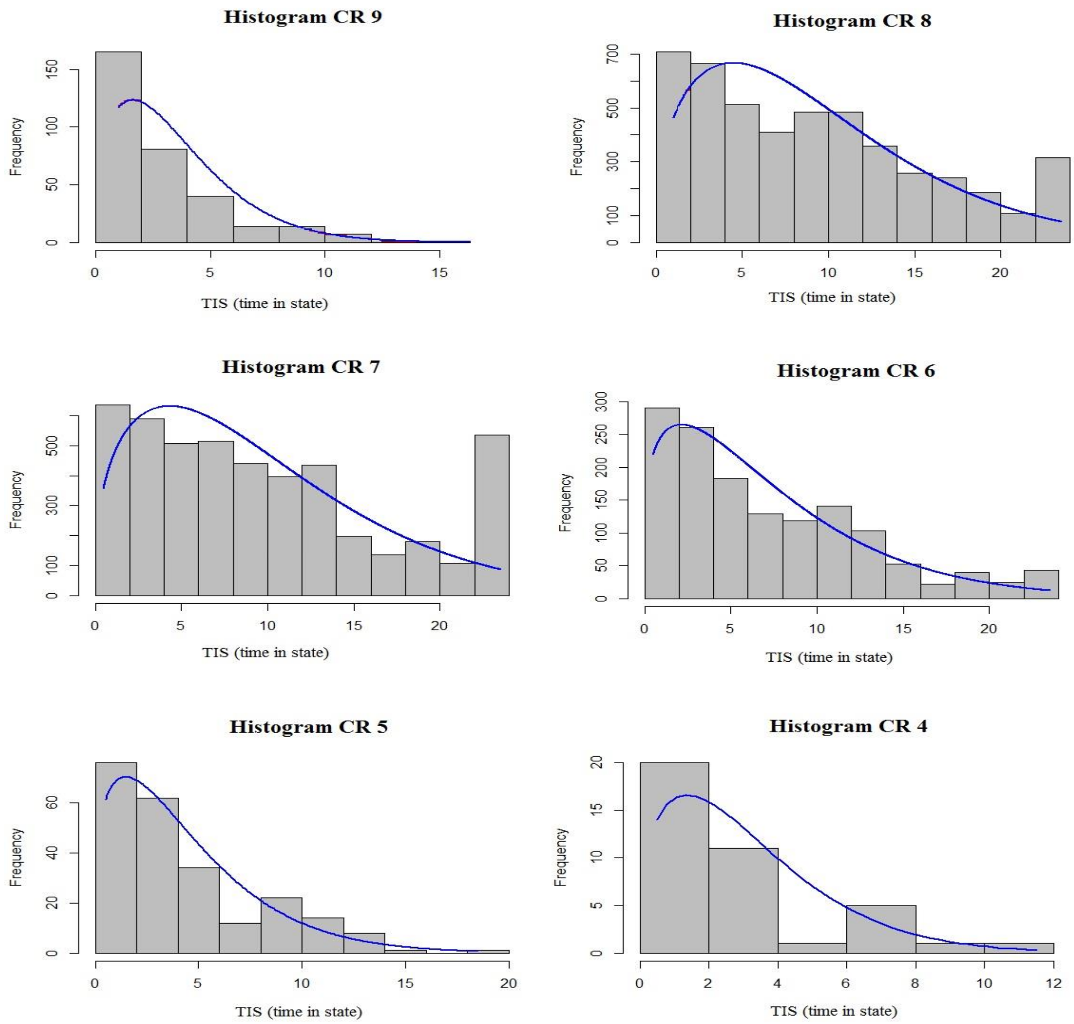


Figure 4. Time in state (TIS) histograms for NBI condition ratings.

Where, ψ is the objective function, h_i^r and h_i^e are the i^{th} recorded and estimated condition ratings, respectively. n denotes the total number of available data points from the selected bridge inventory. Once m is computed during the calibration process, the general life cycle expectancy curve can be back-quantified by using Eq. 1. The acquired model will then act as a general representative of bridge inventory used throughout the calibration.

