Condition Rating Forecast of Bridge Components—Machine Learning Models

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1. Background Information

Machine learning models are bridge deterioration models to forecast condition ratings of bridge components. The model development encompasses bridge decks, superstructures, and substructures. The machine learning models complement the Federal Highway Administration (FHWA) LTBP InfoBridge™ (InfoBridge) (FHWA, 2020a) data visualization tools in depicting future performance trends of highway bridge components.

Historical bridge condition rating data from the FHWA National Bridge Inventory (NBI) (FHWA, 1995; FHWA 2020b) are used in conjunction with climate data to develop machine learning models. The research methodology employed is a deep learning-aided bridge deterioration modeling approach (Liu et al., 2021; Liu and Zhang, 2020). The model development has expanded the training datasets from a single State to the entire Nation.

Deep learning is a machine-learning technique that allows computational models comprising multiple processing layers to learn "data representations" of a high-dimensional and complex dataset. In the context of condition forecast, "data representations" is equivalent to the statistical interrelationships or data patterns that describe how various factors influence the bridge-component deterioration process. The current modeling effort considers 24 factors, such as traffic volumes, construction materials, and climate factors. For a complete list of the factors, see Table 1 at the end of this document. The specific deep-learning algorithm employed for data analysis is the convolutional neural network (CNN); Liu and Zhang (2020) introduce an application of CNN in condition rating data modeling. "Deep Learning" in *Nature* (LeCun et al., 2015) and *Deep Learning* by Goodfellow et al. (2016) provide additional information about deep learning.

The following briefly describes the method overview, the description of the data source, and the technical procedure that was used during the implementation. A full-length technical article is under preparation to be published in a peer-reviewed journal (Liu et al., 2021).

2. Method Overview

The data pattern underlying the historical bridge inspection records contains useful information in describing the deterioration trends of highway bridge decks. Therefore, developing an appropriate algorithm that can identify data patterns buried in history can solve the condition-forecast problem. The data-mining algorithm emphasizes the changing trends of bridge condition ratings along with other factors that may influence the deck-deterioration process. The current research applies CNN for corresponding data-mining and pattern recognition.

Mathematically, the CNN model computes the conditional probabilities of future condition ratings given the values of current bridge information, as described in Equation (1),

$$\Pr(Y|X) = \begin{bmatrix} \Pr(CR = 9|X) \\ \Pr(CR = 8|X) \\ \Pr(CR = 7|X) \\ \Pr(CR = 6|X) \\ \Pr(CR = 5|X) \\ \Pr(CR = 4|X) \\ \Pr(CR = 3|X) \end{bmatrix} \qquad \text{Equation (1)}$$

where X and Y are the input and output of the CNN model, respectively; CR denotes the condition rating (see definitions in the coding guide by FHWA, 1995); Pr represents probability. Condition-rating values are assumed to not be lower than 3. In the NBI, condition-rating data of 3 or below are sparse and would not result in a reliable training dataset.

The probability function incorporates all the bridge factors listed in Table 1. The function is evaluated for every future inspection.

Due to the probabilistic nature of CNN model forecasting, deterioration modeling for long-term forecast, based on CNN, will be subjected to significant uncertainty that may propagate forward in time. The deterioration model incorporates stochastic process modeling to account for uncertainties. The modeling employs a standard Markov chain (Frangopol et al., 2004; Morcous et al., 2003) procedure that assumes the deterioration process complies with the Markov property.

3. Data Source

The research uses NBI and climatic data from InfoBridge. The climatic data refer to the annual numbers (unit in days) of freeze-thaw cycles and snowfalls. The National Aeronautics and Space Administration (NASA) Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) program provides the original source of climate data.

4. Procedure

The step-by-step process of the modeling approach is briefly described as follows:

Step 1, Bridge Selection. This step aims to filter out unsuitable bridges for model development. The modeling assumes no condition improvement in the future. Thereby, bridges with condition rating increases in history were not included in the modeling.

Step 2, Data Preparation. This step aims to restructure original bridge inspection records into the data format that is recognizable to the employed deep learning algorithm. In the current model development, the model input is a data matrix that consists of current values of considered factors. Each input data matrix has an associated data label (i.e., output) to supervise the model training. The data labels are the actual condition ratings that were given by bridge inspectors in the successive inspections to the time of records settled in the data matrices.

Step 3, Deep Learning Model Development. This step trains and validates the developed deep learning model. In initial development, the selected bridge population from Step 1 is randomly split into two subsets for model training and testing. The testing subset validates the trained models by comparing model forecasts with actual condition ratings reported in history. In final modeling, all selected bridges are used for model training.

Step 4, Condition Rating Forecast. This step computes and stores the forecast results in a data table format. The data table contains seven columns for the seven possible condition ratings (from 9 to 3) and multiple numbers of rows representing the forecast time in terms of inspection years. The current effort limits forecast years to 2070. The data entries in the table are probabilities of condition ratings in each inspection year. The computation repeats for each bridge.

Step 5, InfoBridge Implementation. This step converts the forecast results from the data table to the curve plots that are accessible in InfoBridge. The plots contain a pair of upper/lower bounding curves as defined in Equation (2),

$$\begin{cases} \Pr(CR_n < \text{lower bound}) \leq \alpha \\ \Pr(CR_n > \text{upper bound}) \leq \alpha \end{cases} \qquad \text{Equation (2)}$$

where α is a user-specified value that defines the amount of uncertainty below the lower bound or above the upper bound. Currently, the value of α is selected to be 25 percent.

5. References

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Table 1. Description of considered factors for deterioration modeling of bridge decks.

#	Influence Factors	Data Source[1]
1	Global Positioning System (GPS) Latitude Degrees	Item 16
2	GPS Longitude Degrees	Item 17
3	Toll	Item 20
4	Maintenance Responsibility	Item 21
5	Functional Class of Inventory Rte.	Item 26
6	Age	Items 27
7	Lanes on Structure	Item 28A
8	Average Daily Traffic (ADT)	Item 29
9	Average Daily Truck Traffic (ADTT)	Item 109
10	National Highway System	Item 104
11	Skew	Item 34
12	Structural Material/Design	Item 43A
13	Type of Design and/or Construction	Item 43B
14	Number of Spans in Main Unit	Item 45
15	Length of Maximum Span	Item 48
16	Structure Length	Item 49
17	Bridge Roadway Width Curb-to-Curb	Item 51
18	Deck Structure Type	Item 107
19	Type of Wearing Surface	Item 108A
20	Type of Membrane	Item 108B
21	Deck Protection	Item 108C
22	Annual Number of Freeze Thaw Cycles	NASA MERRA-2[2]
23	Annual Number of Snowfalls	NASA MERRA-2[2]
24	Deck Condition Rating (CR) or Superstructure CR or Substructure CR	Item 58 or Item 59 or Item 60

Source: FHWA.

1. Items listed in this column refer to the coding item in the NBI.

2. The NASA Modern-Era Retrospective Analysis for Research and Applications, Version 2 provides the corresponding data source.