KSCE Journal of Civil Engineering (2017) 21(5):1747-1756
DOI 10.1007/s12205-016-1461-x

Highway Engineering
pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Management Scheme of Road Pavements Considering Heterogeneous Multiple Life Cycles Changed by Repeated Maintenance Work

Daeseok Han*, Kiyoyuki Kaito, Kiyoshi Kobayashi***, and Kazuya Aoki******

Received June 24, 2015/Revised July 8, 2016/Accepted August 9, 2016/Published Online September 30, 2016

Abstract

Road agencies provide maintenance work to serve a satisfactory level of road services to the public. However, as time goes on, pavement structure deteriorates for many reasons. Since repeated maintenance work upon deteriorated pavement structures can accelerate the deterioration speed, the pavements require periodic reconstruction work to recover original integrity. However, in the real world, it is difficult to carry out such a high level of maintenance work due to insufficient budgets, and no evidence for a guarantee of better economic efficiency. To support decision making in asset management, this study tries to define changing pavement performance by repeated maintenance work with empirical data. As an analytical tool, mixed hazard model with hierarchical Bayesian estimation method was applied. With the results, a best maintenance scheme on reconstruction timing was suggested by life cycle cost analysis. For the empirical study, a maintenance history data on Korean national highways, accumulated from 1965, was applied. The analysis procedures and results of this paper could be a good reference to build much realistic long-term maintenance strategy and reasonable budget allocation. In addition, the mixed hazard model with the hierarchical Bayesian estimation method is expected to be a useful tool in solving problems with heterogeneous population sampling, and in finding best practice and gaps among competitive alternatives.

Keywords: *asset management, heterogeneous life cycles, life cycle cost analysis, pavement reconstruction scheme, markov mixed hazard model, hierarchical bayesian estimation*

1. Introduction

Over the past two decades, road agencies have adopted the term “asset management” from the private sector to refer to the development, maintenance, operation, improvement, and upgrading of road assets in a systematic manner. Concerns with aging infrastructure, increased public demands for more accountability, and tighter budgets have stimulated interest in asset management internationally (Fwa, 2006). Main interests in the road asset management field could be classified into two types; Life Cycle Cost Analysis (LCCA) of maintenance alternatives, and uncertain deterioration process of the pavement. Since the LCCA result is totally dependent on the deterioration process, establishing reliable forecasting functions is a key factor in the successful implementation of asset management systems. In addition to this, reflecting maintenance schemes and their decision making process in the real world in the LCCA model would be an important factor for securing reliability in the result.

From the numerous references, we can easily find conceptual diagrams that describe the performance history of pavements by a combination of deterioration curves and maintenance effects (USDOT, 2002). They often used different deterioration curves for each cycle to distinguish different maintenance methods, or to express changing trends of deterioration speeds due to repeated maintenance work. Although most road agencies also empirically know the fact that the life spans are shortened by repeated maintenance work, the length of each life cycle (i.e. life expectancy) in the LCCA was generally held at a constant during the analysis period. In addition, reconstruction options and recovered pavement performance have often been excluded from the maintenance criteria. Although it would be good due to a desire for simplicity in modeling, such simplified methods have limitations in their ability to reflect reality.

Defining the changing deterioration process is critical in defining proper reconstruction cycle. This would be an interesting issue to road agencies because reconstruction work usually demands the highest unit costs among the various maintenance types. In addition, it is directly related to a specification regarded as “design life”, which is the time from original construction to a terminal state where the pavement structure needs reconstruction.

*Member, Senior Researcher, Highway and Transportation Research Institute, Korea Institute of Civil Engineering and Building Technology, Goyang 10223, Korea (Corresponding Author, E-mail: handaeseok@kict.re.kr)
**Associate Professor, Dept. of Civil Eng., Osaka University, Osaka 565-0871, Japan (E-mail: kaito@ga.eng.osaka-u.ac.jp)
***Professor, Dept. of Urban Management, Kyoto University, Kyoto 606-8501, Japan (E-mail: kobayashi.kiyoshi.6n@kyoto-u.ac.jp)
****Manager, Research & Development Center, PASCO Corporation, Tokyo 153-0043, Japan (E-mail: kiakzo6013@pasco.co.jp)

However, analyzing the heterogeneity of life spans is not a simple task because it demands well designed and long enough time-series maintenance history data, since it deals with multiple life cycles. In addition, there is a need for statistical solutions in solving inhomogeneous population sampling, severe uncertainty in the deterioration process, numerous explanatory variables, and insufficient samples.

Considering these aspects, this study focused on the following two issues; 1) defining heterogeneous life cycles changed by repeated maintenance work through a statistical method with empirical data, and 2) finding a better maintenance scheme regarding reconstruction timing by life cycle cost analysis. Accordingly, it can be compared with the existing standard to renew the design life. For these purposes, extensive maintenance history data from the Korean National Highway network accumulated since 1965, was applied. With this data, this study introduced an advanced statistical model, the mixed hazard model with the hierarchical Bayesian estimation method, is very advantageous in solving prominent difficulties in practical applications.

As for the analysis order, the changing process of life expectancy differed by the reconstruction, and nth maintenance work (overlay) was first specified by the Markov mixed hazard model, with the results then reflected to LCCA to find the best reconstruction scheme and design life. In the LCCA, life cycles were draw from corresponding distributions by the Monte-Carlo sampling to consider the uncertainty of life expectancy. In addition, the simulation was repeated a thousand times to derive a distribution (or range) of the average annual budget for the entire network, as well as local agencies. Finally, it was compared with the true budget in reality.

2. The Benchmarking Approach with Bayesian Markov Mixed Hazard Model

2.1 A Brief Reviews on Deterioration Models in Pavement Management

There are numerous references on deterioration modeling for various infrastructure facilities. The deterioration models vary in complexity from simple regression (or deterministic models) to sophisticated probabilistic (or stochastic) models (Carnahan *et al.*, 1987; Butt *et al.*, 1987; Shahin and Kohn, 1982; Golabi *et al.*, 1982). In general, simple regression is preferred when sample data is not enough, or the model has very significant explanatory variables. However, most cases or studies have preferred probabilistic approaches because the behavior of pavement deterioration is generally uncertain and curvilinear (Butt *et al*., 1987; Kobayashi *et al.*, 2010; Tomas and Sobanjo, 2013; Han *et al.*, 2014).

