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**BAYESIAN UPDATING PROCEDURE FOR PREDICTION OF CONCRETE BRIDGE
DECK CONDITION USING VISUAL INSPECTION DATA**

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1 INTRODUCTION AND MOTIVATION

Deterioration is among the primary concerns regarding the structural performance and functionality of bridges and their components. Such degradations can potentially lead to various forms of structural deficiencies and eventually failure if adequate repair and rehabilitation actions are not performed at appropriate times. Also, the degraded functionality of bridge decks and the application of time-consuming repairs and rehabilitations lead to increased traffic delays and increased vehicle operating costs. In light of annual budget constraints, infrastructure agencies, such as state Departments of Transportation (DOTs) in the US, prioritize their bridge maintenance needs. Commonly, bridges with higher degradation levels receive higher priority for maintenance. To make trade-offs across bridges and over time, key inputs to the prioritization and decision making process are bridge condition assessments and predictions.

To support such functionalities, the Federal Highway Administration (FHWA) developed the bridge management system AASHTOWare BrM (AASHTO BrM User Manual, 2015) – formerly known as Pontis (Pontis User Manual, 2005) – that has been successfully used in numerous practical decision-making settings. It is based on a discrete Markovian deterioration model in which the type and extent of deterioration of bridge components are expressed in visual terms. Critical parameters of discrete Markovian deterioration models are probabilities that describe the likelihoods of bridge components transitioning from one discrete condition state to another. These transition probabilities are either determined based on expert judgement or, ideally, they are estimated based on field inspection data.

The AASHTO Bridge Element Inspection Guide Manual (2010), subsequently referred to as the AASHTO Manual, establishes a national guideline for performance evaluation of bridge elements and collection of inspection data. In the manual, the state of performance of a bridge element is expressed as a condition state vector. For example, for bridge decks, the focus of this study, four condition states are defined based on the extent of different types of defects, such as cracking, spalls, and delamination. The definition of condition states of bridge decks is characterized in Table 1. For a given bridge, each entry of the condition state vector is the proportion of the deck that is in the corresponding condition state.

TABLE 1: Definition of condition state for bridge deck based on the AASHTO Manual

Defect	Condition State 1	Condition State 2	Condition State 3	Condition State 4
Cracking	None to hairline	Narrow size and/or density	Medium size and/or density	The condition is beyond the limits established in condition state three (3) and/or warrants a structural review to determine the strength or serviceability of the element or bridge
Spalls/ Delaminations/ Patched Areas	None	Moderate spall or patch areas that are sound	Severe spall or patched area showing distress	
Efflorescence	None	Moderate without rust	Severe with rust staining	
Load Capacity	No reduction	No reduction	No reduction	

The AASHTO Manual, which is adopted by all state transportation agencies in the US, requires regular observations and measurements of highway bridges to capture their physical and

functional states. State DOTs usually carry out such bridge inspections once every one to two years. Typically, the resulting inspection data are used on a one-time basis to estimate deterioration models whereby subsequent observations are used only as inputs to forecast deterioration.

The objective of this study is to develop a framework that utilizes the bridge inspection data collected on an ongoing basis to update transition probabilities for concrete bridge decks. Doing so is expected to improve the representativeness of these probabilistic deterioration models and the accuracy of their predictions. An evaluation is also conducted to assess the value of such an approach.

2 DETERIORATION MODEL: MARKOV CHAIN

As noted previously, based on the condition state definitions, each entry in the condition state vector represents the proportion of the deck that is in that condition state. This definition could be interpreted as the probability of each unit of the deck being in each condition state, whereby a deck is divided into a contiguous set of small 1 ft × 1 ft units forming a grid. A widely-used approach to model such deterioration is the Markov Chain (Baik, H.S., H.S. Jeong, and D.M. Abraham., 2005; Micevski, T., G. Kuczera, and P. Coombes, 2002). Markov Chain models are often used to represent the evolution of discrete and finite states of variables at discrete periods. A mathematical representation of a Markov Chain is $Y^{(t+1)} = \mathbf{P} \cdot Y^{(t)}$, where $Y^{(t)}$ and $Y^{(t+1)}$ are the vectors that represent the probability mass functions of the discrete state at time t and time $t+1$, respectively. \mathbf{P} is the transition probability matrix, which consists of transition probability elements p_{ij} . Each of these elements represents the probability of transitioning to state j at time $t+1$ given that the condition state is i at time t . The matrix \mathbf{P} could be invariant or may vary over time. In this representation, the former is assumed.

