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Duration-based Forecasting of Bridge Condition with Non-Parametric Kaplan-Meier Survival Functions

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ABSTRACT: Duration-based multivariate bridge deterioration models were recently developed based on the statewide National Bridge Inventory (NBI) data of North Carolina in the United States, using a combination of the Cox Proportional Hazards survival analysis and non-homogeneous Markov chain theory. Additionally, simplified models were also developed where bridge condition rating transition probabilities were derived from non-parametric Kaplan-Meier survival functions and implemented in a stationary Markov chain to predict future bridge condition ratings. This paper presents a comparison of the two approaches with the objective of evaluating the relative benefits and limitations of using the empirical Kaplan-Meier estimator instead of the more comprehensive Proportional Hazards model (PHM) based on sample subsets of the North Carolina state bridge inventory. It is observed that the semi-parametric PHM model offers a better statistical fit and is valuable in objectively quantifying the effect of explanatory factors on bridge deterioration rates. However, the comparison performed on the bridge inventory subset suggests that it does not necessarily result in improved bridge condition forecasting compared to the Kaplan-Meier model. It is postulated that the similar predictive performance of the models can most likely be attributed to the coarse granularity of the NBI general condition ratings. This finding is significant since the reduced data processing associated with the Kaplan-Meier approach may prove useful in expeditious development of duration-based probabilistic deterioration models for extremely large bridge databases.

1 INTRODUCTION

The United States (U.S.) mandated biennial bridge inspections and recording of bridge inspection data in the early 1980's. As a result, the U.S. National Bridge Inventory (NBI) has currently amassed well over three decades of inspection data for all the bridges in the nation containing wide-ranging information regarding design, construction, traffic and location attributes in addition to visual condition ratings associated with the deck, superstructure, and substructure components. NBI data accumulated over this duration has allowed researchers the opportunity to apply statistical techniques for analysis and development of bridge deterioration models for use within bridge management systems (BMS). Improved accuracy of bridge deterioration models directly supports enhanced BMS performance in optimizing the allocation of available resources to maximize the overall service life of aging bridge inventories.

Duration-based deterioration models based on NBI data were recently developed for the North Carolina state bridge inventory (Goyal 2015, Cavalline et al. 2015). The researchers developed a unique methodology integrating multivariable Cox Proportional Hazards Model (PHM) regression with a novel application of non-homogeneous Markov chain theory to model infrastructure deterioration. In addition to multivariable models, the researchers applied the same methodology to develop relatively simplified models based on the empirical Kaplan-Meier (K-M) estimator and the homogeneous Markov chain theory. Both modeling approaches are briefly described herein, followed by a comparative analysis of the resulting deterioration models for North Carolina's concrete bridge decks, with a view toward identifying the benefits and limitations of the simplified K-M approach versus the more advanced and robust PHM approach.

2 BACKGROUND

Duration-based models are based on analyzing the length of time a bridge component stays in (or survives) a condition state before deteriorating to a lower condition state. The earliest time-based models were developed for the pavement management and bridge management systems of the New York State Thruway Authority (NYSTA), in which life data analysis techniques were applied to bridge inspection data for the first time (Ravirala and Grivas 1995, DeStefano and Grivas 1998). Subsequent researchers used survival analysis techniques to further develop duration modeling approaches for bridge deterioration (Ng and Moses 1998, Mauch and Madanat 2001, Mishalani and Madanat 2002, Kallen and van Noortwijk 2005). Survival analysis techniques have historically been applied in engineering for reliability studies of industrial components, in the biomedical field for survival time analysis of patients diagnosed with a disease, and more recently, in the social sciences for analyzing topics such as duration of unemployment or duration of marriages. Survival analysis can account for typical characteristics of duration data, such as the occurrence of incompletely observed (or censored) observations that arise due to the difficulty of capturing, and describing with finite measurements, observations that occur on a continuous and infinite time basis. Bridge condition rating data contains many censored observations due to the partial measurement of condition rating durations at the beginning and end years of the database and also because of interruption of the natural deterioration process by maintenance and preservation actions. Duration models are considered more suited for modeling the time-dependent and stochastic nature of structural deterioration.