Among the probabilistic approaches, the Markov chain would be the most popular method. The Markov chain models originally suggested by A.A. Markov (Markov, 1907) have been widely applied to various types of infrastructure, such as pavement, bridges and pipelines (Golabi *et al*., 1993; Micevski *et al.*, 2002; Baik *et al.*, 2006; Mishalani and Madanat, 2002; Tsuda *et al.*, 2006; Mizutani and Kaito, 2013; Han *et al*., 2016). Its first implementation to the pavement field was Arizona PMS in the 1980s (Butt *et al*., 1987; Golabi *et al.*, 1982). However, in real applications, the original Markov chain has limitations on time synchronization of data sets, an introduction of explanatory variables, and only network level application (Han *et al*., 2014; Madanat *et al*., 1995). To solve these limitations, many kinds of advanced models have been developed (Tsuda *et al*., 2006; Mishalani and Madanat, 2002; Tomas and Sobanjo, 2013; Kobayashi *et al*., 2012a; Lethanh *et al.*, 2014). Among others, Tsuda *et al.* (2006) has developed the Markov hazard model that disaggregates the Markov Transition Probability through a multi-state exponential hazard model using the MLE (Maximum Likelihood Estimation) method. This model gives great advantages that overcome most limitations of the conventional Markov chain model. Meanwhile, Kaito *et al.* (2007) developed an advanced version based upon Tsuda's model by introducing a non-parametric method called MCMC (Markov Chain Monte-Carlo). This simple change solved general problems in deterioration modeling, such as sample insufficiency, intermittent overflow in calculation as the dimension of a matrix increases, chronic problems in revolving initial value when applying the MLE, and optimization problems related to the local maximum. After that, the MCMC methods were widely adopted for other deterioration models such as the Markov mixed hazard model, the hidden Markov and others (Kobayashi *et al*., 2012b; Han *et al*., 2014, 2016; Lethanh *et al*., 2014).

2.2 Understanding Benchmarking Approach

A model adopted for this study is the Bayesian Markov mixed hazard model (hereinafter, BMH model), which is an advanced version of the Markov mixed hazard model (Obama *et al.*, 2008). The BMH model draws a benchmarking deterioration curve representing all samples, and then draws the sub-groups' deterioration curves by introducing a heterogeneity factor (See Figs. 1~2). For that reason, it is often called the "benchmarking approach." This model has ideal functions estimating life expectancy considering explanatory variables, drawing deterioration curves and quantifying their uncertainly, which are all desired for asset management planning. In statistical aspects, this model solved problems on inhomogeneous sampling related to over-dispersion (refer to Fig. 1). Above all, from the nature of the benchmarking approach, it is very convenient for a comparative analysis that avoids repetitive parameter estimations.

In Fig. 1, two sampling groups have different deterioration speeds. Nevertheless, general statistical models (including the Markov hazard model series (Tsuda *et al.,* 2006; Kaito *et al*., 2007)) result in a deterioration curve between the two groups. The BMH model focused on this matter caused by inhomogeneous sampling.

The root of the BMH model is the Markov process. Inspection data usually expressed with continuous numbers should be converted (or belong) in the discrete condition state $i(i=1,\dots,J)$.

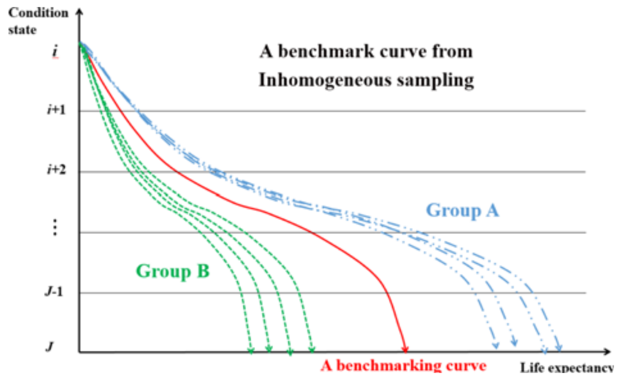

Fig. 1. A Benchmark Curve Derived from Inhomogeneous Samples

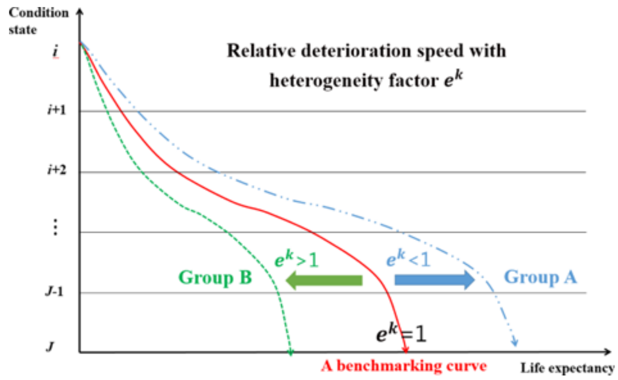

Fig. 2. Adjustment of Deterioration Speeds by using Heterogeneity Factor

Here, the state $i = 1$ is usually allocated to express the best condition, and $i = J$ is applied as the absorbing state which requires maintenance work. And the duration from state $i = 1$ to $i = J$ is called the life expectancy. Basically, the Markov chain model shows the transition probability of the condition states between two time points τ_A and τ_B. Its interval is denoted by $z(z = \tau_B - \tau_A)$. Based on these definitions, the MTP (Markov Transition Probability) matrixΠ and its elements π_{ij} can be expressed as,

$$\mathrm{Prob}[h(\tau_B) = j | h(\tau_A) = i] = \pi_{ij} \tag{1}$$

$$\Pi = \begin{bmatrix} \pi_{11} & \cdots & \pi_{1J} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{JJ} \end{bmatrix} \tag{2}$$

with the preconditions $\pi_{ij} \geq 0$ and $\sum_{j=1}^{J} \pi_{ij} = 1$. Since the model does not consider repair, $\pi_{ji} = 0 (i > j)$ and $\pi_{JJ} = 1$ become additional preconditions, accordingly.

Pavement groups having different characteristics $k(k = 1, \ldots, K)$ or individual members of the group $s_k(s = 1, \ldots, S_k)$ have different deterioration processes to each other by known and unknown factors. To express this heterogeneous population sampling, the BMH model introduces the heterogeneity factor that expresses the difference in hazard rates λ at each condition state $i(i = 1, \ldots, J-1)$ to a road section s_k. Therefore, the mixture mechanism of the hazard rates can be expressed as:

$$\lambda_i^{s_k} = \tilde{\lambda}_i^{s_k} \varepsilon^k \quad (i = 1, \ldots, J-1; s = 1, \ldots, S; k = 1, \ldots, K) \tag{3}$$

where the $\tilde{\lambda}_i^{s_k}$ is the average hazard rate, and the ε^k is heterogeneity factors. The ε^k are always non-negative $(0 < \varepsilon^k < \infty)$ because it is a relative rate of the benchmark deterioration speed at $\varepsilon^k = 1$. That is, a higher the value of ε^k, means a faster deterioration speed, compared with the benchmarked speed (see Fig. 2). However, it is impossible to consider explanatory variables as things are. For that reason, an estimation method of $\tilde{\lambda}_i^{s_k}$ as a function of explanatory variables $\bar{x}^{s_k}$ and unknown parameters $\beta_i = (\beta_{i,1}, \ldots, \beta_{i,M})$ is required, where $m(m = 1, \ldots, M)$ is the number of explanatory variables. The form is given by,

$$\tilde{\lambda}_i^{s_k} = f(\bar{x}^{s_k} : \beta_i') = \exp(\bar{x}^{s_k} : \beta_i') = \exp(\beta_0 + \beta_1 x_1, \ldots, \beta_M x_M) \tag{4}$$