This study uses the same Markov Chain deterioration model that is adopted by AASHTOWare BrM Bridge Management System whereby the following assumptions are made: (a) the condition state drops at most by one (i.e., no multi-step transitions are assumed to occur), and (b) the transition probability matrix \mathbf{P} is independent of age. As a result, the Markov Chain model used in this study takes the following form:

$$Y^{(t+1)} = \mathbf{P} \cdot Y^{(t)} \quad (1a)$$

$$\begin{bmatrix} y_1^{(t+1)} \\ y_2^{(t+1)} \\ y_3^{(t+1)} \\ y_4^{(t+1)} \end{bmatrix} = \begin{bmatrix} p_{11} & 0 & 0 & 0 \\ 1 - p_{11} & p_{22} & 0 & 0 \\ 0 & 1 - p_{22} & p_{33} & 0 \\ 0 & 0 & 1 - p_{33} & p_{44} \end{bmatrix} \cdot \begin{bmatrix} y_1^{(t)} \\ y_2^{(t)} \\ y_3^{(t)} \\ y_4^{(t)} \end{bmatrix} \quad (1b)$$

The only parameters to be determined are p_{11} , p_{22} , p_{33} , and p_{44} . In the case of estimation, $Y^{(t)}$ and $Y^{(t+1)}$ are obtained from data, and in the case of prediction, $Y^{(t)}$ is obtained from data and $Y^{(t+1)}$ is predicted based on Equation 1a.

3 PARAMETER ESTIMATION METHODS

Different statistical estimation methods could be used to estimate the transition probabilities. In this study, Bayesian estimation is used to determine transition probabilities for concrete bridge decks while taking into account the available estimates determined from previous data or expert judgement, thus, allowing for the incorporation of new inspection data to update the estimates of deterioration models as these data become available. As a reference, maximum likelihood estimation (MLE) is also used whereby only inspection data over one period (two consecutive inspections) are used.

3.1 NOTATION

Given the at most one-step deterioration assumption in the Markov Chain model, for each condition state i at time t only two transition probabilities govern the deterioration that takes place between time t and time $t + 1$, namely the transition probabilities p_{ii} and $p_{i\ i+1}$ indicating whether a unit of a deck remains in the same state i or transitions to the next lower state $i + 1$, respectively. Since $p_{i\ i+1} = 1 - p_{ii}$, only p_{ii} needs to be estimated for each condition state i at time t . The variables $N_i^{(t)}$ and $N_i^{(t+1)}$ represent the area of the deck that is in condition state i at time t and the area that remains in condition state i at time $t + 1$, respectively.

3.2 MAXIMUM LIKELIHOOD ESTIMATION

The event that a unit of deck remains in the same condition state or not in the next year can be described as a Bernoulli process, which has two outcomes, success and failure. Assuming that each 1 ft \times 1ft unit of bridge deck remains in the same condition state independently with the same probability p_{ii} , the maximum likelihood estimate of p_{ii} can be shown to be the following:

$$\widehat{p_{ii,MLE}} = \frac{N_i^{(t+1)}}{N_i^{(t)}} \quad (2)$$

That is, the maximum likelihood estimate of p_{ii} is the ratio of the deck area that remains in state i at time $t + 1$ to the deck area that was in state i at time t . In this approach, only the inspection data available from two consecutive inspections are used to estimate the transition probabilities and, as a result, the Markov Chain deterioration model.

3.3 BAYESIAN ESTIMATION

Another approach to estimate transition probabilities is that of Bayesian estimation, whereby the transition probabilities are assumed to follow certain distributions, the parameters of which are updated when new condition observations are made. In this approach, the estimates of the transition available before the two most recent sets of inspection data are collected are taken into account in the estimation process.