To further aggregate the results in order to determine the overall performance of bridge in terms of upper and lower boundaries, Fig. 2 demonstrates the frequency histograms separately derived for each individual condition rating. Different distributions, e.g. normal, can be thereafter tested to find the best fitted distribution. Once the curve fitting process has been accomplished, the lower and upper boundaries are determined on the basis of 5% and 95% percentiles to reflect a confidence level of 95%. The boundaries ensure that the 90% of the bridges performs within the prediction range and eliminate the outliers that could be caused by inspection errors or a special type of bridges, such as signature cable-stayed bridge.

2.3 Adapted Model

The General Model generates the mean result derived from the benchmark data. However, the model does not encompass different characteristics of individual bridges. Among others, external attributes such as environmental condition or traffic volume as well as the bridge type and design specifications can significantly deviate the performance of the bridge from the average expected life. Similar to Eqs. 1-2, Eqs. 4-6 provide the fundamental formulations for calculating the lower, mean, and upper boundaries by means of statistical analysis using probability density function. More details for the basics of formulation can be referred to (9)

$$h_t^L=9/{a'}^3\,(t-Yr_{Built})^3 \quad (4)$$
$$h_t^m=9/{m'}^3\,(t-Yr_{Built})^3 \quad (5)$$
$$h_t^U=9/{e'}^3\,(t-Yr_{Built})^3 \quad (6)$$

Where Yr_{Built} corresponds to the year of bridge construction or reconstruction, whichever is the most recent. h_t^u, h_t^m, and h_t^l denote condition rating corresponding to upper, mean, and lower boundaries, respectively. a', m', and e' indicate the slopes of deterioration curves and can be determined by the following expressions:

$$a'=a.K \quad (7)$$
$$m'=a'+0.6(e'-a') \quad (8)$$
$$e'=e.K \quad (9)$$

Where m’, a’, and e’ correspond to the adapted mean, lower, and upper bound life expectancies, respectively. The values of a and e are estimated by assuming 0.5m and 1.33m, respectively, where m indicates the average expected life. Computation of Eqs. 7-9 requires the determination of K parameter which is a constant value signifying different characteristics of the bridge and the environmental where the bridge is located. The calculation of adjustment factor, K ($=k_1.k_2.k_3.k_4.k_5.k_6$), corresponds to the determination of $k_1 \dots k_6$ and is thoroughly discussed in a later section of this article. k_1 denotes the variation in average life expectancy based on the year of construction or reconstruction. k_2 and k_3 demonstrate the expected service life on the basis of design and materials types, respectively. Alternatively, k_4-k_5 and k_6 respectively quantify the effects of traffic load and environmental condition where the bridge is placed. Similar to General Model, accuracy of the Adaptive Model will be dependent on the accurate determination of K factor. A statistical approach has been utilized to individually compute each of the k_i factors during the calibration process. Throughout the process, for a given k_i parameter, all other k_i parameters were kept equal to unit and non-linear optimization method has been employed to minimize the error function (ψ), as follow:

$$\psi=\left\{\sum_{i=1}^{n} [h_i^r-h_i^e]^2\right\} \quad (10)$$

Where, ψ is the objective function, h_i^r and h_i^e are the i^{th} recorded and estimated condition ratings, respectively. n denotes the total number of available data points from the selected bridge inventory. To calculate h_i^e, the expression established by Eq. 5 has been employed.

2.4 Determination of Adjustment Factor (K)

In the proposed Adaptive Model, two major types of information have been incorporated into the modeling to customize the General Model for individual bridge. The first type itself corresponds to the bridge structural, material, geometrical, and construction properties. It basically includes:
k_1) Year of construction/reconstruction: which embodies the periodic construction quality changes imposed throughout the last decades. The design specifications and construction practices have been extensively modified in the United States during two important milestones. The first period includes the time before 1975 when bridges have been designed and built by traditional code specifications and construction techniques (k_1=0.90). Around 1975 new codes were released to consider the concepts of earthquake and performance-based designs into actual bridge projects. The second period pertains to be between 1975 and 1985 worthwhile to be called the transition decade. Throughout this period, new materials have been introduced to the construction industry as well as the revised code was practically settled down among the civil engineering community (k_1=0.95). After 1985, it may be postulated that the design codes and construction periods have reached a stable plateau where the inconsistency between construction and design is minimal (k_1=1.0).
k_2) Type of design: which reflects the associated redundancies imposed by different design portfolios. As indicated in Table 1, to exemplify the different levels of redundancy among different cross sections, solid cross section has demonstrated more redundancy and rigidity compared to corrugated profile.