By using the obtained hazard function $\tilde{\lambda}_i^{s_k}(i = 1, \ldots, J-1)$, $L_i^{s_k}$ the life expectancy of each condition state i can be defined by means of the survival function (Lancaster, 1990).

$$L_i^{s_k} = \frac{1}{\tilde{\lambda}_i^{s_k}} \tag{5}$$

That is, a life cycle from condition i to J can be easily estimated by $L_{iJ}^{s_k} = \sum_{i=1}^{J-1} L_i^{s_k}$. Understanding the basic concept would be easy. However, the inside of this model is very complex and demands immense statistical knowledge on 1) the Markov chain (Howard, 2007), 2) the multistate hazard model (Lancaster, 1990), 3) the local mixing mechanism (Lancaster, 1990), 4) the MCMC simulation for Bayesian estimations (Metropolis *et al.*, 1953; Hasting, 1970; Train, 2007; Koop *et al.*, 2007), 5) Geweke's diagnostics of convergence of the MCMC process (Geweke, 1992), and 6) their logical relationship and application process (Tsuda *et al.*, 2006; Obama *et al.*, 2007; Kaito *et al.*, 2012; Han *et al.*, 2014; 2016). It is difficult to give a detailed description of all the components in a single paper. It is highly recommended to refer to the listed introductory references and original papers.

4. Empirical Study

This section presents empirical studies regarding the noted two research purposes; 1) defining heterogeneous life cycles changed by repeated maintenance work by a statistical method with empirical data, and 2) finding a better maintenance scheme regarding reconstruction timing by life cycle cost analysis. For the analysis, maintenance history data from the Korean National Highway (KNH) network accumulated from 1965 was applied. As the analysis order, changing process of life expectancy differed by the reconstruction, and nth maintenance work (overlay) were firstly specified by the BMH model, and the results were reflected to LCCA to find the best reconstruction scheme and its design life. In the LCCA, life cycles were drawn from corresponding distributions by the Monte-Carlo sampling to consider uncertainty of life expectancy. In addition, the

Table 1. Information on the Used Samples Classified by Maintenance Type and Frequency

Contents	All sample (K)	Construction group (G)	Overlay group (M_n)		
			M_1	M_2	M_3
Sample size	2,340	1,353	695	245	47
Standard deviation (year)	3.83	3.89	2.48	2.57	2.07
Variance (year)	14.73	15.17	6.15	6.62	4.29
Avg. of MESAL(lane/year)	0.13	0.13	0.13	0.12	0.15

Table 2. Parameters of the BMH Model

Groups	Model coefficients		Heterogeneity factors	Exp. Variable (traffic loads)[a)]	Hazard rate[b)]	Life expectancy (year)[b)]
	β_0	β_1	ε^k	$\bar{x}_1^k$	λ^k	L^k
K (benchmark)	-1.923 (-0.026)[c)]	0.432 (-0.002)	1.000	0.101	0.153	6.55
G ((re)construction)			0.666 (0.018)	0.101	0.102	9.84
M_1 (1st overlay)			1.046 (0.019)	0.099	0.160	6.26
M_2 (2nd overlay)			1.030 (0.012)	0.097	0.157	6.37
M_3 (3rd overlay)			1.136 (0.05)	0.119	0.175	5.72

Note: a) Normalized by (0,1]
b) Calculation of λ^k and L^k refer to Eq. (3)~(5)
c) Geweke's z-score in the parenthesis (0 means perfect convergence, and tolerance interval [-2, 2]

simulation was repeated a thousand times to derive the distribution (or range) of the average annual budget for the entire network, as well as local agencies. Finally, it was compared with the true budget of the KNH in the most recent 5 years. Note that the content of the LCCA was limited only to agency costs, and the costs are limited to the maintenance costs once again.

4.1 Application Data

Application data for empirical study is limited to maintenance history data. It is classified into 1) (re)construction G, or 2) 'n'th maintenance work over rehabilitation level (*i.e.* overlay) denoted M_n ($n = 1, ..., N$). The difference between the two types of work is whether the maintenance work includes underground structures. (*i.e.* new or reconstruction, or cutting to underground layers). Potential samples which do not have any maintenance history from the first construction were excluded. Since the data only have maintenance timing in calendar years, they only have two conditions at state $\tau_A = 1$ and $\tau_B = J$. This study assumes their time difference as measured life $\bar{L}$, which belong to heterogeneous groups $k(k = G, M_n, ..., M_N)$ respectively.

After data processing, 2,354 pair samples were obtained. For explanatory variables, a traffic load characterized by MESAL (Million Equivalent Single Axle Loads) was applied. Through the results of the data processing, M_4 and M_5 groups (i.e. 4th and 5th maintenance) were excluded from analysis because their sample scale was too small, having only 11 and 3 samples, lacking statistical meaning. This characteristic tells road agency usually conducted reconstruction work at 3rd or 4th maintenance, or not so many road sections have long elapsed years from the construction. In conclusion, the number of groups k in this study became 4 groups classified into G, M_1, M_2 and M_3. Table 1 summarizes data processing results with basic statistics.

4.2 Comparison of Heterogeneous Life Cycles and Risk Level

The BMH model estimated parameters with Geweke's diagnostic (Geweke, 1992). Based on the parameters, a benchmark process (by β, $\varepsilon = 1$) and heterogeneous processes (by β, ε^k) on life expectancy for each group were obtained. For estimation, 40,000 iterations (*i.e.* 40,000 samples) were carried out. Here, the first 20,000 samples were considered burn-in samples, and the others were used for parameter samples. Basic form of estimation of the hazard function λ^k and life expectancy L with unknown parameters β, ε^k were given in Eq. (3)~(5). The estimation results are introduced in Tables 2 and 3, and Fig. 3.