As in the case of maximum likelihood estimation, the event that a 1 ft \times 1ft unit of the deck remains in the same condition state or not in the next year is also described as a Bernoulli process. For such events, the Beta distribution is commonly selected as the prior distribution for mathematical convenience whereby the posterior distribution is derived to also be a Beta distribution through the application of Bayes' law. Using the mode of the posterior distribution as the point estimate of p_{ii} , the Bayesian estimation of p_{ii} can be shown to be the following:

$$\widehat{p}_{u,BYE} = \frac{a_{prior} + N_i^{(t+1)} - 1}{a_{prior} + b_{prior} + N_i^{(t)} - 2} \quad (3)$$

Note that when the parameters of the prior distribution a_{prior} and b_{prior} take the values of 1, corresponding to a uniform prior distribution, the Bayesian point estimates of p_{ii} are identical to the Maximum Likelihood estimates. Also note that when a_{prior} and b_{prior} take the values of 0, mode and mean of the posterior distribution are approximately equal if $N_i^{(t)}$ and $N_i^{(t+1)}$ are sufficiently large, which is the case for the dataset used in this study.

4 DATA

To evaluate the performance of the above two methods in forecasting future condition states of concrete bridge decks, an empirical investigation is conducted based on available data. In this analysis, the inspection records of a set of bridges for the year 2015 and 2016 are compiled. Once various discrepancies and inconsistencies discussed in more detail subsequently are addressed, a total of 357 bridge deck records are considered. This dataset is then divided into training and validation datasets, which are discussed in more detail in section 5.

4.1 DATA COLLECTION AND DEFINITION

The data used in this study are gathered from the Ohio Department of Transportation bridge inspection database for the years 2015 and 2016. The variables in the inspection report database and their definitions are presented in Table 2.

TABLE 2: Variables in the inspection report database and their definitions

Name	Definitions
STATE	STATE is the Federal Information Processing Standards (FIPS) code assigned to each state, and it is 39 for all bridges in Ohio.
STRUCNUM	STRUCNUM is the structure file number to identify bridges; this number is unique for every bridge.
EN	EN is the element number for a certain bridge element. In this project, bridge element to be analyzed is reinforced concrete deck, and the element number for it is 12. Therefore all records with EN of 12 are selected from the database.
EPN	EPN is the parent element number for bridge elements. In this project, the element to be analyzed is reinforced concrete deck, and the only element that is attached to concrete decks is wearing surface (element number: 510). Therefore, all records with EN of 510 and EPN of 12 are selected from the database. From these data, protection system factors in concrete deck deterioration models can be determined.
TOTALQTY	TOTALQTY is the total quantity of the bridge element. The unit of quantity for bridge decks is square foot.
CS1, CS2, CS3 and CS4	CS1, CS2, CS3 and CS4 are the quantity of a bridge element in condition states 1 to 4, respectively. In this project, they represent the deck area in condition states 1 to 4 based on the condition state definitions provided by AASHTO Bridge Element Inspection Guide Manual (2010).

4.2 DATA FILTERING

Some procedures are applied in this study to organize, compile, and select the original inspection records. This section provides a description of the preparation of the dataset used.

4.2.1 BRIDGE ELEMENT FILTER

The focus of this study is reinforced concrete deck. Thus, all inspection records with the element number (EN) of 12, indicating bridge decks, are selected.

4.2.2 INSPECTION RECORDS PAIR-UP

Since not all bridges are inspected every year and the analysis necessitates that condition inspection data have to be available for two consecutive years, inspection reports in 2015 and 2016 are paired up based on the structure number. For all the records of reinforced concrete decks in 2015, 914 out of 3,183 decks are inspected in 2016. For these bridges, the inspection records in 2015 and 2016 are extracted.

4.2.3 BRIDGE DECK AREA DISCREPANCY

The area of bridge decks is found to vary from year to year. Small variation could be a result of measurement errors, while large differences could be indicative of record keeping errors. In this study records that exhibit large differences are discarded. Considering the empirical cumulative distribution function of the difference in deck area between 2015 and 2016, records with differences between -5 to $+5$ square feet are deemed acceptable. All other records are not considered further.

4.2.4 DETERIORATION ASSUMPTION CONSISTENCY

The estimation methodologies in Section 3 are based on the assumption that there are no improvement in the condition state of bridge decks from year t to $t+1$ and no multi-step deterioration transition within one unit period (i.e., no condition state transitions from 1 to 3 or 4, and from 2 to 4). The subset of bridges that comply with these criteria considering a tolerance of -5 to $+5$ square feet are, therefore, selected for analysis in this study.