2.1 Parametric, Semi-parametric and Non-parametric Survival Functions

Duration data can be modeled using parametric, semi-parametric, or non-parametric survival functions. Parametric models are those that follow a theoretical distribution mathematically defined by one or more parameters. The exponential distribution that applies to the constant hazard rate model is one such parametric distribution. A parametric generalization of the exponential distribution that allows for a duration dependent hazard rate is the Weibull distribution. Bridge deterioration models incorporating Weibull survival analysis were recently developed in some states like New York (Agrawal et al. 2010), and Florida (Sobanjo 2011). The Weibull distribution is characterized by shape and scale parameters, which are estimated by maximizing the statistical likelihood function. Weibull based models are, however, limited by their ability to only model monotonically increasing or decreasing hazard rate functions. They are not suited for modeling unimodel distributions that are frequently observed in deterioration of bridge structural components (Yang 2013).

Semi-parametric models are generally the preferred method of survival analysis since they do not make assumptions about the shape of the distribution and also support multivariate analysis. The Cox Proportional Hazards Model (Cox 1972) is such a semi-parametric approach that is most frequently used in applied settings. The Cox PHM hazard function, $h(t, z)$, is expressed as a product of two functions:

1. A non-parametric baseline hazard function, $h_0(t)$, which signifies the dependence of the hazard function on survival time, and
2. A time-independent exponential function, $e^{\boldsymbol{z\beta}}$, that represents the effects of the covariates, z, on the hazard function, such that,

$$h(t, \boldsymbol{z}) = h_0(t)e^{\boldsymbol{z\beta}} \tag{1}$$

where, z is a row vector of covariates or explanatory factors and $\boldsymbol{\beta}$ is a column vector of the corresponding regression coefficients that define the effect of the covariates on the hazard rate. Researchers applied Cox PHM to survival analysis of bridge condition rating data as early as 2001 (Mauch and Madanat) to understand the effects of design, functional and environmental factors on concrete bridge deck deterioration, but were constrained due to lack of availability of long duration NBI data. Cox PHM was preferred by the authors to develop bridge deterioration models for the NCDOT bridge database because of its ability to model unusual distributions encountered in infrastructure deterioration and the ease of relating it to multiple influential variables.

Non-parametric methods are empirical in nature and are completely unconstrained by any prescribed distribution. The most commonly used non-parametric method of survival analysis is the Kaplan-Meier estimator, also known as the product limit estimator (Kaplan and Meier 1958). The use of this approach in bridge deterioration modeling was first proposed in 1998 (DeStefano and Grivas) to improve the state increment models developed previously for NYSTA that were based on a uniform distribution of transition time. The Kaplan-Meier approach is simple and flexible, although, similar to most parametric approaches, it does not support multivariate analysis.