Table 2 summarizes the main results of the BMH model. The benchmark $\varepsilon^k = 1$ was around 6.55 years, and the explanatory variable, the traffic load, was significant (refer to Geweke's Z-score of β_1). In Table 3, the confidence interval of each parameter at 90% suggested as a case. Analyzers can check statistical ranges of life expectancy (e.g. 3-sigma rule (68%-95%-99.7%)). This is an important benefit of the Bayesian estimation method which provides information on uncertainty. It enables join risk management with asset management. In addition, Geweke's z-

Table 3. Statistical Intervals of Estimated Parameters

Parameters	Threshold at 5%	Expectation values	Threshold at 95%
β_0	-2.131	-1.923	-1.732
β_1	0.098	0.432	0.758
$\varepsilon^{k(G)}$	0.549	0.666	0.822
$\varepsilon^{k(M_1)}$	0.848	1.046	1.288
$\varepsilon^{k(M_2)}$	0.827	1.030	1.275
$\varepsilon^{k(M_3)}$	0.853	1.135	1.467

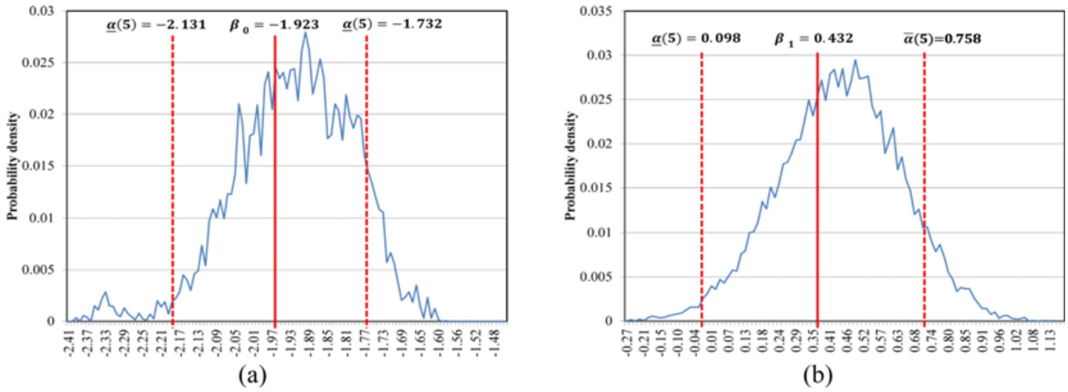

Fig. 3. Probability Density with Confidence Interval (at 90%) of Drawn Parameter Samples: (a) Case β_0, (b) Case β_1

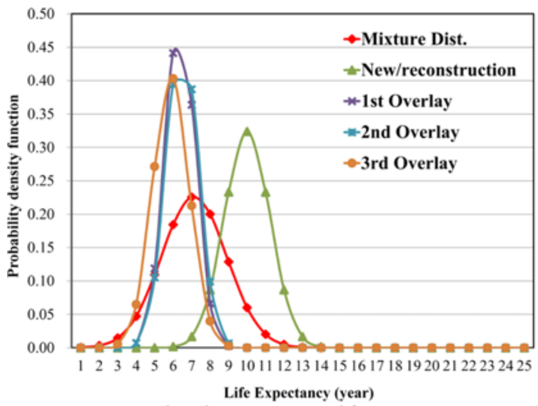

Fig. 4. Heterogeneous Life Distributions of Groups, and Their Benchmark

score of all parameters satisfied with the hypothesis tests.

The mixed distribution of heterogeneous groups attained from parameter samples is introduced Fig. 4. And the results are compared with previous research on the estimation of life expectancies conducted for the KNH in Table 4.

Contents in Fig. 4 and Table 4 could be interpreted as follows; 1) distributions of life cycles of new/reconstruction and nth overlay work groups were approximated to the normal distribution, but they have different variances and expected values. 2) The BMH model results a benchmark which has 6.55 year life expectancy. And the other maintenance groups' life expectancies were 9.84 (reconstruction), 6.26 (1st overlay), 6.37 (2nd overlay) and 5.72 (3rd overlay) year respectively. There was a definite difference in pavement performance between reconstruction G and overlay groups M_n. However, differences among the overlay groups were relatively insignificant, though it begins to get shorter by the 3rd overlay. 3) Difference in life expectancies among the research is not so serious even though different data obtained from different time and places were used.

4.3 Life Cycle Cost Analysis for the Maintenance Strategy

The changing process of life expectancy by repeated maintenance work was analyzed in the previous sections. Perhaps the road agency would like to use the information for better maintenance strategy. As an application, this paper suggests a life cycle cost analysis method for finding an optimal maintenance scheme regarding the reconstruction cycle. The life cycle cost analysis can be conducted in both a deterministic and probabilistic way.

Table 4. Comparison of Life Expectancies with Previous Studies (years)

Related research		$K^{a)}$	G	M_1	M_2	M_3	Data and estimation methods
This study	BMH model[a)]	6.55 (0.87)[b)]	9.84 (1.23)	6.26 (0.82)	6.37 (0.86)	5.72 (0.98)	– By BMH model – Maintenance history data – 1965~2010 from entire network
Reliability theory (Do, 2010)	High load[c)]	N/A	7.90 (1.94)	9.11 (3.54)			– Reliability theory using log-normal distribution (MLE-based) – Maintenance history data – 1999~2008 from capital region only
	Medium load[c)]		7.18 (1.94)	7.81 (2.97)			
	Low load[c)]		6.51 (1.52)	7.32 (3.32)			
Bayesian Markov hazard model (MCMC-based) (Han *et al*., 2014)		6.49	N/A				– Maintenance and time-series monitoring data – 2007~2010 from entire network
Conventional Markov hazard model (MLE-based) (Kobayashi *et al*., 2010)		9.21	N/A				– Maintenance and time-series monitoring data – 2003~2006 from entire network

Note : a) Benchmark representing all the groups
b) Standard deviations
c) Classified by the MESAL (Low: less than 0.2, medium:0.2~0.5, high: over than 0.5)

Table 5. Maintenance Alternatives for LCCA

Alternatives	Description	Corresponding maintenance scheme
G	Reconstruction only	$G_1, G_2, G_3, ..., G_n$
GM1	Reconstruction at 2nd maintenance	$G_1, M_1, G_2, M_1, ..., G_n, M_1$
GM2	Reconstruction at 3rd maintenance	$G_1, M_1, M_2, G_2, M_1, M_2, ..., G_n, M_1, M_2$
GM3	Reconstruction at 4th maintenance	$G_1, M_1, M_2, M_3, G_2, M_1, M_2, M_3, ..., G_n, M_1, M_2, M_3$
MT	Overlay only	$M_1, M_2, M_3, ..., M_n$

The deterministic way uses fixed life expectancies as a constant (see Table 4), while the probabilistic way draws samples from the distributions G, M_n (see Fig. 4). A difference between the two methods is whether the LCCA results are expressed as a fixed cost, or as a range considering its variance. Since the probabilistic way can give the statistical range of annual budget demand, it would be useful for negotiation between road agency and budget holder. In summary, from the LCCA, road agencies can obtain reconstruction scheme and an appropriate budget range at specific significance levels.