5 EMPIRICAL ANALYSIS

5.1 ANALYSIS SET-UP

The dataset consisting of 357 bridge deck records described in section 4 is divided into training and validation datasets. The training dataset contains 282 to 287 records (depending on the two cases considered as discussed subsequently) and is used to determine estimates of transition probabilities using the two methods. The estimated transition probabilities are then applied to the year 2015 inspection records of bridge decks in the validation dataset containing the remaining 75 to 70 records to predict their condition state in the year 2016. The similarity between the predicted and reported condition states is used as a measurement to assess the performance of the two methods.

The squared Hellinger distance (HD^2) metric is commonly used to measure the degree of similarity between two probability mass functions. This metric is used in this study to assess the similarity between two condition states, whether measured or predicted. The squared Hellinger distance is expressed as following:

$$HD^2 = \frac{1}{2} \sum_{i=1}^k (\sqrt{p_i} - \sqrt{q_i})^2 \quad (4)$$

where p_i and q_i are the elements of two probability mass functions for which the degree of similarity is to be assessed. The upper and lower limits of HD^2 are 1 and 0, respectively. A smaller value indicates a higher degree of similarity between the two probability mass functions.

To use measured condition states in calculating HD^2 , the reported condition state vectors of bridge decks must be converted to probability mass functions. This conversion is achieved by normalizing the state vector depicting the bridge deck area in each state by dividing the area in each state by the total area. In the case of predicted condition states, the predictions based on Equation 1a directly take the form of a probability mass function.

Based on an exploratory analysis, a few bridge decks are identified as having unique characteristics. As a result, the records for these bridge decks are given special treatment in the analysis.

As noted previously, there are 357 records of bridge decks in the dataset. Among the 357, 70 reflect observed deterioration between 2015 and 2016. Figure 1 shows the extent of this deterioration as measured by HD^2 capturing the degree of similarity between the condition state vectors in 2015 and 2016 where the values are ordered from largest to smallest along the x-axis. Clearly, four bridge decks exhibit substantial deterioration as reflected in the large HD^2 values with respect to those of the other bridge decks.

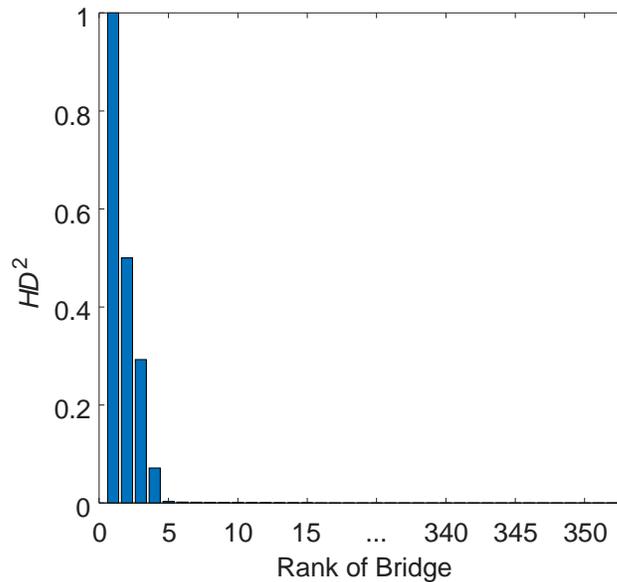


FIGURE 1: Bar chart of HD^2 between 2015 and 2016 for all bridges

Note that bridge decks represented in the training dataset contribute to the estimates in accordance to their bridge deck area whereby decks with larger deck areas have larger contributions. The proportion of deck area for these four bridge decks with respect to the total area of all bridge decks in the training dataset (if these four bridges were to be included in the training dataset) are 0.18%, 2.96%, 0.05%, and 0.08%, respectively.

In addition, one bridge deck is found to exhibit a different deterioration pattern with respect to all other bridge decks. More specifically, this bridge deck is the only one that has some deck area in

condition state 3 in 2015 where part of this deck area deteriorates to condition state 4 in 2016. The inspection record for this bridge deck is shown in Table 3. All the other bridge decks either have no deck area in condition state 3 in 2015 or have some deck area in condition state 3 in 2015 but none of this area deteriorates to state 4 in 2016.

