

An Empirical Markov Process Model for Optimal Bridge Inspection

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There are more than 650,000 bridges in the United States. The US Department of Transportation requires routine inspections every 24 months to monitor bridge deterioration. The 24-month inspection interval was determined in early 1970s solely based on engineering judgement regardless of the current condition of the bridges. This uniform interval approach has resulted in a very costly and inefficient quality control process. This study presents a probabilistic approach to forecast bridge deterioration and statistically determine the optimal inspection intervals. A probabilistic model based on the classic Markov process is created to predict future bridge conditions based on historical data. A statistical process is developed using the forecasting model to determine the optimal inspection intervals. The proposed methodology in this study is implemented on a dataset consisting of information about more than 27,000 bridges in Ohio from 1992 to 2017. The forecasting results indicate that the model can predict future bridge conditions with less than 3.5% error. The outcomes of the statistical analysis indicate that the typical 24-month inspection interval is considerably pessimistic and not necessary for all bridges currently in condition 5 or higher. However, the 24-month interval is too optimistic and risky for bridges currently in condition 4 or lower. This study helps decision makers determine optimal bridge inspection intervals to monitor and protect depreciated bridges more carefully and use maintenance resources more efficiently.

Key Words: Bridge Condition, Inspection Interval, Probabilistic Models, Markov Process

Introduction

The National Bridge Inspection Standard (NBIS) developed by the Federal Highway Administration (FHWA) requires regular and periodic inspection of more than 650,000 bridges in the United States. The typical inspection interval is 24 months (FHWA 1988). Based on the NBIS procedure, whenever a bridge is inspected, a rating condition from 1 to 9 is assigned to the bridge. Table 1 describes the bridge condition ratings by the NBIS.

Table 1

NBIS Bridge Condition Rating

Condition Rating	Description
9	Excellent Condition
8	Very Good Condition
7	Good Condition
6	Satisfactory Condition
5	Poor Condition
4	Fair Condition
3	Serious Condition
2	Critical Condition
1	Imminent Failure Condition

The 24-month routine inspection interval was determined by the FHWA in 1970s solely based on engineering judgement, regardless of the current condition of the bridges. This uniform interval approach has resulted in a very costly and inefficient process (Nasrollahi and Washer 2014, Reising et al. 2014, and Washer et al. 2016). Many bridges in proper condition do not need to be inspected every 24 months. On the other hand, some bridges with a high deterioration rate may need a shorter inspection period.

Today, the availability of historical records of bridge conditions allow the creation of a systematic process based on historical deterioration data to empirically determine the optimal inspection interval. This study presents a data-driven approach to systematically determine the optimal inspection intervals. The outcomes of this study will help decision makers quantitatively determine inspection intervals, thus using bridge inspection resources efficiently and saving millions of dollars that can be invested in other infrastructure development projects.

Although finding optimal inspection intervals is critical, most previous studies in this area focused on modeling bridge deterioration rates. Madanat et al. (1995) developed a probit model with a random-effect specification for bridge-deck deterioration. Miyamoto et al. (2000) proposed a biquadratic deterioration curve for concrete bridge members. Bolukbasi et al. (2004) tried to analyze the relationship between bridge condition rating and bridge age by simply fitting a third-degree polynomial line and compared deterioration rates for decks, superstructures, and substructures. Morcous (2006) investigated the validity of Markov chain basic assumptions for the infrastructure deterioration process. Zhang et al. (2008) developed a discrete event simulation to find an optimal combination of resources in bridge-deck rehabilitation projects. Agrawal et al. (2010) described an approach based on the Weibull distribution to create bridge element deterioration curves. Tolliver and Lu (2012) analyzed the relationship between bridge deterioration rates and age; they observed that the relationship between these two factors is linear for bridges less than 65 years old, after which they have a polynomial relationship. Nasrollahi and Washer (2014) conducted a statistical analysis to find the best conventional distribution that describes the distribution of the time that a bridge may stay in one specific condition; the fitted distributions for different condition ratings showed that, on average, bridges stay in higher conditions for longer periods and the 24-month maximum inspection interval is pessimistic. Washer et al. (2016a) developed a framework for risk-based bridge inspection that identifies bridges for which inspection intervals shorter or longer than 24 months are more appropriate; their proposed framework uses a qualitative approach based on a simple risk matrix. Washer et al. (2016b) conducted two case studies to present the implementation of their proposed framework. Ghodoosi et al. (2017) developed a genetic algorithm model to optimize lifecycle costs of bridge utilization. Ghonima (2017) created a binary logistic regression to analyze the effects of bridge characteristics such as Average Daily Traffic (ADT), age, deck area, and number of lanes on deterioration rate.