4.3.1 Maintenance Alternatives and LCCA Options

This study established 5 maintenance alternatives. As described, a focus of the LCCA is set to find better maintenance scheme taking into consideration reconstruction timing. The standard for judgment is the minimum agency cost. Applied alternatives are summarized in Table 5.

As for the alternative *MT*, it does not have a standard for life expectancy at $M_{3+n}(n = 1, ..., \infty)$. For the case, we assumed the life expectancy to be $L(M_{3+n}) = L(M_3)$. In addition, LCCA requires many kinds of options, such as a definition of LCC, discount rate, analysis period, target sections, and so on. Conditions for the LCCA in this study are summarized in Table 6.

4.3.2 Condition Updates by Monte-Carlo Sampling

With the options defined in Table 6, LCCA procedures can be summarized as 1) define life expectancy, 2) define detailed options, 3) draw life expectancy samples from distributions, 4) record the years and corresponding agency costs considering discount rate, 5) repeat iterations (step 1~4), and 6) summary and compare the results. Fig. 5 describes are detailed procedures concerning this.

As shown in Fig. 5, this study adopted the simplest form of the LCCA model including only agency costs. In the procedure, only the Monte-Carlo sampling part for the sample drawing will be briefly explained. At first, this study used approximated normal distributions $\mathcal{N}$ with the average $\dot{\mu}^k$ and variance $\dot{\sigma}^{2k}$ of life expectancies attained from the parameter samples $\beta^{(n)}, \varepsilon^{k(n)}, \bar{x}^k$ $(n = \underline{n}+1, \ldots, \bar{n};\ k = 1, \ldots, K)$. Characteristics of the distribution of the group k were introduced in Fig. 5 and Tables 3 and 4. Series of life expectancies of a section $\hat{L}_s^{k(t)}$ is determined by the following form,

$$\hat{L}_s^{k(t)} = \exp(\beta_0 + \beta_1 x_1^s)\cdot\varepsilon^{s_{k(t)}} \sim \mathcal{N}\{\dot{\mu}(\varepsilon)^{k(t)}, \dot{\sigma}^2(\varepsilon)^{k(t)}\}$$
$$(k = 1, \ldots, 4;\ t = t_0^s + 1, \ldots, T;\ s = 1, \ldots, 2340) \tag{26}$$

where the t is nth maintenance or reconstruction work in an analysis period, and the t_0^s indicates information on the current group of a section s before simulations. That is, $t_0^s + 1$ differs

Table 6. A Brief Summary of LCCA Options

Contents	Description
Analysis period	40 years
Number of sections	2,340 sections (Entire network of the KNH)
Alternatives	5 alternatives (*G*, *GM1*, *GM2*, *GM3* and *MT*)
Definition of LCC	Agency cost only = maintenance cost – salvage cost
Life expectancy	Probabilistic way by Monte-Carlo sampling (Iteration = 1,000 times for each alternative)
Unit costs	Interest: 5.5% (MOLIT, 2011) Unit cost for maintenance in million KRW[a] (KICT, 2009): Overlay 50 mm = 50.24 lane/km, reconstruction = 82.36 lane/km

Note: a) USD 1 = KRW 1,105 (18th Feb. 2015)

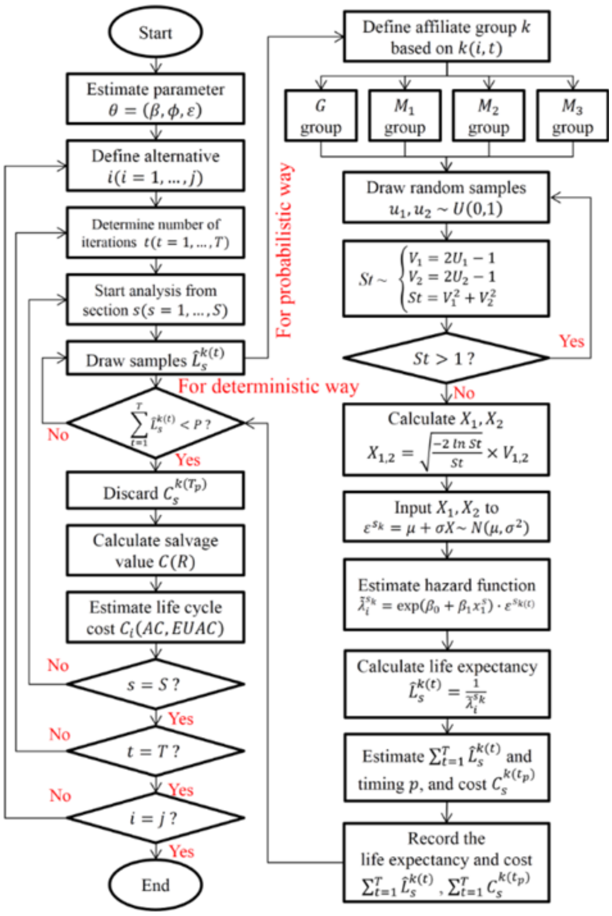

Fig. 5. Algorithm for a Probabilistic LCCA

section by section based on previous maintenance history. Since the road sections dynamically change their affiliated group at every t, in fact, each section uses the whole or part of the mixed distribution based on a definition of the alternatives.

A major technique for the simulation is generating probabilistic samples from distribution. For this process, the Box-Muller algorithm (Box and Muller, 1958) or the polar method (Knopp, 1969) can be applied. Both methods use two random samples from uniform distribution $u_1, u_2 \sim U[0,1)$ with a property, $x \sim \mathcal{N}(\mu, \sigma^2) \rightarrow Y = \mu + \sigma X \sim \mathcal{N}(\mu, \sigma^2)$. In this study, the polar method was applied for much easier sample drawing (see Fig. 5).

4.3.3 Estimation of Agency Cost

The sample drawing is continued until the sum of life expectancy $\sum_{t=1}^{T}\hat{L}_s^{k(t)}$ exceeds the analysis period P. Each maintenance work generates agency costs at a specific year in continuous numbers. In these cases, we assumed that maintenance costs happened in the next year (*e.g.* 25.4 year = 26 years) to consider the fiscal year. Thus, the discounting of agency costs was carried out based on discrete numbers $p(p = 1, ..., P)$.