TABLE 3: Inspection record for unique deterioration pattern bridge (Structure number: 7904983, unit: square feet)

Year	Total Deck Area	Area in Condition State 1	Area in Condition State 2	Area in Condition State 3	Area in Condition State 4
2015	14433	12267	1877	289	0
2016	14433	12234	1876	289	34

Given that these five bridge decks appear to be distinctly different from all other decks in the dataset, the impact their corresponding records could have on the results may be substantial. Therefore, two scenarios are considered. In Scenarios 1 the records of these five bridge decks are included in the validation dataset, resulting in a total of 282 records in the training dataset. In Scenarios 2 these five records are included in the training dataset resulting in a total of 287 records in this dataset. The records of all other bridges are randomly assigned to each of the two datasets.

To evaluate the performance of the maximum likelihood and Bayesian estimation methods, transition probabilities are determined using the training dataset. Applying the estimated transition probabilities to the condition state vector of bridge decks in the validation dataset for the year 2015, the condition states of these bridges are predicted for the year 2016. The similarity between the predicted and reported condition states for 2016 are then compared across the two methods.

As discussed in session 3.3, in the Bayesian estimation method, the transition probabilities available before the collection of condition data for 2015 and 2016 are assumed to follow Beta distributions defining the priors in the Bayesian framework. In section 3.3 the Beta distribution is described through its parameters a_{prior} and b_{prior} . For the purpose of this analysis, the Beta distribution is conveniently parameterized through the mean and sample size, referred to as the prior mean and confidence “parameters”. The relationship between this parameterization and the one in section 3.3 is that the confidence (sample size) is the summation of a_{prior} and b_{prior} and the prior mean is the ratio of a_{prior} to the sample size. The prior mean represents the prior belief about the mean value of p_{ii} . The sample size represents the number of samples used to derive p_{ii} , which is a measure of confidence in the prior belief about p_{ii} .

In this analysis the confidence is set to vary between 0 and 400,000 square feet. When the confidence is set to 0, the Bayesian point estimate (the mode of the posterior distribution) is equal to the maximum likelihood estimate. The upper limit sample size of 400,000 is selected based on recommendations in Pontis Technical Manual (1993). This manual suggests that it is reasonable to assume that the prior distribution of transition probabilities is developed based on observations for 10 to 20 bridges. Considering that the average deck area for the considered

bridge dataset is about 20,000 square feet, 20 bridge observations yield the upper limit of 400,000 square feet for the assumed confidence.

As for the prior mean, 10,000 mean values of prior transition probabilities (p_{11} , p_{22} and p_{33}) are generated independently from a uniform distribution that ranges between zero and one. Each set of the prior transition probabilities is updated using the training dataset through the application of the Bayesian updating method presented in section 3.3.

Combined with confidence values ranging from 0 to 400,000 in increments of 1,000, 4,000,000 sets of transition matrices are determined based on Bayesian estimation. Applying these transition matrices to 2015 condition state vectors of bridge decks in the validation dataset, the condition state vectors of these bridges are predicted for 2016. The similarity between the predicted and reported condition states for 2016 are then measured using the HD^2 metric.

The HD^2 metric is computed for each bridge deck in the validation dataset for all generated prior mean values of p_{11} , p_{22} and p_{33} and the levels of confidence in these mean values. Thus, for a given bridge deck and one set of generated mean values, a curve of HD^2 versus confidence can be plotted. Figures 2 and 3 show two examples of such plots. Since, as discussed in section 3, the Bayesian estimates are approximately equal to the maximum likelihood estimates at zero confidence for large values of $N_i^{(t)}$ and $N_i^{(t+1)}$, which are the case for the training datasets, Figure 2 indicates a case where a greater-than-zero confidence in the prior mean values leads to Bayesian estimates that produce a superior prediction for 2016 (lower HD^2) than that of the maximum likelihood estimates. Figure 3 indicates a case where a confidence greater than zero leads to an inferior prediction to that based on the maximum likelihood estimates. That is, the Bayesian and maximum likelihood estimates would reflect the same prediction performance when the confidence in the prior mean values is assumed zero for the Bayesian estimation method.