3 PHM BRIDGE DETERIORATION MODEL

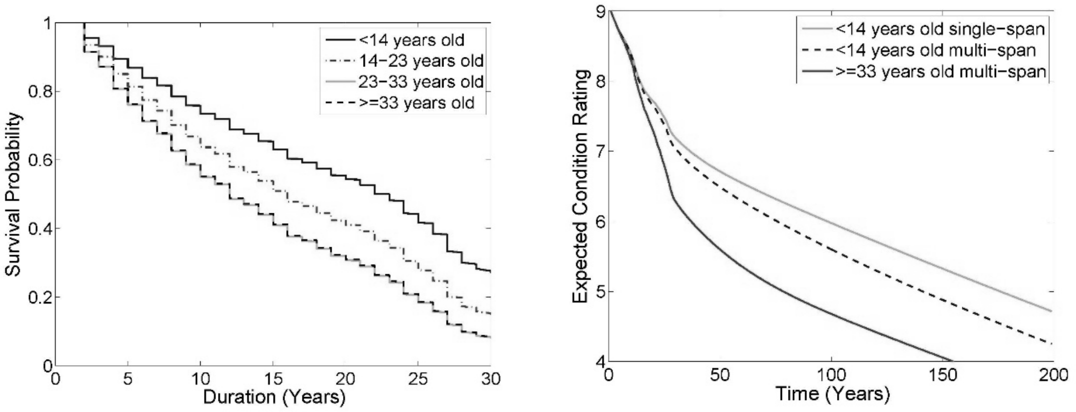
Although survival analysis has been previously applied to quantify deterioration rates at individual condition ratings, the current study has developed the first probabilistic duration-based bridge deterioration models for a complete state bridge inventory. The main contributions of the developed methodology are the use of semi-parametric and multivariate PHM survival functions to quantify the effects of various external factors on the deterioration of bridge components at various stages of lifecycle, development of non-stationary transition probabilities from the PHM survival function incorporating multivariable effects, and prediction of future condition rating probabilities with non-homogeneous Markov chain forecasting. The developed PHM bridge deterioration model can be simply represented in terms of structure-specific transition probability matrices, $\boldsymbol{P_i}$, associated with each year, i, of the prediction period,

$$\boldsymbol{P_i} = \begin{bmatrix} P_{99}^{HR_9} & 1 - P_{99}^{HR_9} & .. & .. & 0 & 0 & 0 & 0 \\ 0 & P_{88}^{HR_8} & .. & .. & 0 & 0 & 0 & 0 \\ \vdots & \vdots & .. & .. & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & .. & .. & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & .. & .. & P_{44}^{HR_4} & 1 - P_{44}^{HR_4} & 0 & 0 \\ 0 & 0 & .. & .. & 0 & 0.85 & 0.15 & 0 \\ 0 & 0 & .. & .. & 0 & 0 & 0.85 & 0.15 \\ 0 & 0 & .. & .. & 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where HR_k are the structure-specific hazard ratios developed for a bridge based on the factors identified as significantly influencing deterioration at condition ratings, k, and P_{kk} are the staythe-same transition probabilities for condition ratings, *k*, associated with every year of the prediction period for baseline values of explanatory factors. HR_k is calculated as the product of hazard ratios for the factors associated with the specific bridge that are identified as significantly influencing deterioration at condition rating, *k*. The yearly transition probability matrices are used in a non-homogeneous Markov chain to predict the future condition state vector, $\mathbf{Z_n}$, of a bridge component after *n* years if its present condition state vector, $\mathbf{Z_0}$, is known, using

$$\boldsymbol{Z_n} = \boldsymbol{Z_0} \prod_{i=1}^{n} \boldsymbol{P_i} \tag{3}$$

The condition state vectors comprise of the probabilities of the bridge component being at all possible condition ratings at any given time. The future state vector $\boldsymbol{Z_n}$ can be multiplied by the column vector of condition ratings to produce the expected condition rating of the bridge component after *n* years.



(a) (b)