At the end of the analysis year, salvage costs always occur. The term can be defined, "The remaining worth of service life of construction or maintenance work at the end of the analysis year". Many LCCA practices did not consider the cost because its scale reaches a negligible level by the discount rate with the long-term analysis period (Han, 2011). However, this study included the contents in the definition of the LCC to check its scale and effects on the final LCCA results. Calculation of the salvage cost $C_s(R)$ is given by,

$$C_s(R) = \left[\frac{C_s^{k(T-1)}}{(1+r)^p}\right]\cdot\left[\frac{\sum_{t=1}^{T}\hat{L}_s^{k(t)} - P}{\hat{L}_s^{s(T-1)}}\,\middle|\,\sum_{t=1}^{T}\hat{L}_s^{k(t)} \ge P\right] \tag{27}$$

where the $C_s^{k(T-1)}$ and $\hat{L}_s^{k(T-1)}$ indicates maintenance cost and life expectancy of the last maintenance work before the end of analysis period, respectively. r is the discount rate. Thus, agency costs under the alternative $i = (i = 1, \ldots, 5)$ is defined as follows;

$$\begin{aligned} C_i(AC) &= \sum_{s=1}^{S}\sum_{t=1}^{T} C_s^{k(t)} - C_s(R) = \sum_{s=1}^{S}\sum_{t=1}^{T}\left\{\frac{C_s^{k(t_p)}}{(1+r)^p}\,\middle|\,\sum_{t=1}^{T}\hat{L}_s^{k(t)} \le P\right\} \\ &\quad - \left[\left\{\frac{C_s^{k(T)}}{(1+r)^p}\right\}\cdot\frac{\sum_{t=1}^{T}\hat{L}_s^{k(t)} - P}{\hat{L}_s^{k(T-1)}}\,\middle|\,\sum_{t=1}^{T}\hat{L}_s^{k(t)} \ge P\right] \end{aligned} \tag{28}$$

$C_i(AC)$ may be inconvenient for understanding because it is the sum of discounted costs over a long period. Thus, this study introduced an economic indicator, EUAC (Equivalent Uniform Annual Cost), which converts the total cost into annual budget demands in average (Blank and Tarquin, 2002). Note that the general economic decision indicators, such as Net Present Value (NPV), Benefit/Cost Ratio (BCR), cannot be estimated under current LCCA structure because benefit cannot be considered. To consider the economic decision indicators, additional approaches to users and socio-environmental costs are essential.

4.3.4 Summary of the LCCA results

For the LCCA, the Monte-Carlo simulation by each alternative were conducted 1,000 times. Their trace plots and probability density were compared in Figs. 6 and 7.

The above two graphs briefly show the average level and uncertainty of annual budget demands. Determining ranking of the alternatives is also visible. For more detail information, the results were interpreted by the three-sigma rule (rules of 68-95-99.7) in Table 7.

Table 7 shows that the alternative *MT* shows the best economic feasibility in agency costs. The reason is expected to be that the LCCA option has a bias caused by the effect of the discount rate. Since the reconstruction work is assigned as the first order of the maintenance schemes, the effects of the discount rate to the reconstruction work were always higher than the overlay work. As evidence, this study checked undiscounted total agency costs (see Table 8).

As shown in Table 8, ranks among the alternatives have been changed. In this case, the alternative *GM2*, which indicates reconstruction at the 3rd maintenance work, shows the best economic feasibility. Considering the life expectancies of $G + M1 + M2$, the reconstruction cycle can be defined as around 23 years (refer to Table 4). Even though the alternative *MT* showed minimal cost when discounted, too much maintenance

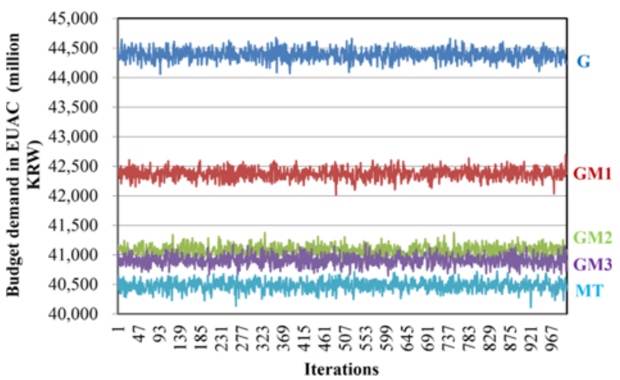

Fig. 6. Comparison of Trace-plots of EUACs by Monte-Carlo Simulation

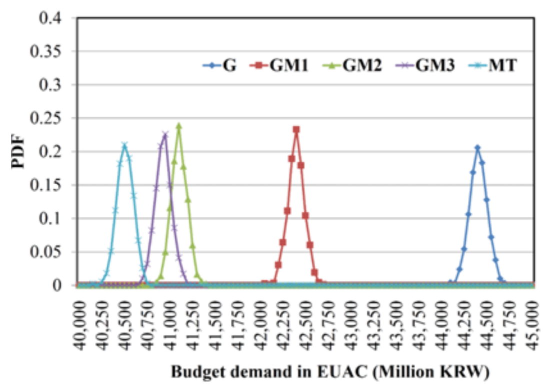

Fig. 7. Comparison of Probability Densities of EUACs by Alternative

Table 7. Results of Life Cycle Costs in EUAC by Three-sigma Rule (in million KRW[a])

Alter.	Equivalent Uniform Annual Cost			Expected budget demand at confidence levels[b]					
	EUAC	Salvage value	Num. of maintenance	3-sigma (min)	2-sigma (min)	1-sigma (min)	1-sigma (max)	2 sigma (max)	3-sigma (max)
				$\mu-3\sigma$	$\mu-2\sigma$	$\mu-1\sigma$	$\mu+1\sigma$	$\mu+2\sigma$	$\mu+3\sigma$
G	44,385	5.48%	1,618	44,090	44,216	44,341	44,433	44,555	44,646
*GM*1	42,370	5.07%	1,919	42,106	42,211	42,326	42,412	42,523	42,602
*GM*2	41,078	4.17%	2,043	40,848	40,934	41,035	41,119	41,226	41,326
*GM*3	40,905	3.83%	2,169	40,674	40,752	40,862	40,946	41,065	41,147
MT	40,480	3.25%	2,526	40,228	40,329	40,437	40,523	40,630	40,698

Note: a) USD 1 = KRW 1,105 (18th Feb. 2015)
b) 3-sigma rule (1σ = 68.26%, 2σ = 95.44%, 3σ = 99.73%)

Table 8. Total Agency Cost (undiscounted, million KRW)

Alternatives	Reconstruction		Overlay		Total cost	Rank
	Frequency	Cost	Frequency	Cost		
G	1,618	133,253	0	0	133,253	5
*GM*1	1,032	85,008	887	44,548	129,555	3
*GM*2	690	56,795	1,353	67,975	124,771	1
*GM*3	505	41,607	1,663	83,565	125,173	2
MT	0	0	2,526	126,905	126,905	4

work is demanded nearly double compared with the *GM*2. It has a possibility of becoming the worst alternative if the LCCA contains work-zone delay effects. Thus, this study concludes *GM*2 is the best scheme among the alternatives. By referring to the facts that sample size was significantly decreased at 3rd maintenance work (i.e. M_4), as well as that the design life in Korea is practically considered as 20 years, *GM*2 could be considered the most similar reconstruction scheme to KNH. Uncertainty in the estimated annual budget demand was not so serious. This is because the attained parameter samples have relatively low variance. Meanwhile, the salvage value accounts for around 3~5% of the total agency costs. Its interpretation could differed from readers' viewpoints. However, in the case of this study, it was a negligible level that cannot change the priority ranking of the alternatives.