Although previous studies provide useful insights and information about the bridge deterioration process, little is known about a systematic and quantitative approach to empirically determine inspection intervals based on historical data. This gap in knowledge makes it difficult to use facility management resources efficiently. The objective of this study is to create and test the applicability of probabilistic models to determine optimal inspection intervals based on historical inspection data.

The inspection records of more than 27,000 bridges in the state of Ohio from 1992 to 2017 were collected. A statistical forecasting model based on the classic Markov process is created. A probabilistic process based on organizations' (i.e., bridge owners) risk tolerance then is conducted to determine the optimal inspection intervals. The remainder of this paper is structured as follows: First, the National Bridge Inventory (NBI) dataset is briefly introduced. Next, the research methodology and steps conducted in this study are described. The proposed methodology is then applied to the Ohio NBI dataset to statistically determine the optimized inspection intervals and evaluate the performance of the proposed methodology. Finally, the results are presented, and future works are recommended.

NBI Dataset: Data Preprocessing and Cleaning

The NBI is a publicly available dataset published by the FHWA consisting of detailed information including bridge condition values for all bridges in the US. Currently, the recorded data from 1992 to 2017 are available (FHWA 2018). With 27,345 bridges, Ohio has the second highest number of bridges in the country after Texas.

Because a condition rating of 3 indicates a serious problem, bridges with a condition rating of 3 or less need immediate attention and typically undergo major rehabilitation (Nasrollahi and Washer 2014). Therefore, in this study, these three ratings were combined to develop the caution condition, indicating bridges that need particular attention. During the inspection process, it is critical to predict whether the bridge will transition to this condition in the near future.

Deterioration of a bridge results in a transition from a higher condition rating to a lower condition rating. Therefore, typically, a bridge stays in its current condition or transitions to a lower condition rating unless it undergoes rehabilitation or there is an error in data collection. Because the focus of this study is deterioration through time, upward transitions from lower ratings to higher ratings were removed from the dataset. Furthermore, miscoded ratings with value of 0 or N were removed from the dataset as well. These data preprocessing operations were suggested by previous studies, such as that by Nasrollahi and Washer (2014). The proposed data preprocessing and cleaning operation led to removal of less than 5% of the original data.

Research Methodology

Deterioration of a bridge through its lifecycle can be analyzed by a discrete function that models the transition from higher condition rates (e.g., 9 when the bridge is newly constructed or recently maintained) to lower condition ratings. These transitions can be modeled using a Markov chain process (Morcous (2006) and Agrawal et al. (2010)). The classic Markov chain model is a memoryless stochastic process that predicts transitions of a variable among discrete states solely based on its current state.

$$\Pr(X_{n+1} = x | X_1 = x_1,\ X_2 = x_2,\ X_3 = x_3, \ldots, X_n = x_n) = \Pr(X_{n+1} = x | X_n = x_n)$$

The main component of a Markov process is the transition matrix that describes the probability of a transition from one state to another. The elements of the transition matrix are calculated using the historical data, as follows:

$$P_{ij} = \frac{n_{ij}}{n_i}$$

where

P_{ij} is the probability of a transition from state *i* to state *j*
n_{ij} is the total number of transitions from state *i* to state *j* within a given time period
n_i is the total number of bridges in state *i* before transition
Using the transition matrix, future states can be predicted as follows:

$$S(t+n) = S(t) \times P^n$$

where

S(t) is an array that shows the state at time *t*
S(t+n) is an array that shows the state at time *t+n*
P is the transition matrix