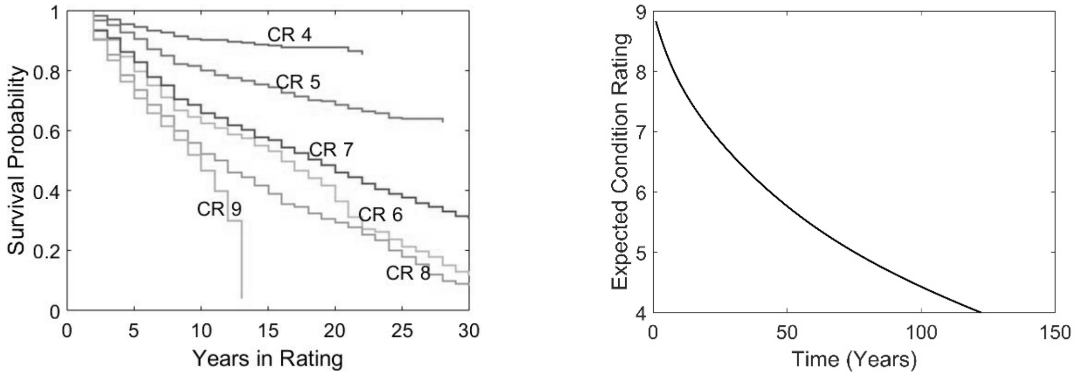
Figure 1. (a) PHM survival functions for concrete decks at condition rating 8 for bridges in various age groups; (b) PHM bridge deterioration models for concrete decks on single-span and multi-span bridges in various age groups.

Figure 1 (a) shows the proportional hazards effects of bridge age on the survival of concrete decks at condition rating 8. Figure 1 (b) shows proportional hazards effects of bridge age as well as number of spans across the lifecycle in the PHM bridge deterioration models developed for North Carolina's concrete bridge decks. The figures illustrate the value of the models in not only predicting future condition rating but in understanding the varying influence of factors on the deterioration process. Details of PHM deterioration model development are available in previous publications by the authors including, the Ph.D. dissertation that stemmed from this research project (Goyal 2015, Goyal et al 2016, 2018).

4 K-M BRIDGE DETERIORATION MODEL

Kaplan-Meier-based probabilistic deterioration models developed in this study follow a similar but simplified version of the methodology devised for the PHM multivariable models. Kaplan-Meier empirical survival functions are developed for each condition rating in the bridge component lifecycle and used to calculate transition probabilities of deterioration to a lower condition rating. The mean transition probabilities, P_{kk}, calculated across each survival function are used to construct a stationary transition probability matrix, $\boldsymbol{P}$, which is used in a stationary Markov chain to predict the future condition of a specified bridge component if its present condition is known using equation (5):

$$\boldsymbol{Z_n} = \boldsymbol{Z_0}(\boldsymbol{P})^n \tag{5}$$



(a) (b)

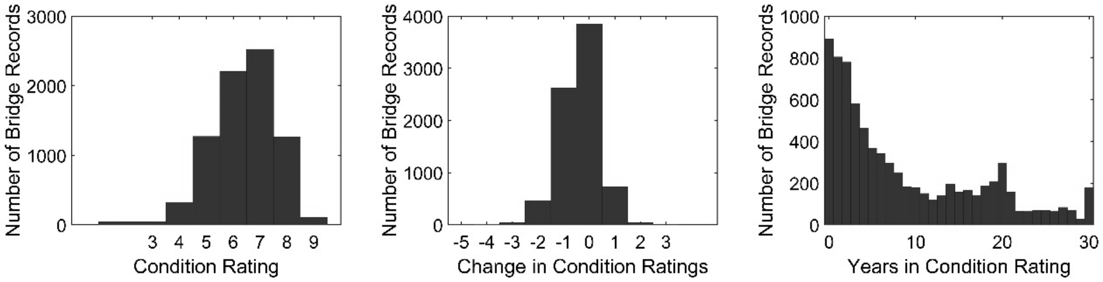
Figure 2. (a) K-M survival functions for concrete decks at condition ratings 9 through 4; (b) K-M bridge deterioration model for concrete decks.

The developed K-M deterioration model, similar to the PHM model, uses maximum partial likelihood estimation to account for the effects of censoring on condition rating data, but is applicable to all of the bridge components in the classification used to develop the model through statistical regression irrespective of the covariates associated with each bridge. In this study, the simplified K-M probabilistic deterioration models were developed for each bridge component after first pre-classifying the components by material type. This strategy follows an assumption that deterioration rates are most significantly affected by the material type, as deterioration of different materials are often driven by different mechanisms or affected by common mechanisms at the same rate. It is further noted that duration-based models are based on underlying data that includes routine maintenance practices, and forecast future service life based on the assumption of continuation of such routine interventions. Figure 2 (a) shows the K-M survival functions for North Carolina concrete deck bridge components in condition ratings 9 through 4, and figure 2 (b) shows the concrete deck K-M bridge deterioration model.