It is still difficult to judge whether the estimated EUAC is appropriate or not. For this reason, this study reorganized the results by local agency level, and then compared them with the true budget of the KNH in the most recent 5 years. The total costs were divided into 5 local agencies by referring to the identification of each road section. Note that the true budget defined executed budget only for maintenance work, except for the other expenditures. The results are summarized in Table 9.

Although details of the maintenance schemes in reality differed somewhat with the alternatives applied in the LCCA, the total estimated budget demands were relatively similar to the true budget (112%). The reason why the estimated budget was smaller than the true budget is considered to be that the true budget includes costs for the other maintenance types such as potholes patching, crack sealing, surface treatment. In order to improve the reliability of budget estimation in local agency level, the types of routine maintenance works have to be included in

Table 9. Comparison with True Budget (million KRW)

Alters.	Total	Local agencies				
		Seoul	Daejeon	Iksan	Pusan	Wonju
G	44,385	5,101	9,026	11,047	13,731	5,480
*GM*1	42,370	4,871	8,643	10,525	13,113	5,217
*GM*2	41,078	4,705	8,385	10,209	12,720	5,060
*GM*3	40,905	4,687	8,350	10,166	12,664	5,038
MT	40,480	4,651	8,257	10,059	12,531	4,982
True budget[a]	45,825 (112%)[b]	6,549 (139%)	8,698 (104%)	18,023 (177%)	8,382 (66%)	4,172 (82%)

Note: a) True budget level in the most recent 5 years (average)
b) A relative rate with the "GM2" which is a similar scheme of the KNH

the LCC calculation, Above all, the deterioration curves differed by local conditions should be independently defined by local agency level.

5. Conclusions

This research tried to define changing deterioration speeds caused by repeated maintenance work, and to suggest a better maintenance scheme considering their characteristics. To define life expectancies, the Bayesian Markov mixed hazard model was employed. In addition, life cycle cost analysis was conducted to define the optimal maintenance strategy and budget ranges at specific confidence levels by Monte-Carlo simulation method. In the end, estimated budget demands were compared with the true budget of the Korean national highway. This study yielded some remarkable findings as follows; 1) distributions of life cycles of new/reconstruction and nth overlay work groups were approximated to the normal distribution, but they have different variances and expected values. 2) Estimated model parameters by the BMH model results a benchmark which has 6.55 year life expectancy. And the other maintenance groups' life expectancies were 9.84 (reconstruction), 6.26 (1st overlay), 6.37 (2nd overlay) and 5.72 (3rd overlay) year respectively. There was a definite difference in pavement performance between reconstruction and overlay groups. However, differences among the overlay groups were relatively insignificant, though it begins to get shorter by the 3rd overlay. 3) The LCCA results tell the alternative *GM2* which indicates that reconstruction at the 3rd maintenance work, is the optimal solution. Considering the life expectancies of the groups, the reconstruction cycle could be considered to be 23 years, similar to the general design life of 20 years in Korea. 4) Scale and effects of salvage value were not so significant. This accounts for 3~5% of total agency costs. The differences were not enough to change their rankings. 5) Although the maintenance scheme in reality is somewhat different from applied maintenance alternative, the estimated budget demands were relatively similar at 90% level to the most recent 5 years' budget for Korean national highways.

The analysis procedures and results of this study could be a good reference to build much realistic long-term asset management strategy and reasonable budget allocation. In addition, the estimation methodology and mixed hazard model with the hierarchical Bayesian estimation method is expected to be a useful tool in solving problems with heterogeneous population sampling, and in finding best practice and gaps among competitive alternatives.

References

Baik, H. S., Jeong, H. S., and Adraham, D. M. (2006). "Estimating transition probabilities in Markov chain-based deterioration models for management of wastewater systems." *J. of Water Resources Planning and Management*, Vol. 132, No. 1, pp. 15-24, DOI: 10.1061/(ASCE) 0733-9496(2006)132:1(15).

Blank, L. and Tarquin, A. (2002). *Engineering Economy (5th eds.)*, McGraw-Hill, N.Y.

Box, G. E. P. and Muller, M. E. (1958). "A note on the generation of random normal deviates." *The Annals of Mathematical Statistics*, Vol. 29, No. 2, pp. 610-611, DOI: 10.1214/aoms/1177706645.

Butt, A. A., Shahin, M. Y., Feighan, K. J., and Carpenter, S. H. (1987). "Pavement performance prediction model using the Markov process." *Transportation Research Record 1123*, pp. 12-19.

Carnahan, V. J., Davis, W. J., Shahin, M. Y. Keane, P. L., and Wu, M. I. (1987). "Optimal maintenance decisions for pavement management." *J. of Transportation Engineering*, Vol. 113, No. 5, pp. 554-572.

Do, M. (2010). "Estimation of mean life and reliability of highway pavement based on reliability theory." *J. of the Korean Society of Civil Engineering*, Vol. 30, No. 5D, 2010, pp. 497-504 (In Korean).

Fwa, T. F. (2006). *The Handbook of Highway Engineering*, Taylor & Fransis Group, LLC, London.

Geweke, J. (1992). "Evaluating the accuracy of sampling-based approaches to calculating posterior moments." *Bayesian Statistics 4* (*eds.* J. M. Bernardo, J. O. Berger, A. P. Dawid, and A. F. M. Smith), Oxford, Clarendon Press, pp. 169-193, DOI: 10.1.1.27.2952.

Golabi, K, Kulkarni, R. B., and Way, G. B. (1982). A statewide pavement management system, *Interface 12*, Providence, R.I.

Golabi, K., Tompson, P. D., and Hyman, W. A. (1993). *Pontis version 2.0 technical manual; A network optimization system for bridge improvements and maintenance*, Rep. FHWA-SA-93-031, Office of Technology, Applications, Federal Highway Administration, Washington, DC.

Han, D. (2011). Development of Open-source Hybrid Pavement Management System for An International Standard, *A Doctoral Dissertation*, Kyoto University, Japan. URL: http://hdl.handle.net/2433/151957.