To quantify the improvement in prediction by using Bayesian estimation at the optimal confidence value for a set of prior mean values, the following measure is defined:

$$Reduction = \frac{HD_{MLE}^2 - HD_{BYE}^2}{HD_{MLE}^2} \quad (5)$$

where HD_{MLE}^2 and HD_{BYE}^2 are the HD^2 values for the predictions based on the maximum likelihood and Bayesian estimates, respectively. This measure of Reduction is depicted in Figure 2. Naturally, for a case like the one shown in Figure 3, the measure Reduction takes a value of zero.

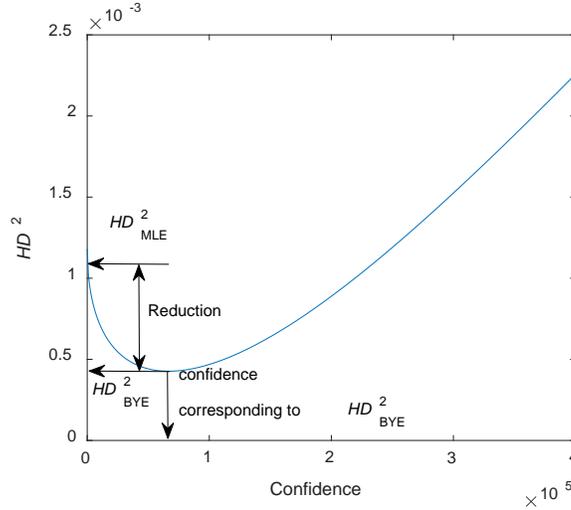


FIGURE 2: Example HD^2 versus confidence plot where Bayesian estimates at the optimal confidence level are superior to those of maximum likelihood



FIGURE 3: Example HD^2 versus confidence plot where Bayesian estimates at the optimal confidence level are equivalent to those of maximum likelihood

5.2 RESULT

All 4,000,000 sets of the Bayesian updated transition probabilities based on the combinations of prior mean values and confidence levels and the one set of maximum likelihood estimated transition probabilities are applied to the bridge decks of the Scenario 1 and Scenario 2 validation datasets as defined in section 5.1. Figure 4 shows the number of cases for each bridge where the Bayesian estimates are superior to the maximum likelihood estimates (i.e., Reduction > 0%) under Scenario 1 as shown in Figure 4(a) and under Scenario 2 as shown in Figure 4(b). Note that in Scenario 1 there are 75 bridge deck records in the validation set, while in Scenario 2 there are 70 records.

In Figure 4, bridge ID is defined to be the rank among the 75 bridge deck records in the validation dataset of Scenario 1 based on the descending order of the values of HD^2 measuring

the similarities of the reported condition states in 2015 and 2016. The counts reported in Figure 4 for each bridge represent the number of sets of prior transition probabilities out of the 10,000 generated ones that lead to Bayesian estimates that produce predictions that are superior to the prediction produced by the maximum likelihood estimates.

Based on Figure 4, the performance of Bayesian updating is clearly different for the two scenarios. Under Scenario 1, where the records of the five distinctly different bridge decks belong to the validation dataset, Figure 4(a) indicates that Bayesian updating is superior to maximum likelihood for a substantially large number of cases associated with a fairly small number of bridge decks, specifically those that exhibit more substantial deterioration between 2015 and 2016.

The bridge decks that are associated with the superiority of Bayesian updating over maximum likelihood include the four decks found to exhibit the most deterioration between 2015 and 2016 – bridge ID values of 1 through 4 in Figure 4. They also include the one and only deck that exhibits deterioration that involves a transition to state 4 in 2016 – bridge ID value of 5 in Figure 4 (the deck with the eighth largest change in deterioration between 2015 and 2016 when considering all bridge decks as depicted in Figure 1). These results are consistent with the expectation that for decks that experience deterioration that is not well represented in the training dataset, incorporating prior information with the two most recent condition inspections via Bayesian updating is advantageous.