In this study, the classic Markov process is used to create probabilistic forecasting models for the bridge deterioration process. The forecasting model then is used to statistically determine the optimal bridge inspection intervals. In summary, the following steps are taken:

- Calculation of transition probabilities and creation of the transition matrix using historical data from 1992 to 2016
- Prediction of bridge conditions in 2017 based on their conditions in 2016 using the transition matrix
- Analysis of the prediction accuracy and validation of the model
- Calculation of the probability of possible future conditions for a bridge based on its current condition under the classic Markov model
- Selection of a risk tolerance for the bridge owner
- Determination of inspection intervals based on the predicted transition probabilities and the risk tolerance

Analysis of Bridge Conditions in Ohio

Transition probabilities from each bridge condition to other conditions are calculated using Ohio NBI data from 1992 to 2016. More than 503,000 acceptable transitions were recorded. Table 2 shows the resulting transition matrix. The transition matrix indicates that at any condition rate, there is a significantly higher chance that the bridge remains at that condition rate. For example, if a bridge is in condition 6, there is a 93.36% chance that the bridge will stay in condition 6 until the next year.

Table 2

Transition Matrix for the Classic Markov Model

Conditions	9	8	7	6	5	4	3 to 1
9	85.80%	12.55%	1.28%	0.31%	0.04%	0.02%	0.01%
8	0.00%	89.08%	9.42%	1.35%	0.10%	0.04%	0.01%
7	0.00%	0.00%	89.86%	9.41%	0.59%	0.12%	0.02%
6	0.00%	0.00%	0.00%	93.36%	5.80%	0.77%	0.07%
5	0.00%	0.00%	0.00%	0.00%	92.53%	7.05%	0.42%
4	0.00%	0.00%	0.00%	0.00%	0.00%	95.03%	4.97%
3 to 1	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100%

The probabilities that the bridge condition will change to condition 5, 4, and 3 or lower are 5.8%, 0.77%, and 0.07%, respectively. Now, the prediction ability of the Markov process should be tested to validate the model. The expected number of bridges in each condition rate in 2017 is predicted using the developed classic Markov model based on the 2016 data. Table 3 shows the actual number of bridges in each condition rate in 2016, the predicted number of bridges in each condition in 2017, and the actual number of bridges in each condition in 2017.

Table 3

Actual and Predicted Number of Bridges in each Condition

Year / Condition	9	8	7	6	5	4	3 to 1
Actual Numbers in 2016	2545	5393	7416	6817	2623	1104	284
Forecast Numbers for 2017	2183.7	5123.4	7204.7	7143.4	2872.7	1297.6	356.4
Actual Numbers in 2017	2307	5289	7328	6884	2804	1212	358

The predicted number of bridges in each condition in 2017 was calculated as follows:

$$S(2017) = S(2016) \times P^1$$

The mean absolute percentage error (MAPE) calculated using the following formula is 3.44%.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right|$$

where
A_i is the actual value
F_i is the forecast value
n is the number of fitted points

The absolute percentage error for each condition varies from less than 1 percent to 7 percent. The very low forecasting error measure indicates that the model has robust prediction power.

Determining Inspection Intervals Using Classic Markov

A bridge in condition *j* can be represented using a unit array that has zero in all elements except the corresponding element to condition *j*, which is 1. For example, the corresponding unit array to a bridge in condition 6 is

$$[0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0]$$

To determine the optimized inspection interval, first the Markov forecasting process is conducted for the unit bridge array for the next *n* years. The outcomes show the probability of transition from the origin condition (i.e., condition *j*) to other conditions at the end of each year. For example, Table 4 shows the transition probability for a bridge currently in condition 5 during the next 10 years.