Han, D., Kaito, K., and Kobayashi, K. (2014). "Application of Bayesian estimation method with Markov hazard model to improve deterioration forecasts for infrastructure asset management, *KSCE J. of Civil Engineering*, Vol. 18, No. 7, pp.2107-2119, DOI: 10.1007/s12205-012-0070-6.

Han, D., Kaito, K., Kobayashi, K., and Aoki, K. (2016). "Performance evaluation of advance pavement materials by Bayesian Markov mixture hazard model." *KSCE J. of Civil Engineering*, Vol. 20, No. 2, pp. 729-737, DOI: 10.1007/s12205-015-0375-3.

Hastings, W. K. (1970). "Monte Carlo sampling methods using Markov chains and their applications." *Biometrika,* Vol. 57, No. 1, pp. 97-109, DOI:10.1093/biomet/57.1.97.

Howard, R. A. (2007). *Dynamic Probabilistic Systems, Volume 1: Markov Models*, Dover Publication INC, Mineola, New York.

Kaito, K. and Kobayashi, K. (2007). "Bayesian estimation of Markov deterioration hazard model." *J. of Japan Society of Civil Engineers (JSCE)*, Vol. 63, No. 2, pp. 336-355 (in Japanese).

Kaito, K., Kobayashi, K., Aoki, K., and Matsuoka, K. (2012). "Hierarchical Bayesian estimation of mixed hazard models." *J. of Japan Society of Civil Engineers (JSCE)*, Vol. 68, No. 4, pp. 255-271, DOI: 10.2208/jscejipm.68.255 (in Japanese).

KICT (Korea Institute of Construction Technology) (2009). *Final-report of the National Highway Pavement Management System 2008*, Ministry of Land, Transportation, and Maritime Affair (MLTM) (in Korean).

Knopp, R. (1969). "Remark on algorithm 334 [G5]: Normal random deviates." *Communications of the Association for Computing Machinery (CACM)*, Vol. 12, No. 5, pp. 275-281, DOI: 10.1145/362946.362996.

Kobayashi, K., Do, M., and Han, D. (2010). "Estimation of Markovian transition probabilities for pavement deterioration forecasting." *KSCE J. of Civil Engineering*, Vol. 14, No. 3, pp. 343-351, DOI: 10.1007/s12205-010-0343-x.

Kobayashi, K., Kaito, K., and Lethanh, N. (2012a). "A Bayesian estimation method to improve deterioration prediction for infrastructure system with Markov chain model." *International Journal of Architecture, Engineering and Construction*, Vol. 1, No. 1, pp. 1-13, DOI: 10.7492/IJAEC.2012.001.

Kobayashi, K., Kaito, K., and Lethanh, N. (2012b). "A statistical deterioration forecasting method using hidden Markov Model for infrastructure management." *Transportation Research Part B: Methodological*, Vol. 46, No. 4, pp. 544-561, DOI: 10.1016/j.trb.2011.11.008.

Koop, G., Poirier, D. J., and Tobias, J. L. (2010). *Bayesian Econometric Methods*, Cambridge University Press, N. Y., 2007.

Lancaster, T. (1990). *The Econometric Analysis of Transition Data*, Cambridge University Press, N.Y.

Lethanh, N., Kaito, K., and Kobayashi, K. (2014). "Infrastructure deterioration prediction with a Poisson hidden Markov model on time series data." *J. of Infrastructure Systems*, Vol. 21, No. 3, pp. 04014051(1-10), DOI: 10.1061/(ASCE)IS.1943-555X.0000242, 04014051.

Madanat, S. M., Mishalani, R., and Wan Ibrahim, W. H. (1995). "Estimation of infrastructure transition probabilities from condition rating data." *J. of Infrastructure Systems*, Vol. 1, No. 2, pp. 120-125, DOI: 10.1061/(ASCE)1076-0342(1995)1:2(120).

Markov, A. A. (1907). "Extension of the limit theorems of probability theory to a sum of variables connected in a chain." *Reprinted in Appendix B of: R.A Howard, Dynamic Probabilistic Systems (Volume I: Markov Models)*, Dover Publication INC, Mineola, New York.

Metropolis, N., Rosenbluth, A.W., Rosenbluth, M. N., Teller, A., and Teller, H. (1953). "Equations of state calculations by fast computing machines." *J. of Chemical Physics*, Vol. 21, No. 6, pp. 1087-1091, DOI: 10.1063/1.1699114.

Micevski, T., Kuczera, G., and Coombes, P. (2000). "Markov model for storm water pipe deterioration." *J. of Infrastructure Systems*, Vol. 8, No. 2, pp. 49-56, DOI: 10.1061/(ASCE)1076-0342(2002)8:2(49).

Mishalani, R. G. and Madanat, S. M. (2002). "Computation of infrastructure transition probabilities using stochastic duration models." *J. of Infrastructure Systems*, Vol. 8, No. 4, pp. 139-148.

Mizutani, D. and Kaito, K. (2013). "Statistical selection of deterioration factors in RC slab of urban expressway." *Proc. of the 13th East Asia-pacific Conference on Structural Engineering and Construction (EASEC-13)*, Sapporo, Japan, URI: http://hdl.handle.net/2115/54381.

MOLIT (Ministry of Land, Infrastructure, and Transport) (2011). *A Guidebook for Investment of Transportation Facilities (4th edition)*, Report ID 2011-655, MOLIT, Sejeong-Si, Korea (in Korean).

Obama, K., Okada, K., Kaito, K., and Kobayashi K. (2008). "Disaggregated hazard rates evaluation and bench-marking." *J. of JSCE*, Vol. 64, No. 4, pp. 857-874, DOI: 10.2208/jsceja.64.857 (in Japanese).

Shahin, M. Y. and Kohn, S. D. (1982). *Overview of the 'PAVER' pavement management system, Technical Manuscript M-310*, U.S. Army Construction Engineering Laboratory, Champaign, Illinois.

Tomas, O. and Sobanjo, J. (2013). "Comparison of Markov chain and semi-Markov models for crack deterioration on flexible pavements." *J. of Infrastructure Systems*, Vol. 19, No. 2, pp. 186-195, DOI; 10.1061/(ASCE)IS.1943-555X.0000112.

Train, K. E. (2009), *Discrete Choice Methods with Simulation (2nd Eds.)*, Cambridge University Press, N.Y.,

Tsuda, Y., Kaito, K., Aoki, K., and Kobayashi, K. (2006). "Estimating Markovian transition probabilities for bridge deterioration forecasting." *J. of Structural Engineering and Earthquake Engineering, JSCE.*, Vol. 23, No. 2, pp. 241–256, DOI:10.1007/s12205-010-0343-x.

USDOT (U.S. Department of Transportation) (2002). *Asset Management Primer*, USDOT.