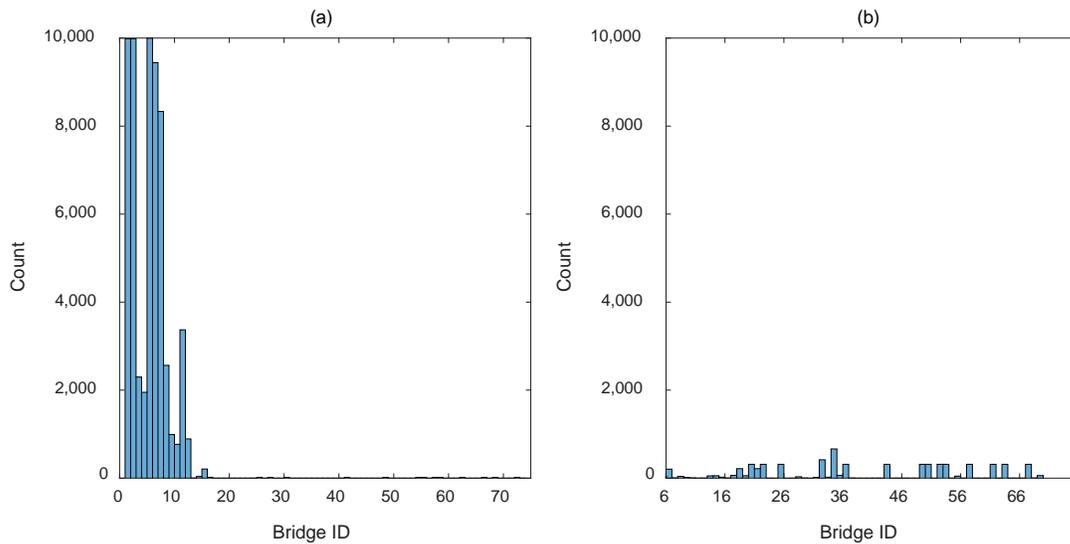


FIGURE 4: Bar chart by Bridge ID when Reduction > 0%; (a) Scenario 1; (b) Scenario 2

Under Scenario 2, where the records of the five distinctly different bridge decks identified in section 5.1 belong to the training dataset, Figure 4(b) indicates that Bayesian updating is superior to maximum likelihood only for a small number of cases spanning most bridge decks in the validation dataset. This result suggests that due to the unrepresentative impact the five distinctly different decks have on the estimates, only a small set of prior mean values and confidence levels lead to more accurate Bayesian estimation based predictions with respect to the maximum likelihood estimation based predictions. That is, only a few combinations of prior mean values

and confidence levels lead to Bayesian estimates that counter the maximum likelihood estimates that are corrupted by the presence of the five distinctly different bridges in the training dataset.

6 SUMMARY AND FUTURE RESEARCH

A Bayesian updating procedure is proposed to estimate a Markov Chain based concrete deck deterioration model in a manner that combines condition data collected over two inspection cycles and the deterioration information available prior to the collected condition data. Single period (one year) transition probabilities are estimated using Bayesian updating and maximum likelihood estimation where in the case of the latter only the collected condition data over two inspection cycles are used.

A dataset of bridge deck condition assessments based on AASHTO condition state definitions collected by a state infrastructure agency spanning two years is used to evaluate the performance of the two methods. A training and validation datasets are selected from the original dataset where the former is used for estimation and the latter for prediction and evaluation.

The evaluation is based on measuring the degree of similarity between reported condition states and those predicted based on the estimated transition probabilities using the two methods. While Bayesian updating is found to be superior to maximum likelihood estimation for many cases, this superiority is highly dependent on the deterioration nature of the bridge decks reflected in the training dataset.

Several possible areas for future research are worth pursuing. First, it is important to further investigate the effect of the nature of the datasets on the results and conclusion. A more refined experimental design could be used for this purpose. Second, the sensitivities of the results to various assumptions are worthwhile to explore. Such assumptions could then be relaxed if the results are found to be sensitive to them, especially those with high sensitivity. For example, adjacent bridge deck units are not expected to deteriorate independently as is assumed in this study. Also, deterioration could lead to more than a one-level change in condition state, unlike the single-level change assumed in this study. In addition, the transition probabilities may not be age-independent as is assumed in this study. Moreover, confidence in the prior mean values are not likely to be known as is also assumed in considering the Bayesian estimates that correspond to the maximum improvement in the quality of the corresponding predictions with respect to the quality of the predictions based on the maximum likelihood estimates. Furthermore, observed condition values are not error-free as is assumed in the estimation and evaluation aspects of the study. Third, additional variables could be taken into account in the deterioration model such as the effects of age, environment, loading, and protection systems.

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