Table 4

Transition Probability for a Bridge Currently in Condition 5

Prediction Step / Condition	9	8	7	6	5	4	3 to 1
Current Year	0.00%	0.00%	0.00%	0.00%	100%	0.00%	0.00%
After 1 Year	0.00%	0.00%	0.00%	0.00%	92.53%	7.05%	0.42%
After 2 Years	0.00%	0.00%	0.00%	0.00%	85.63%	13.22%	1.15%
After 3 Years	0.00%	0.00%	0.00%	0.00%	79.23%	18.60%	2.17%
After 4 Years	0.00%	0.00%	0.00%	0.00%	73.32%	23.26%	3.42%
After 5 Years	0.00%	0.00%	0.00%	0.00%	67.85%	27.27%	4.88%
After 6 Years	0.00%	0.00%	0.00%	0.00%	62.78%	30.70%	6.52%
After 7 Years	0.00%	0.00%	0.00%	0.00%	58.09%	33.60%	8.30%
After 8 Years	0.00%	0.00%	0.00%	0.00%	53.76%	36.03%	10.22%
After 9 Years	0.00%	0.00%	0.00%	0.00%	49.74%	38.03%	12.23%
After 10 Years	0.00%	0.00%	0.00%	0.00%	46.03%	39.65%	14.32%

Table 4 indicates that the likelihood that a bridge in condition 5 will transition to the caution state (i.e., condition 3 or below) after 5 years is 4.88%. Therefore, if the risk tolerance of the bridge owner is 5%, the optimal inspection interval is 5 years, which is the longest duration that has a probability of transition to the caution state that is less than the risk tolerance (i.e., 5%). If the risk tolerance were 3%, for example, the optimized inspection interval would be 3 years.

Table 5 shows the optimal inspection intervals for bridges currently in different conditions based on a 5% risk tolerance.

Table 5

Optimal Inspection Intervals for 5% Risk Tolerance

Current Condition	Optimal Inspection Interval
9	25 years
8	21 years
7	16 years
6	12 years
5	5 years
4	1 year

The outcomes presented in Table 5 indicate that with a 5% risk tolerance, the 24-month inspection interval is too long for bridges in condition 4 because there is a 9.68% chance that those bridges will transition to condition level 3 or below within the next 2 years. For bridges currently in condition 5 or higher, the 24-month is too pessimistic. The optimized inspection interval ranges from 5 years for bridges in condition 5 to 25 years for bridges in condition 9.

Conclusion and future works

A probabilistic model based on the classic Markov process was created to predict future bridge conditions based on historical data. The model was applied on a dataset consisting of information about more than 27,000 bridges in the state of Ohio from 1992 to 2017. The forecasting results indicate that the model can predict future conditions accurately with less than 3.5% error. Using the Markov forecasting model, a statistical process to determine optimal inspection intervals was developed. The statistical process is flexible and can be adjusted based on the risk tolerance and the threshold for caution state. In this study, the empirical analysis was conducted based on a 5% risk tolerance, and condition 3 was considered the threshold for the caution state. However, other risk tolerances and thresholds can be used as well. The results of this study indicate that the typical 24-month inspection interval is considerably pessimistic and not necessary for all bridges currently in condition 5 or higher. However, a 24-month interval is too optimistic and risky for bridges currently in condition 4 or lower. The primary contribution of this study to the body of knowledge is its creation of probabilistic models to forecast bridge deterioration and statistically determine the optimal inspection intervals. The outcomes of this study help bridge owners and transportation agencies assign maintenance resources efficiently and invest the millions of dollars currently funding unnecessary inspections into much-needed infrastructure development projects. Although this study was conducted using the FHWA bridge data for the state of Ohio, the proposed methodology and analysis could be used for similar datasets in other states. Analyzing the impacts of bridge characteristics such as design, material, age, deck area, and ADT on deterioration rates and developing causal models that predict future bridge conditions based on their main characteristics is a topic for future studies.

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