5 COMPARATIVE ASSESSMENT OF PREDICTIVE FIDELITY

A methodology to assess the predictive fidelity of deterioration models was developed to compare the accuracy and precision of the deterioration models developed in this research program (Goyal 2015, Cavalline et al. 2015). Since the models are based on bridge inspection records from 1981 to 2015, there is currently an opportunity to evaluate the forward predictive accuracy of the models using the additional three years of inspection records now available from 2016 to 2018. Accordingly, model assessment was performed on concrete deck condition rating records corresponding to a 7-year period from 2011 to 2018.

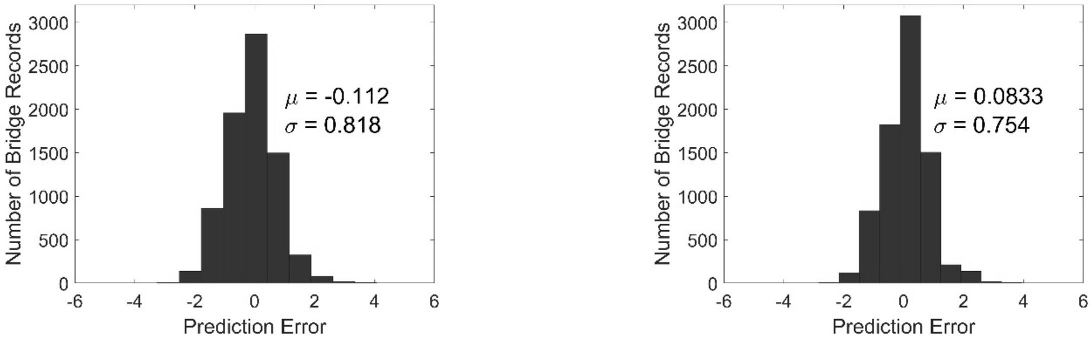
The bridge records were prefiltered to include only structures with a continuous record of deck condition ratings without exhibiting an improvement by more than one rating between consecutive years. The filtering algorithm was designed to exclude cases with significant improvement in condition rating evidencing an interruption of the natural deterioration process presumably due to maintenance actions or reconstruction. Characteristics of the 7737 records meeting this criteria are presented in Figure 3 in the form of histograms. It can be observed that the initial deck condition ratings at the beginning of the 7-year prediction period are nearly normally distributed with 61% of the concrete decks residing at a condition rating 6 or 7. Almost 60% of the decks exhibited no deterioration in condition rating over the 7 year period, with nearly 34% deteriorating by 1 rating, 6% by 2 ratings and less than 1 percent by 3 ratings.



(a) Initial condition rating (b) Change in condition ratings (c) Pre-existing duration

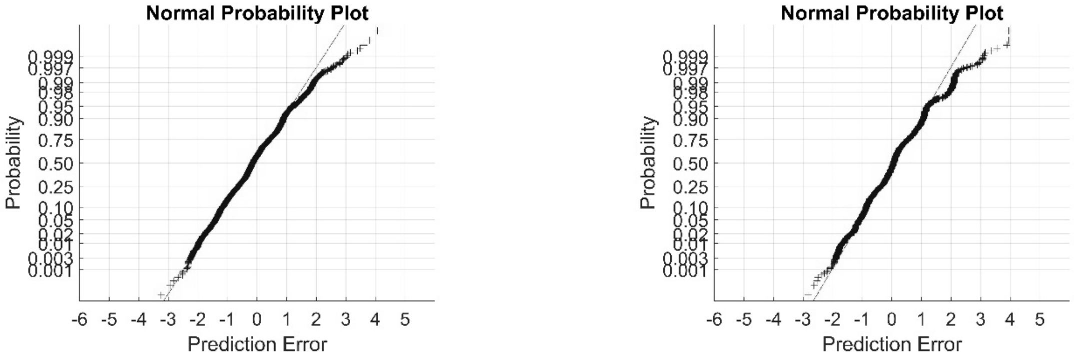
Figure 3. Characteristics of concrete deck condition rating bridge records utilized for model assessment over a 7-year predicton period (2011-2018).