Table 1. Designation of k_2 for Type of Design

Code	Description	k-factor
01	Slab	1.05
02	Stringer/Multi-beam or girder	0.95
03	Girder and floor beam system	0.95
04	Tee beam	0.95
05	Box beam or girders - Multiple	1
06	Box Beam or girders - Single or Spread	1
07	Frame	0.95
08	Orthotropic	0.95
09	Truss - Deck	0.95
10	Truss - Thru	0.95
11	Arch - Deck	0.95
12	Arch - Thru	0.95
13	Suspension	0.95
14	Stayed girder	0.95
15	Movable - Lift	1
16	Movable - Bascule	1
17	Movable - Swing	1
18	Tunnel	1
19	Culvert	1
20	Mixed types	1
21	Segmental box girder	0.95
22	Channel beam	0.95

k_3) Types of Materials: Different materials are employed for bridge fabrications, including but not limited to reinforced concrete, steel, pre/post-tension, wood, masonry, etc. The functionality and expected service life are significantly dependent on the types of materials being used for the construction of deck and superstructure. Table 2 demonstrates the final values of k_3 designated for each type of material mainly used by bridge industry.

Table 2. Designation of k_3 for Type of Material

Code	Description	k-factor
1	Concrete	1.1
2	Concrete continuous	1.1
3	Steel	1
4	Steel continuous	1
5	Prestressed concrete	0.9
6	Prestressed concrete continuous	0.9
7	Wood or timber	0.8
8	Masonry	0.8
9	Aluminium, Wrought Iron or Cast Iron	1
0	Other	1

The second type of information used for adjusting the Adapted Model refers to the external attributes influencing the bridge performance, including environmental conditions and freight traffic volume.
k_4-k_5) Weather and Environmental Characteristics: To evaluate the environmental effects on bridge performance, two weather data sets (numbers of snowfalls and freeze-thaw cycles) are extracted from the National Oceanic and Atmospheric Administration (NOAA) database. The number of recorded snowfalls and the temperature histograms (freeze-thaw) represent the average of the recorded values from nearby weather stations. The number of snow falls is determined based on the number of days in a year during which snowfalls of more than 0.2 inches (0.5 mm) occurred. The number of freeze-thaw cycles is the number of days in a year for which the following conditions were met:

A minimum temperature of $\leq$ -2.2 °C / 28.04 °F

A maximum temperature of $\geq$ 0 °C / 32 °F

k_6) Freight traffic volume: In general, the daily traffic does not seriously impact the performance of the bridge while the truck traffic considerably degrades the bridge components. Overweighed trucks and improper suspension systems are among the most vulnerable effects assisting steep degradation for the structural elements. To portray for such effects, average daily truck traffic (ADTT) has been taken into account within the modeling scheme, as provided by FHWA-PD-96-001, 1995.

2.5 Refined Model

As more complete information becomes available about the structural condition, the remaining service-life predictions will be more accurate by incorporating additional structural information into the life expectancy model. Campaign of advanced visual inspection, structural health monitoring, and non-destructive testing is an example of performance-specific information which could play a significant role in modifying the remaining service-life prognosis.

3. RISK MANAGEMENT

It is the nature of predictions that uncertainties define the range of probable results. In order to manage this range, to consider the expected consequences of structural failure, and to evaluate the background strategies chosen by the owners, uncertainties are to be quantified. This often leads to a widespread area of potential results and the often-unwanted residual risk.
In order to deal with this situation, it is proposed to introduce a respective inspection and monitoring procedure which first of all reduces uncertainties by replacing subjective assessment by measured values. Permanent monitoring campaigns furthermore show the advantage that performance is permanently monitored and the models can be updated periodically or even in real time. Particularly in case of earthquake damages, this would be a most desired functionality. A monitoring system that is able to record the performance of a structure during an earthquake can fulfil this function.

4. CONCLUSIONS

A mathematical formulation of aging has been introduced that provides a prediction of structural performance over time. This management tool is supported by many key performance indicators. In case these are monitored the included uncertainties can be reduced. This will lead to precise predictions and a better asset management of our constructed environment.

5. ACKNOWLEDGMENTS

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