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A statistical deterioration forecasting method using hidden Markov model for infrastructure management

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ABSTRACT

The application of Markov models as deterioration-forecasting tools has been widely documented in the practice of infrastructure management. The Markov chain models employ monitoring data from visual inspection activities over a period of time in order to predict the deterioration progress of infrastructure systems. Monitoring data play a vital part in the managerial framework of infrastructure management. As a matter of course, the accuracy of deterioration prediction and life cycle cost analysis largely depends on the soundness of monitoring data. However, in reality, monitoring data often contain measurement errors and selection biases, which tend to weaken the correctness of estimation results. In this paper, the authors present a hidden Markov model to tackle selection biases in monitoring data. Selection biases are assumed as random variables. Bayesian estimation and Markov Chain Monte Carlo simulation are employed as techniques in tackling the posterior probability distribution, the random generation of condition states, and the model's parameters. An empirical application to the Japanese national road system is presented to demonstrate the applicability of the model. Estimation results highlight the fact that the properties of the Markov transition matrix have greatly improved in comparison with the properties obtained from applying the conventional multi-stage exponential Markov model.

1. Introduction

Statistical deterioration forecasting with Markov models has been widely documented as an important methodology for hazard analysis in the practice of infrastructure management (Madanat et al., 1995; Shin and Madanat, 2003; Shahin, 2005; Lethanh, 2009). A good example of its application is the PONTIS program (Golabi and Shepard, 1997), which was developed for bridge management systems (BMSs). In Markov models, the deterioration of an infrastructure system is represented by the transition probability among its discrete condition states, which reflect the status of its health.

In order to apply Markov models for prediction, it is necessary to employ monitoring data from historical inspections, the quality of which is a decisive factor in the accuracy of estimation results. In infrastructure management practice, however, monitoring data are often marred by errors and bias. Measurement errors can arise from the measurement system itself, the inspector (human or machine), the inspected objects, or problems with data processing and interpretation (Humplick, 1992). Such errors tend to cause bias in the estimation results of deterioration models, especially when there is a small pool of monitoring data.

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Researchers have proposed methods of tackling problems related to measurement errors in monitoring data. Efforts have been made to perfect evaluation techniques for quantifying the error term (Cochran and Cox, 1968; Grubbs, 1973; Humplick, 1992). In addition, to cope with small sampling populations of monitoring data and measurement errors, researchers have proposed estimation methodologies using the Bayesian estimation technique (Hong and Prozzi, 2006; Park et al., 2008). To overcome problems in spatial sampling, which is viewed as contributing to measurement errors, Madanat (1993a,b) propose an optimization model using the latent Markov decision process (LMDP) to select the best sample size. To our knowledge, a paper by Humplick (1992) is considered the fundamental measurement errors model for later models using LMDP in infrastructure management.

In the paper of Humplick (1992), the author proposed a factor analytical model focused on differentiating the causes of measurement errors as influenced by three categories: monitoring technologies, specific items, and measurement locations. Measurement errors are quantified by weighting factors for error terms with respect to the three categories. The best technology offering least measurement error becomes preferable in adjusting the error term and defining performance distress. Later research on LMDP then utilizes the estimation results of this measurement error model as input (Madanat, 1993a,b).

Another research orientation toward elimination of measurement errors, which is continuous-state expression of the LMDP approach, is with the application of Kalman filter. This mathematical method originated from the field of statistic and has been widely applied in many engineering fields. Theoretically, Kalman filter is an algorithm to generate estimates of the true values of observations and their associated calculated values by predicting a value, estimating the uncertainty of the predicted one, and finally computing a weighted average of the predicted value and the measured value. The weighted average is calculated from the covariance, a measure of the estimated uncertainty of the prediction of the system's state. As the weighted average has a better estimated uncertainty than either alone, the estimates produced by the algorithm tend to be closer to the true values than the original observations (Kalman, 1960). To the best of the authors' knowledge, application of Kalman filters for management of infrastructure system has been recently documented in the papers of Durango-Cohen (2007) and Chu and Durango-Cohen (2007, 2008). Of the cited papers, continuous state-space models are discussed. The performance or condition of an infrastructure system is reflected in a continuous performance indicator. Using the framework of Kalman filter algorithm, authors of the cited papers have successfully discussed and proposed an approach for deterioration prediction within a dynamic infrastructure management system, in which, heterogeneity factors, time-series and panel data are used; effects of interventions over the life cycle of infrastructure system, and measurement errors are included.

The hidden Markov model is a special case of Markov chain model, which has been widely used in several research areas such as image processing, speech recognition, and applied statistics (Robert et al., 2000; MacDonald and Zucchini, 1997; Lawrence, 1989). One of the great advantages of the hidden Markov model is that it allows the unobserved condition state to be captured, eliminating the noise and bias associated with monitoring data. Of cited studies on hidden Markov models, the main focus has been on the accumulation of discrete-value in time series. In addition, several profound research studies on hidden Markov models with unobserved states of regimes can be found in economics and finance engineering literature (Hamilton, 1989; Diebold and Inoue, 2001; Hamilton and Raul, 1994), where the authors attempt to simulate and evaluate the business cycle and switching of regimes by using non-stationary time series. One important finding is that the change of longitudinal data can be simulated by means of transition probability. In addition, research has shown that the transition probability can be identified in the non-linear auto-regressive approach using the Markov chain theory (Hamilton, 1989; Kim and Nelson, 1999). However, a majority of past research on hidden Markov models has proposed estimation methods to uncover unobserved condition states based on true condition states, which must be available as monitoring data. Under such an assumption, it is certain that the true condition states of a system are no longer random variables. This fact is considered as a limitation of the cited research.

Apparently, research on the hidden Markov model has not been applied elsewhere in the literature of infrastructure management. In this paper, we develop a hidden Markov model to tackle a type of measurement errors in monitoring data so that estimation outcomes can be more reliable for practical use. It is noted that the term "measurement errors" in our model is referred as selection bias, which is explained in detail in Section 2. In the model, we assume that "true condition states" and "observed condition states" of road sections are random variables. This assumption reflects the real possibility of having selection biases in the system. In another words, we consider selection biases as random variables. This assumption is one of the key features of our model, which is different from the assumption in past models. To describe selection biases as random variables, a mixture of mathematical forms between "true condition states" of road sections and "observed conditions states" or "selection biases" is proposed using the conditional probability distribution function. Also in our model, an innovative numerical estimation approach using Bayesian estimation and MCMC simulation is presented to overcome the difficulty of the complete likelihood function so that optimal values of the model's parameters can be obtained.

In comparison with the proposed methods in the research work of Humplick (1992) and the use of Kalman filter in the papers of Durango-Cohen (2007) and Chu and Durango-Cohen (2007, 2008), our paper is different from them in two fundamental research standpoints. Firstly, in our paper, we basically deal with a special type of measurement errors called selection bias. Precisely, we assume that measurements carried out by monitoring devices are precise. Selection biases occur due to the maladjustments of engineers. A greater description of our assumption is presented later in Section 2. Secondly, the hidden Markov model in our paper is developed for discrete space, while in Kalman filter models; the state-space is continuous. Additionally, the hidden Markov model can represent an arbitrary distribution for the next value of the state variables, in contrast to the Gaussian noise model that is used in the models employing Kalman filter (Capper et al., 2005).