Assessment of predictive accuracy of the K-M bridge deterioration model relative to the statistically more advanced PHM deterioration model was performed by subtracting the actual inspector recorded condition ratings from the condition ratings predicted by each model during the 7-year prediction period and comparing the distribution of residual prediction errors. Figure 4 shows histograms of the prediction errors for both the models. It is observed that the mean error of 0.0833 for the K-M model is slightly better relative to the mean error of -0.112 for the PHM model. The K-M model prediction errors are also somewhat more concentrated around the mean, giving a slightly lower standard deviation of 0.754 compared to a standard deviation of 0.818 for the PHM model. It is observed, however, that the PHM model, in addition to producing slightly conservative condition rating predictions, also exhibits more normally distributed prediction errors and provides a better fit to the underlying data than the simplified K-M model. Comparison of the normal probability plots of the prediction errors, presented in Figure 5, reveals more clearly the greater skew in the K-M prediction error distribution.



(a) PHM Model (b) K-M Model

Figure 4. Histograms of prediction errors for survival based probabilistic bridge deterioration models applied to concrete decks for a 7-year prediction period.



(a) PHM Model (b) K-M Model

Figure 5. Normal probability plots of prediction errors for survival based probabilistic bridge deterioration models applied to concrete decks for a 7-year prediction period.

The assessment results suggest that both the PHM and the K-M models achieve similar levels of accuracy although the K-M model tends to provide slightly more optimistic predictions compared to the PHM model. Keeping in view that the K-M model is developed based on a relatively unclassified dataset, its accuracy may be attributed mainly to its ability to account for censoring similar to the PHM model. On the other hand, the contribution of the additional capability of the PHM model to explicitly discriminate between the effects of external factors is not immediately obvious. Considering the fact that the PHM models are statistically more advanced and robust, the authors believe that the coarse granularity of the NBI condition rating is the reason for its inability to adequately reflect the effect of most geographic, design, and functional features on deterioration rates.

5 CONCLUSIONS

In this paper, proportional hazards based multivariable models that use non-stationary Markov chain prediction and comprise the main contribution of this research, are compared with simplified Kaplan-Meier based stationary Markov chain models. Both models were developed using bridge inspection condition ratings over a 35 year duration ending in 2015. Predictive fidelity of both the models with actually observed condition ratings was assessed based on a 7-year prediction period from 2011-2018. It was observed that the simplified K-M models exhibit similar predictive accuracy as the more advanced PHM models, although the latter are statistically more robust and provide valuable insights into the effects of external factors on deterioration rates over the lifecycle of the bridge components. Although the simplified K-M models were developed with similar unclassified datasets but without explicitly accounting for external factors, the authors believe that the comparable predictive accuracy achieved with the simplified K-M models can be attributed to the coarse granularity of the NBI condition rating scale, which may preclude sufficiently reflecting the effect of most design, functional and environmental factors. The PHM model may offer important advantages over the simplified K-M model, when bridge inspection data of greater granularity (i.e. element-level condition ratings) accumulates in sufficient duration. Meanwhile, the K-M model can be utilized beneficially to develop accurate bridge deterioration models without excessive preclassification of bridge components. The reduced data processing associated with the development and forecasting with K-M models can prove to be particularly advantageous in expeditiously applying bridge deterioration models to extremely large bridge databases.

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